Water Supply

Comprehensive evaluation and scenario simulation of carrying capacity of water resources in Mu Us Sandy Land, China

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ABSTRACT

With the rapid improvement in socioeconomic conditions globally, the demand for water resources has dramatically increased. Evaluating water resource carrying capacity (WRCC) is crucial for regional sustainable development. To date, limited attention has been paid to WRCC in areas of predominantly sandy land, with the impact of vegetation restoration in ecologically degraded areas on WRCC remaining unclear. In this study, using a comprehensive evaluation index and a system dynamics model, we evaluated the WRCC of the Mu Us Sandy Land, Inner Mongolia, China, from 2000 to 2019 then projected to 2030. Our results show WRCC has decreased since 2000, reaching a general state by 2019. In a future scenario where historical development remains unabated, WRCC will continue to decline to a poor carrying state by 2030. The comprehensive scheme based on industrial restructuring and water conservation performed the best in terms of WRCC, continuously increasing and returning to a general carrying state by 2030. Our findings highlight the WRCC of the Mu Us Sandy Land is not optimistic and subsequent ecological restoration should proceed with caution. A comprehensive scheme is an optimal development strategy for the future.

Key words: analytic hierarchy process, ecological restoration, entropy weight, system dynamics model, water resources policy optimization

HIGHLIGHTS

- Water resource carrying capacity (WRCC) in the Mu Us Sandy Land has decreased since 2000.
- An increase of vegetation is one reason for the decline of WRCC.
- The WRCC based on industrial restructuring and water conservation is optimal.
- Ecological restoration of Mu Us Sandy Land should proceed with caution.

GRAPHICAL ABSTRACT
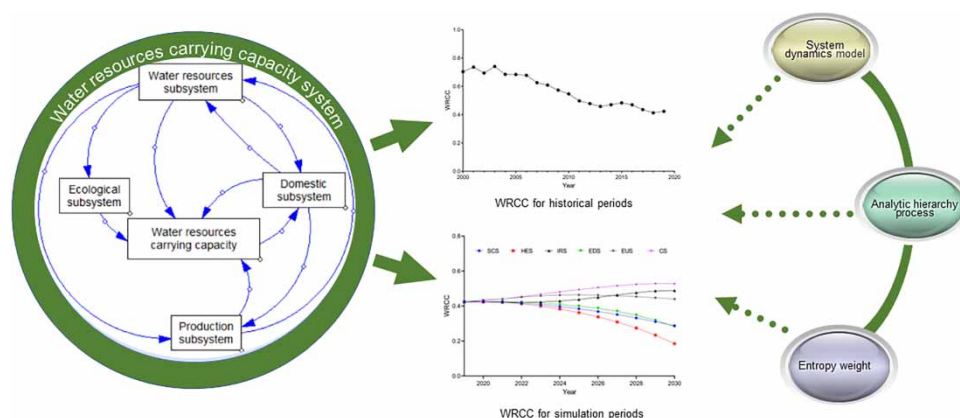
1. INTRODUCTION

Water is an essential natural resource that plays a vital role in supporting healthy human survival, regional socioeconomic development, and ecological sustainability. Water resources are widely distributed; however, the freshwater resources available for human use account for only 2% of the total. Although the threshold of freshwater resources (planetary boundary) for human use is being approached (Rockström *et al.* 2009), water scarcity is a globally growing problem. The water-stressed population has increased from 240 million in 1900 (Kummu *et al.* 2016) to 2.3 billion in 2022 (Desertification 2022). By 2050, approximately 5.7 billion people worldwide are estimated to face water shortages (Boretti & Rosa 2019). Rosa *et al.* (2020) found that water-constrained agricultural areas accounted for approximately 25% of global farmland. Water scarcity has become a serious challenge for human survival and sustainable development; therefore, rationally using water resources is a hot topic of concern for experts and scholars.

Water resource carrying capacity (WRCC) is a comprehensive index to evaluate whether water resources, economic society, and ecological environment develop in harmony (Wang *et al.* 2017b). Since the WRCC concept was proposed in the late 1980 s, research methods have been continuously enriched and improved (Zuo 2017). The analysis of the carrying capacity of water resources can be a basis for the utilization of water resources (Yang *et al.* 2019). Previous studies have evaluated WRCC at different scales: global (Simonovic 2002), continental (Zhao *et al.* 2022), national (Simonovic & Rajasekaram 2004), and regional (Yang *et al.* 2019). As research on WRCC at the regional scale becomes increasingly targeted, evaluation at this scale requires attention (Liao *et al.* 2020). The study of WRCC encompasses various areas, including natural resources, environmental, social, and economic. In terms of natural resources, WRCC levels can be used to evaluate thresholds for water resource extraction (Feng *et al.* 2009; Wang *et al.* 2018). The environmental area of WRCC commonly focuses on pollution of the water environment (Zhang *et al.* 2021). In social areas, WRCC is primarily used to evaluate the size of the urban population (Song *et al.* 2011). In the economic areas, WRCC can be used to analyze the scale of agriculture, optimize planting structure, and evaluate the production scale and water demand structure of the industry (Kang *et al.* 2019). Through the analysis of WRCC, future scenarios can be developed and used to inform different systems, including cities and agriculture (Feng *et al.* 2009).

In recent years, three main research methods have been used to evaluate WRCC, including empirical formulas, comprehensive evaluations, and system analyses. The empirical formula method includes the ecological footprint (Li *et al.* 2018) and index system methods (Zhang *et al.* 2021). Comprehensive evaluation methods include the analytic hierarchy process (AHP) (Wang *et al.* 2018; Yang *et al.* 2019), fuzzy comprehensive evaluation (Meng *et al.* 2009), and entropy weight (EW) (Cui *et al.* 2018). System analysis methods include the system dynamics (SD) (Yang *et al.* 2019) and pressure-state-response (Wei *et al.* 2014) models. Many deep-learning-based approaches, such as artificial neural networks (Shi & Zhang 2021) and the variable precondition S-type cloud algorithm (Wu *et al.* 2021), have recently been used to analyze WRCC, further enriching the available methods. Specially, the SD model emphasizes feedback mechanisms between factors. The SD model can also treat regional water resources and social, ecological, and economic coordination as a dialectically integrated system, and be used to simulate higher-order and nonlinear systems. Moreover, the SD model has been widely applied to optimize system models with multiple feedbacks and complex spatial and temporal changes (Yang & Wang 2021).

The Mu Us Sandy Land is located in the agro-pastoral ecological region of northern China; its environment is ecologically fragile and water-scarce (Liu *et al.* 2020). Many researchers have focused on the impact of sandy vegetation on groundwater (Cheng *et al.* 2017), exploring the optimal use of soil and water resources in the region (Zhao *et al.* 2021a). For example, Wang *et al.* (2014) proposed an integrated land and water development framework that combined irrigation management and cultivation practices. Despite widespread attention paid to water resources in Mu Us Sandy Land, the WRCC of the region is still unknown and future optimal water resource use patterns has yet to be explored. In this study, we first assess changes in the WRCC based on socioeconomic and water resources data from 2000 to 2019. We then explore the WRCC under six development scenarios: situation continuation scheme (SCS), high economic scheme (HES), industrial readjusted scheme (IRS), ecological development scheme (EDS), efficient use scheme (EUS), and comprehensive scheme (CS). Our aim is to explore development strategies that balance resources, production, society, and ecology based on the WRCC, thus providing scientific guidance for sustainable regional development.

2. MATERIALS AND METHODS

2.1. Overview of the study area

The Mu Us Sandy Land in Inner Mongolia (107 °20′–111 °30 E, 37 °27′–39 °22′ N) is located in the transitional zone between the Ordos Plateau and Loess Plateau. The elevation ranges from 1000–1800 meters, with the terrain sloping from northwest to southeast. The region has a temperate arid and semiarid continental monsoon climate (Liu *et al.* 2020), with mean annual precipitation is 287.2 mm, mainly concentrated between July and September, when over 70% of the annual precipitation occurs. The average annual temperature is 6–9 °C. Prior to the 1980s, the Mu Us Sandy Land was one of China's most severely desertified areas (Figure 1). In 2000, China launched a number of ecological restoration projects to control desertification. Subsequently, desertification in the region has decreased, with only 19.1% of the area covered by sand in 2015 (Guo *et al.* 2021). The region has experienced rapid economic development and steady population growth since the early 2000s. For example, Gross Domestic Product has increased 34.92 times from RMB 4.40 billion in 2000 to RMB 153.660 billion in 2019, while population growth has increased over this period by 20%, from 395,500 to 475,400.

2.2. Data collection

We obtained socioeconomic and water resource data from the *Ordos Statistical Yearbook* and the *Ordos Water Resources Bulletin*, respectively, for the years from 2000 to 2019. The statistical yearbook records statistical data on economic development, domestic life, ecological construction, and wastewater discharge and treatment. Economic development considers industrial production value, the number of livestock, and effective irrigated area of crops, among other factors. Domestic life comprises both urban and rural populations. Ecological construction considers grassland, woodland, and urban green
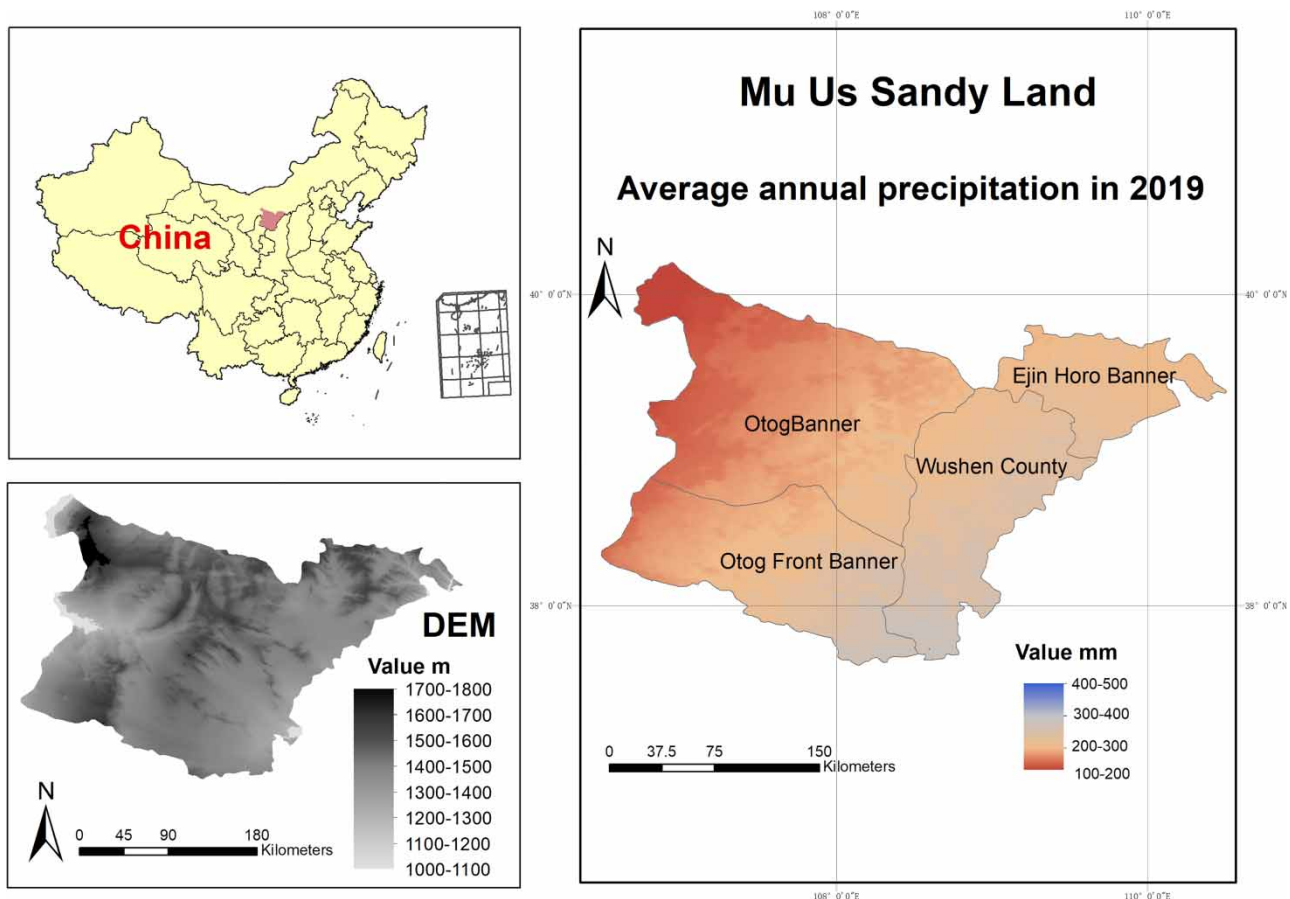
Figure 1 | Geographical location of Mu Us Sandy Land.

areas. The Water Resources Bulletin is a comprehensive report on current water resources, documenting the regional water supply, availability, consumption, and the environment. We also obtained other information (such as industrial water quotas) from the Statistics Bureau of the Inner Mongolia Autonomous Region (http://tj.nmg.gov.cn/).

2.3. Research methodology

Based on the statistics data, the SD model is established, combined with comprehensive evaluation indicators, to evaluate the comprehensive WRCC in the historical period and under different scenarios in the future. Finally, we can obtain the optimal development strategy suitable for the region. In this study, we followed the methodological flowchart shown in Figure 2.

2.4. SD models

We used an SD model as they are widely applied in water resource management and water environment safety assessments (Chen & Wei 2014; Zhang et al. 2021). Concepts used to build a SD model include boundaries and hierarchy, feedback loops, level variables, and rate variables. The SD model is divided into two stages: model construction and simulation. The model construction stage is based on causal relationships and reflects the internal mechanism of the system through a system structure flowchart. In the latter simulation stage, responses in a system are simulated by adjusting sensitive parameters using different development strategies in order to determine the optimal development model (Zomorodian et al. 2018).

There are two important variables in SD models: a level variable and a rate variable. Level variables represent the cumulative result of material or information changing with time; rate variables reflect the speed of the cumulative effect in the system. Through the analysis of the internal dynamic structure of the subsystem, the total population, the number of sheep, etc., are selected as level variables, and the birth rate, the change rate of the average annual number of sheep, etc., are selected as rate variables.

We divided the SD model in our study into water resources, production, domestic, and ecological subsystems. The water resource subsystem considers surface, ground, and recycled water, where recycled water mainly refers to the recycling of production and domestic wastewater. The production subsystem considers water demand for animal husbandry, agriculture, and production in secondary and tertiary industries. The domestic subsystem considers the domestic water of urban and rural residents. The ecological subsystem mainly consists of grassland, woodland, and urban green area water consumption.

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We considered the administrative region of the Mu Us Sandy Land in Inner Mongolia as the spatial boundary for the SD model. The time scale was from 2000–2030, with the data error analysis period from 2000–2019, the simulation period from 2020–2030, the simulation base year being 2019, and the simulation time step is one year. We then established the SD model of WRCC consisting of 20 table functions, 15 level variables, 16 rate variables, 37 auxiliary variables, 22 constants, and 115 system dynamics equations. The SD model is shown in the figure below (Figure 3). The formulas are detailed in Appendix A.

2.5. Comprehensive evaluation index system

Scientific and reasonable judgment of an evaluation index weight plays a vital role in determining the accuracy and credibility of the quantitative results of the studied objectives (Yang et al. 2019). Current methods for obtaining weights of evaluation indicators are divided into two categories: subjective and objective measurements. AHP is a commonly used subjective calculation method (Yan et al. 2021), and objective calculation methods include EW (Cui et al. 2018) and fuzzy comprehensive evaluation (Gong & Jin 2009). As WRCC is a system affected by many aspects, such as the economy, society, ecology, and other elements, it is complex and uncertain. To improve the scientific and accuracy of the WRCC assessment results, we integrated subjective and objective methods using a comprehensive index calculation formula to combine the weights determined from AHP and EW methods.

We used the average method to obtain the comprehensive weights (Chen et al. 2015; Ren et al. 2021) (Table 1):

$$w_i = (a_i + b_i)/2 \tag{1}$$

where w_i is the comprehensive weight of the ith indicator in the WRCC evaluation index system, a_i is the weight of the ith indicator calculated by the AHP, and b_i is the weight of the ith indicator calculated using the EW. All computational details about a_i and b_i can be found in appendix B.
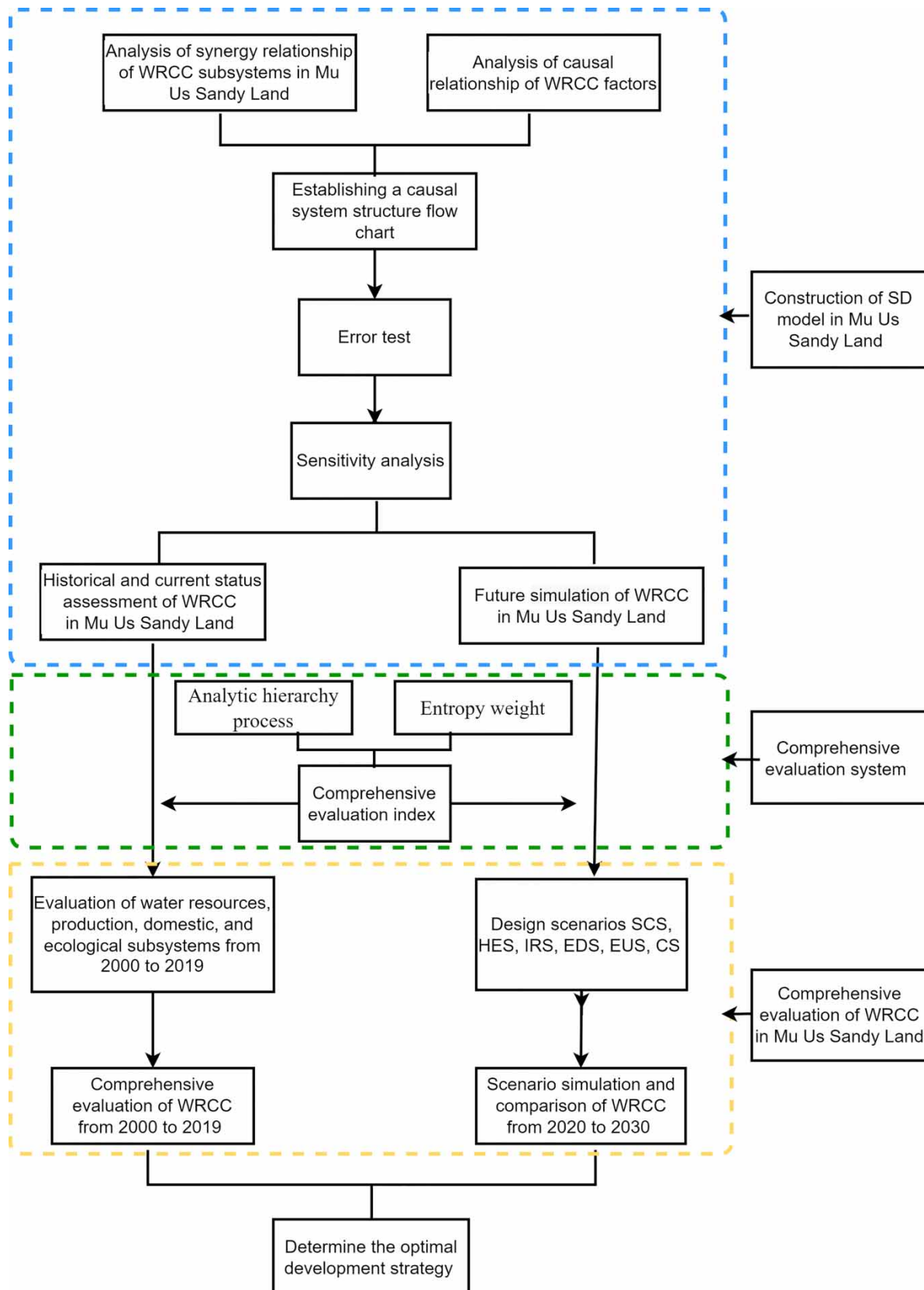
Figure 2 | Flowchart of our research methodology on the WRCC in Mu Us Sandy Land.
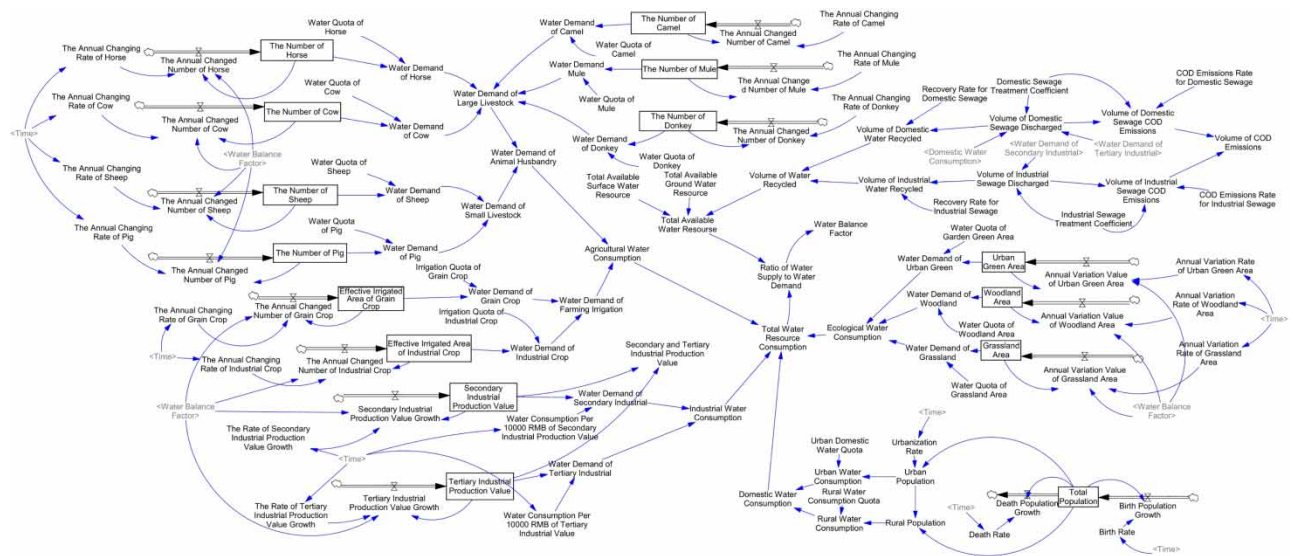
Figure 3 | System dynamics flowchart of the water resources in Mu Us Sandy Land, Inner Mongolia, northern China.

2.6. Calculation of the WRCC

To determine the comprehensive WRCC score, we weighted and summed the scores for all indicators after standardizing the data. Drawing on the results of previous studies and using the natural fracture method, we classified WRCC into five classes: weak (0–0.2), poor (0.2–0.4), general (0.4–0.6), positive (0.6–0.8), and excellent (0.8–1.0) (Yang *et al.* 2019; Yan *et al.* 2021).

$$WRCC_j = \sum_{i=1}^{n} W_i D_{ij} \tag{2}$$

where $WRCC_j$ is the WRCC indicator value in jth year, where the value range of j is [2000, 2030]; w_i is the comprehensive weight of the ith indicator in the WRCC evaluation indicator system; and D_{ij} is the standardized data of the ith indicator in jth year.

2.7. Error test

Conducting error analysis is a critical step for SD models (Wang *et al.* 2017a). We used the statistical data from 2000 to 2019 for both model construction and simulation, thus verifying the accuracy of the simulated data against the statistical data. Based on the characteristics of the integrated model and the representative indicators of the four subsystems, we investigated six indicators for the error analysis: the available groundwater resource, total population, effective irrigated area of grain crop, tertiary industrial production value, the number of sheep, and grassland areas. When the error was within 10%, the model was considered to be valid due to not substantially different from the real value.

$$Error\ (\%) = \frac{Simulated\ data - Historical\ data}{Historical\ data} \tag{3}$$

2.8. Sensitivity analysis

We performed a sensitivity analysis to verify the robustness of the model and determine its reliability (Yan *et al.* 2021). To do this, we adjusted the parameters with the help of the 'sythesim' tool in the Vensim software. We used a stratified sampling method to select 20 test parameters, such as the annual changing rate of grain crop and birth rate, and eight target variables, such as the ratio of water supply to water demand and volume of COD emissions. We adjusted each test parameter to increase at a rate of 10% per year during the simulation period from 2020 to 2030, and then observed the extent of change in the target

Table 1 | Basic composition of the evaluation index system and weights of each evaluation index

Object hierarchy	Water supply/ demand system	Rule hierarchy	Rule hierarchy weighted value	Indicator hierarchy	Indicator description	Weighted indicator value	Synthesized weighted value
WRCC of Mu Us Sandy Land	Water supply system	Water resources subsystem	0.4048	Total available surface water resource	Reflects the amount of total available surface water resource	0.1795	0.0726
				Total available ground water resource	Reflects the amount of total available ground water resource	0.2240	0.0907
				Recovery rate for industrial sewage	Reflects the recovery rate for industrial sewage	0.1008	0.0408
				Ratio of water supply to water demand	Reflects the level of water supply capacity	0.3642	0.1474
				Volume of COD emissions	Reflects the pollution status of the water environment	0.1316	0.0533
	Water demand system	Production subsystem	0.2362	Water demand of farming irrigation	Reflects the water consumption of farming irrigation	0.1319	0.0312
				Effective irrigated area of grain crop	Reflects the actual irrigated cultivated land area	0.0993	0.0235
				Water demand of animal husbandry	Reflects the water consumption of animal husbandry	0.1053	0.0249
				Water consumption per RMB 10,000 of secondary industrial production value	Reflects the amount of water consumption per RMB 10,000 of gross output of secondary industrial	0.1392	0.0329
				Water consumption per RMB 10,000 of tertiary industrial production value	Reflects the amount of water consumption per RMB 10,000 of gross output of tertiary industrial	0.1174	0.0277
				Water demand of secondary industry	Reflects the water consumption of secondary industry	0.1731	0.0409
				Water demand of tertiary industry	Reflects the water consumption of tertiary industry	0.2339	0.0552
		Domestic subsystem	0.1907	Urbanization rate	Reflects the level of urbanization	0.1954	0.0372
				Total population	Reflects the regional population	0.3313	0.0632
				Domestic water consumption	Reflects the water consumption of domestic	0.4732	0.0902
		Ecological subsystem	0.1683	Water demand of woodland	Reflects the water consumption of woodland	0.2897	0.0488
				Water demand of grassland	Reflects the water consumption of grassland	0.3886	0.0654
				Water demand of urban green	Reflects the water consumption of urban green	0.3218	0.0542

variables after the change in the test parameters. The relationship between the test and target variables is expressed as follows:

$$S_t = |[(Y'_{(t)} - Y_{(t)})/Y_{(t)}] \times [X_{(t)}/(X'_{(t)} - X_{(t)})]| \tag{4}$$

$$S = \frac{1}{n} \times \sum_{i=1}^{n} S_{t(i)} \tag{5}$$

where, t is the simulation period time and takes values in the range from 2020 to 2030; S_t is the sensitivity of the test parameter to the target variable at time t; $Y_{(t)}$ and $Y'_{(t)}$ are the original and changed values of the target variable at time t, respectively; $X_{(t)}$ and $X'_{(t)}$ are the original and modified values of the test parameter at time t, respectively. The S denotes the average degree of sensitivity. If $S \geq 0.15$, the variable is very sensitive; if $0.15 > S \geq 0.1$, the variable is more sensitive; if $0.1 > S \geq 0.05$, the variable is less sensitive; and if $S < 0.05$, the variable is not sensitive (Yang et al. 2019). The model is considered robust and valid if it is sensitive to only a few parameters and insensitive to most parameters and structural adjustments (Wang et al. 2017a).

2.9. Scenario setting

We designed the following six scenarios to explore the changes of WRCC under different schemes (Table 2).

Table 2 | Scenario type setting

Scenario type	Detailed description
Situation continuation scheme (SCS)	This scenario follows the historical development trend without disturbance or change. All parameters remain unchanged.
High economic scheme (HES)	In this scenario, the rate of secondary and tertiary industrial production value growth increases by 15%, the annual rate of grain and industrial crops increases by 20%, the birth rate increases by 8%, and the urbanization rate increases by 8%. The remaining parameters were not changed.
Industrial readjusted scheme (IRS)	This scenario optimizes the type of industrial structure and actively transforms it into a green and environmentally friendly tertiary industry. The annual rates of grain and industrial crops decrease by 10%. The change rates of secondary and tertiary industrial production value growth reduce by 10 and 20%, respectively, and the urbanization rate increases by 8%. The remaining parameters were not changed.
Ecological development scheme (EDS)	In this scenario, the cultivated land area moderately reduces green area investment is vigorously promoted. The annual rates of grain and industrial crops decrease by 10 and 5%, respectively; the annual variation in urban green areas increases by 7%; and the annual variations in grassland and woodland areas increase by 10%. The COD emission rate for industrial and domestic sewage reduces by 20%. The remaining parameters were not changed.
Efficient use scheme (EUS)	Strict water resource conservation indicators are implemented, and the water demand quotas for various units are reduced. Among them, the water consumption per RMB 10,000 secondary and tertiary industrial value decreases by 30%, and the irrigation quota of grain and industrial crops decreases by 40%. Urban and rural domestic water decrease by 15%; the areas of various types of ecological water such as grassland, woodland, and urban green areas reduce by 20%; and the water consumption for the breeding of livestock undergoes a 10% reduction. The remaining parameters were not changed.
Comprehensive scheme (CS)	We constructed a comprehensive use development model according to the water resource carrying capacity trend of the first five single development types. Based on the adjustment of IRS and EUS, the rate of secondary industrial production value growth reduces by 10%, the rate of tertiary industrial production value growth increases by 20%, the birth rate increases by 8%, the urbanization rate increases by 8%, ecological construction remains at the current level, and urban green areas increase by 1%. We implemented other relevant water quotas following the EUS. The remaining parameters were not changed.

3. RESULTS

3.1. SD model validation

The error analysis results indicated that the absolute values of the errors were within 10% (Appendix C). However, the sensitivity of each parameter did vary widely. Although most parameters were not sensitive, individual parameters generally were more sensitive. Therefore, the SD model was found to be robust and modifying parameters was possible to investigate the six scenarios (Table 3). In other words, the simulation results of the SD model fit the collated data, and could be used for forecasting the WRCC of the Mu Us Sandy Land.

3.2. Analysis of the WRCC in Mu Us Sandy Land

As a water supply system, the carrying capacity of the water resources subsystem in the Mu Us Sandy Land has been general for most of the study period, with positive states in 2003, 2005, and 2006 (Figure 4(a)). Overall, it showed a trend of fluctuation between 2000 and 2005, reaching the lowest value of 0.4022 in 2011, after which the carrying capacity began to increase.

Table 3 | Sensitivity analysis results for some representative variables used in the SD model

Test parameter \ Target variable	Effective irrigated area of grain crop	Grassland area	Ratio of water supply to water demand	Secondary and tertiary industrial production value	Number of sheep	Total population	Total water resource consumption	Volume of COD emissions
Annual change rate of grain crops	0.3963	0	0.1106	0	0	0	0.1536	0
Annual change rate of industrial crops	0	0	0.0102	0	0	0	0.0108	0
Rate of secondary industrial production value growth	0	0	0.0103	0.1372	0	0	0.0563	0.0860
Rate of tertiary industrial production value growth	0	0	0.0016	0.1726	0	0	0.0422	0.2700
Birth rate	0	0	0	0	0	0.0731	0.0004	0.0028
Urbanization rate	0	0	0.0001	0	0	0	0.0014	0.0090
Urban domestic water quota	0	0	0.0003	0	0	0	0.0043	0.0273
Irrigation quota of grain crop	0	0	0.3534	0	0	0	0.3664	0.0000
Water consumption per RMB 10000 of secondary industrial production value	0	0	0.0451	0	0	0	0.2725	0.4107
Water consumption per RMB 10000 of tertiary industrial value	0	0	0.0053	0	0	0	0.0923	0.5819
Annual variation rate of grassland area	0	0.2513	0.0273	0	0	0	0.0310	0
Annual variation rate of woodland area	0	0	0.0023	0	0	0	0.0023	0
Annual variation rate of urban green area	0	0	0.0011	0	0	0	0.0011	0
Annual change rate of sheep	0	0	0.0028	0	0.2764	0	0.0029	0
Annual change rate of cows	0	0	0.0020	0	0	0	0.0020	0
Irrigation quota of industrial crops	0	0	0.0911	0	0	0	0.0920	0
Recovery rate of industrial sewage	0	0	0.3183	0	0	0	0	0
Recovery rate of domestic sewage	0	0	0.0902	0	0	0	0	0
Water quota of grassland area	0	0	0.1320	0	0	0	0.1337	0
Water quota of woodland area	0	0	0.0199	0	0	0	0.0199	0

*Note: Different colors represent different degrees of sensitivity. Red, very sensitive; orange, more sensitive; blue, less sensitive; gray, not sensitive.
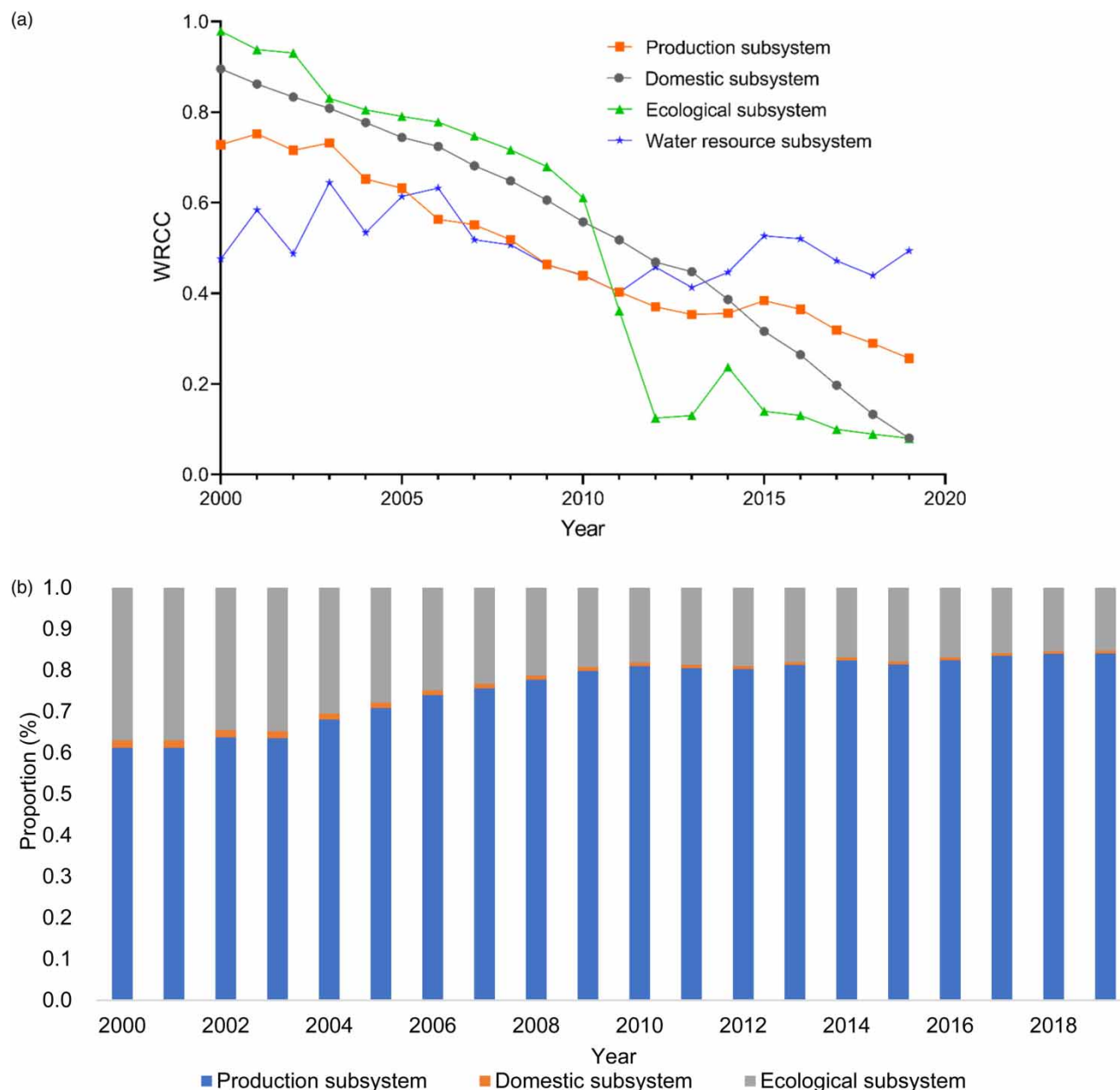
Figure 4 | (a) Historical trend of WRCC for subsystems. (b) Proportion of water in the water demand subsystems.

The three water demand subsystems are production, domestic, and ecological subsystems. Among them, the production subsystem accounted for the largest proportion of water consumption, with ecological and domestic subsystems ranking second and third over the past 20 years, respectively (Figure 4(b)). The carrying capacity of the production, domestic, and ecological subsystems had an overall decreasing trend (Figure 4(a)). The carrying capacity of the production subsystem showed a fluctuating decline, with a carrying capacity indicator of 0.2567 by 2019, representing a poor carrying status. The carrying capacity of the domestic subsystem declined at an even rate, with a carrying capacity of 0.0804 by 2019, representing a weak carrying status. The ecological subsystem maintained an optimal carrying capacity in 2000, but by 2019, the carrying capacity was weak, showing the largest decline and a carrying capacity indicator of 0.0802 (Figure 4(a)).

The change in the carrying capacity of the comprehensive subsystems, indicated by the comprehensive WRCC of the Mu Us Sandy Land, has shown an overall downward trend since 2000. From 2000 to 2008, it was positive; in 2003, it reached a

30-year high, with a carrying capacity of 0.7407. From 2009 to 2019, it was in a general state. In 2018, the carrying capacity decreased to a minimum of 0.4131 (Figure 5).

## 3.3. Simulation results for different scenarios

The simulation results showed that the CS scenario produces the highest integrated WRCC, which continuously increases to a general carrying capacity of 0.5278 by 2030 (Figure 6). The worst scenario is HES, with a low carrying capacity of 0.1852 by 2030, representing a weak carrying capacity. The carrying capacity in SCS continues to drop to 0.2875 by 2030, representing a poor carrying state. EDS outperforms SCS in the short term, but by 2030 carrying capacity will be slightly lower, making EDS less optimistic in the long term. In the EUS scenario, WRCC showed a relatively stable state, rising slightly in the short term, reaching a maximum value of 0.4638 in 2025, and then slightly decreasing after 2026. In the IRS scenario, the overall WRCC does not considerably increase in the short term but is effectively improved over the long term, rising to 0.4888 by 2030, representing a general carrying capacity.

In particular, we updated the actual WRCC in 2020 based on the latest data. The results show that the WRCC is 0.4106, and the error compared with the SCS is 4.33%. Obviously, the result is less than 10%, further demonstrating that our simulations are robust and reliable.

3.4. Comparison of scenarios

The results of the SCS scenario showed that the WRCC will struggle to meet the needs under the current development plan, degrading to a poor status by 2024 and continuously trending downward (Figure 6). The ratio of water supply to water demand (Figure 7(a)), volume of COD emissions (Figure 7(b)), and ecological water consumption (Figure 7(d)) of SCS were in the medium range among the six considered simulation scenarios, with the production value being lower than that of HES and CS (Figure 7(c)).

The HES scenario results showed increasing the development speed of various sectors in society is conducive to rapid economic development. Under this development scenario, the production output value will be 2.08 times higher than that of SCS by 2030 (Figure 7(c)), dramatically improving social productivity. However, the ratio of water supply to water demand will decrease to 0.6698 times that of SCS (Figure 7(a)), exacerbating water stress. The volume of COD emissions will reach its highest level; thus, the water pollution problem will become severe, with COD rising to 2.01 times the SCS scenario (Figure 7(b)).
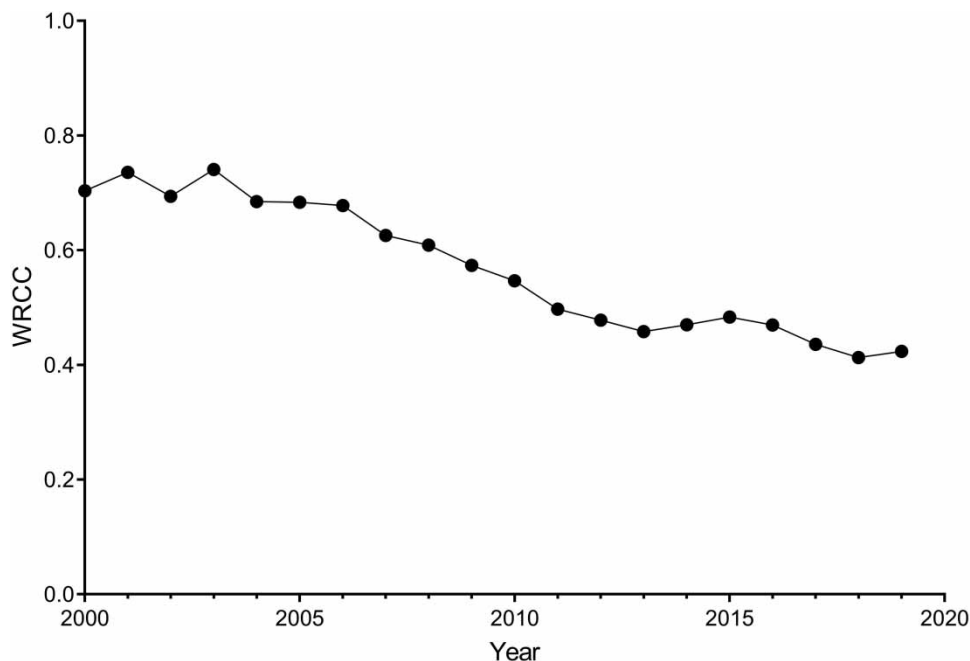
Figure 5 | WRCC in Mu Us Sandy Land, Inner Mongolia, over a 20-year period.
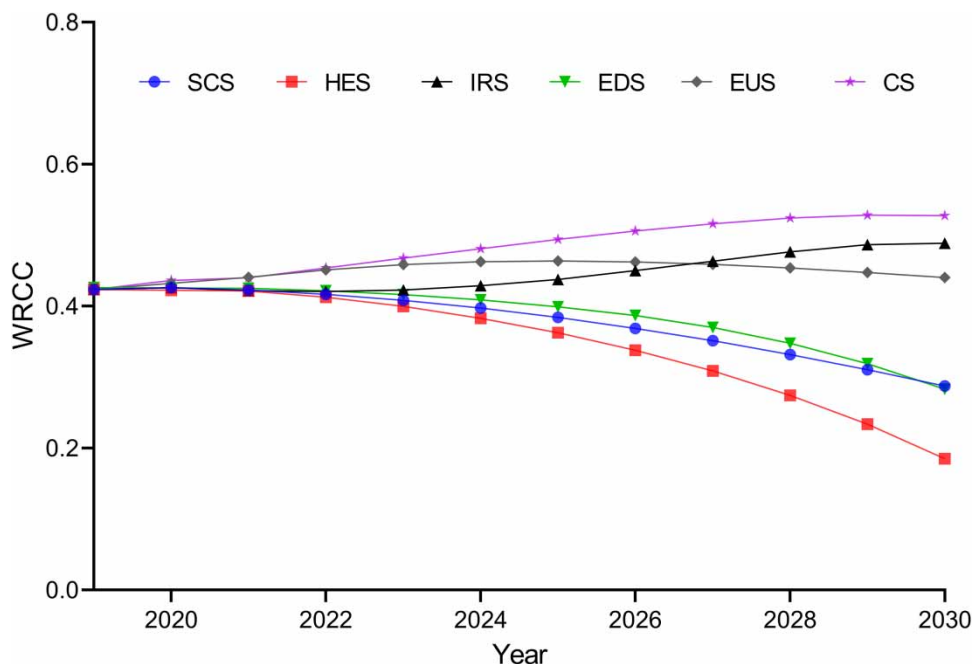
Figure 6 | WRCC in Mu Us Sandy Land for the years from 2019 to 2030.

The results of the IRS scenario showed that the ratio of water supply to water demand will be lower and higher than that of the SCS in the short- and long-term, respectively (Figure 7(a)). Similarly, the production value in the IRS scenario will begin to exceed that of SCS in 2027, increasing to 1.21 times that of SCS of 2030 and continuing to rise, which may contribute to the economy to some extent (Figure 7(c)). The volume of COD emissions will be lower than HES in the long term and 1.5777 times higher than SCS (Figure 7(b)).

The EDS scenario results showed the ratio of water supply to water demand will be lower than the SCS (Figure 7(a)), indicating that the demand for water increases when the ecological area reaches a certain size. This scenario suggested that implementing environmental protection policies may slow COD emissions to a certain extent (Figure 7(b)). The EDS scenario results suggest total ecological water consumption will substantially increase 1.61 times that of SCS by 2030 (Figure 7(d)).

The results for EUS showed that this scenario will remarkably improve the ratio of water supply to water demand by only saving water. However, with the development of the socio-economy, the demand for water resources will increase, which will reduce the optimization effect (Figure 7(a)). The impact of EUS on environmental protection is pronounced. It will beneficially reduce COD emissions (Figure 7(b)) and effectively reduce the use of ecological water resources, being approximately 20.01% lower than the SCS scenario (Figure 7(d)).

The CS scenario results showed that this scenario will optimize the ratio of water supply to water demand, and a balance between supply and demand can be achieved in the long term (Figure 7(a)). The volume of COD emissions will be much lower than that of SCS, being approximately 0.53 times lower than the SCS scenario by 2030 (Figure 7(b)). The production output will be higher than that of SCS by 2030 (Figure 7(c)). The ecological water demand will be stabilized by controlling the ecological water quota while maintaining the current ecological status, reducing water consumption by 35.53% compared with the SCS scenario (Figure 7(d)).

4. DISCUSSION

The WRCC is often used to evaluate the role of water resources in supporting social life, economic development, and ecological construction within a specific time and region by providing the basis for implementing sustainable development strategies (Liao *et al.* 2020). Previous studies quantifying WRCC show wide regional heterogeneity, categorized poor (Yang & Wang 2021), general (Yang *et al.* 2019), and positive (Peng *et al.* 2021) states. Even in humid and semi-humid regions where water resources are abundant, water demand can be higher than water supply, and therefore, the WRCC is weak (Feng
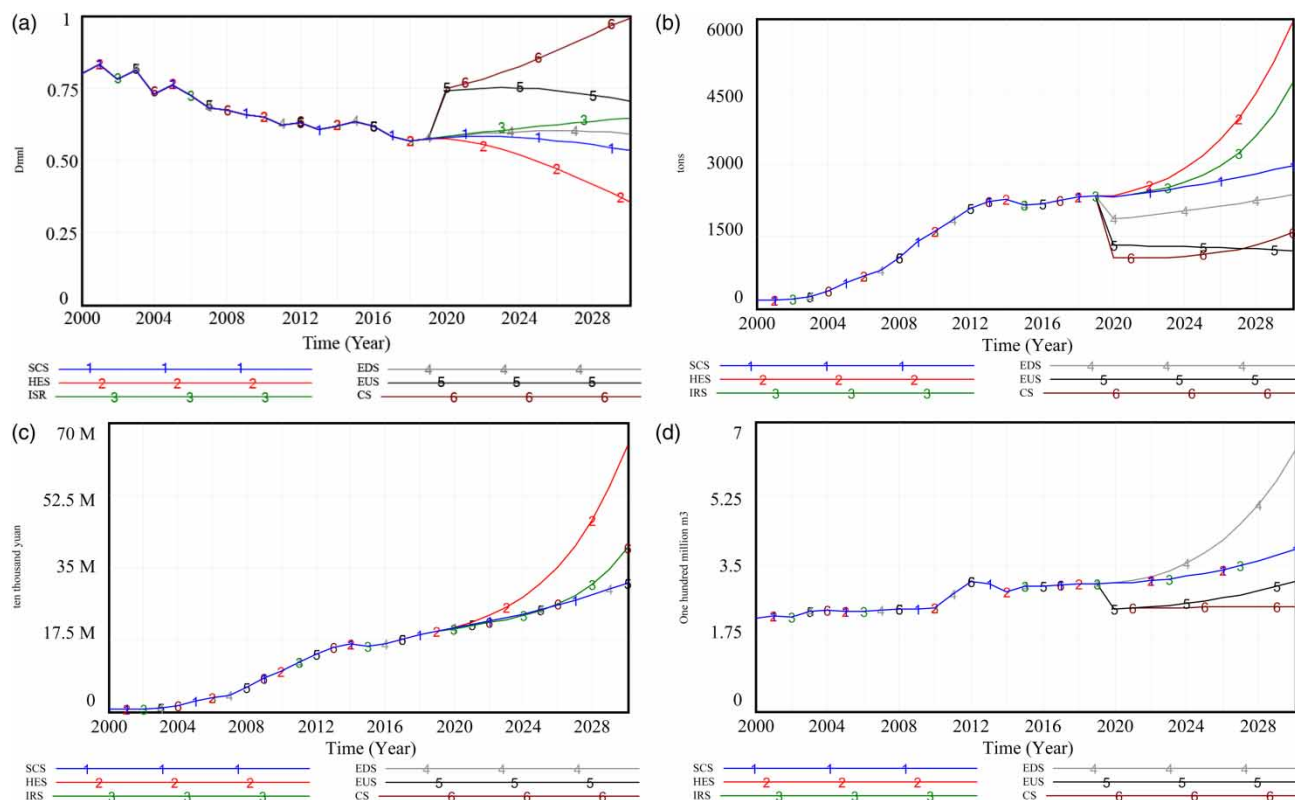
Figure 7 | (a) Ratio of water supply to water demand. (b) Volume of COD emissions. (c) Production value. (d) Ecological water consumption.

et al. 2009; Yang & Wang 2021). Our results suggest the WRCC of the Mu Us Sandy Land has declined from a positive to general carrying capacity over the period from 2000 to 2019 (Figure 5). If the current trend continues, WRCC will deteriorate further and reach a poor status by 2024 (Figure 6). These findings are similar to those of previous studies on the Loess Plateau (Gong & Jin 2009), Guanzhong Plain (Yang *et al.* 2019), Tarim River Basin (Meng *et al.* 2009), Bosten Lake Basin (Wang *et al.* 2018), and Weihe River Basin (Yan *et al.* 2021) in arid and semiarid regions in China. Therefore, the WRCC status of arid and semiarid regions in China is generally poor and requires further attention.

Many researchers have found that social and economic factors, as opposed to natural factors, are often the leading causes of the decline in regional WRCC (Zhao *et al.* 2021b). Based on our analysis of subsystems, rapid social and economic development appears to be the main factor causing the overall decline in WRCC in the Mu Us Sandy Land over the 20-year period. The main city in Mu Us Sandy Land is Ordos, which is a crucial energy-rich area and heavy-industry base in China. Coal is the primary energy source in the region, and each ton of mined coal requires 0.18 m^3 of water. Since 2000, the coal production in the area has increased from 10.18 million tons to 293.13 million tons, a 28.779-fold increase (Appendix D. Figure 1). In addition, the main industry in the region revolves around the coal-chemical industry, with an industrial water consumption rate of approximately 40.02 m^3/RMB 1 million. The production subsystem consumes a tremendous amount of water (accounting for approximately 60% or more of the total water consumption) and is the main use of the water resources (Figure 4(b)). Consequently, rapid economic development has led to the deterioration in regional WRCC. Furthermore, the number of people in the region has increased annually over the 20-year period, with the urbanization rate continuing to increase (Appendix D. Figure 2). The increase in population has led to a gradual deterioration in the WRCC of the domestic subsystem. Social development has also led to a decline in the regional WRCC.

China has implemented numerous ecological restoration projects to restore degraded ecosystems (Liu *et al.* 2020). Ecological restoration projects help prevent wind and sand pollution and improve the ecological environment (Su *et al.* 2022). However, recent studies have begun to increasingly pay attention to the impact of ecological restoration on water resources, arguing that ecological restoration requires large amounts of water consumption, which affects soil moisture and exacerbates

regional drought (Xiao *et al.* 2020). Ecological restoration increases vegetation growth and has been shown to lead to an eco-system water imbalance in the Loess Plateau and Kubuqi Sands (Li *et al.* 2016; Chen *et al.* 2022). Our results suggested the WRCC of ecological subsystems decreased from excellent in 2000 to weak by 2019 (Figure 4(a)). Future scenario simulations showed the EDS scenario could help to improve the WRCC in the short term but might increase pressure on WRCC at longer time scales (Figure 6). This is likely due to ecological restoration of Mu Us Sandy Land in recent years has led to increases in the vegetated area and in the ecological water demand of plants, which exceeds the regional ecological threshold. A previous study by Zheng *et al.* (2020) also suggested the ecological restoration of the Mu Us Sandy Land could exacerbate water scar-city in the region. Therefore, in addition to social and economic factors, ecological restoration might contribute to the deterioration in WRCC. Considering the possible opportunity costs of ecological restoration in arid and semiarid areas, we recommend ecological restoration should be conducted under the WRCC threshold to avoid the overexploitation of groundwater resources (Lu *et al.* 2018). We also advocate the promotion of sand-tolerant plants with low water consumption and high survival rates, ensuring a balance between water resources and regenerating vegetation (Zhao *et al.* 2021a).

After quantitatively evaluating regional WRCC, previous studies have explored future strategies for WRCC under different local development scenarios based on the current WRCC. In arid and semiarid regions, optimal development patterns include scenarios such as increasing water resource supply (Wang *et al.* 2018), optimizing agricultural water consumption (Yang *et al.* 2019), implementing water conservation measures (Meng *et al.* 2009), and optimizing and upgrading industrial structures (Yang & Wang 2021). We found that under the CS scenario, the WRCC of the Mu Us Sandy Land remains in a general status, showing a stable upward trend (Figure 6). The ratio of water supply to demand is good (Figure 7(a)), the pro-duction value develops more rapidly (Figure 7(c)), and the volume of COD emissions (Figure 7(b)) and ecological water consumption (Figure 7(d)) are low. This strategy combines the advantages of the IRS and EUS scenarios and is more effective at enhancing WRCC than a single strategy. Compared with the single-strategy design, EUS is much better at improving WRCC on short time scales and IRS on long time scales (Figure 6). The former confirms the effectiveness of water conservation measures. However, the rapid increase in water demand cannot be balanced by water-saving policies and technologies in the long term because of the further increase in water demand as society develops. The latter reflects the current industrial structure of the Mu Us Sandy Land will likely require further adjustment and optimization. People should actively seek indus-trial transformation in favor of the tertiary sector, which consumes less water. Given the above findings, a comprehensive strategy based on water conservation and an industrial adjustment plan is the most appropriate development strategy for the region (Figure 6).

Combining the comprehensive index evaluation and the SD model is a widely used method to scientifically and objectively evaluate regional WRCC (Yang *et al.* 2019). Although we used these two methods, our study still has limitations. First, the *Ordos Statistical Yearbook* and the *Ordos Water Resources Bulletin* were published from the year 2000 only. This means we were not able to utilize earlier historical data, limiting the model construction of WRCC for the Mu Us Sandy Land to only 20 years. Notably, some of the ecological restoration projects in the area, such as the restoration of farmland to forest and grass, began around 2000. Therefore, obtaining data before 2000 would have been useful in gaining a longer-term understanding of WRCC dynamics in the region. Second, studies dealing with higher-order, nonlinear, and spatially and temporally complex system problems have commonly used the SD model to describe and simulate water resource sys-tems for WRCC analysis (Chen & Wei 2014). However, the SD model has certain constraints, mainly owing to the complexity and uncertainty of the real-world situation. Although our study involved multiple elements of natural resources, production, society, and ecology, the complex system we constructed is still a simplified model compared to the actual, real-world system. Therefore, in future research, we recommended building further integrated models that combine SD with other methods, such as dynamic neural networks (Zomorodian *et al.* 2018), to assess the carrying capacity of local water resources more accurately.

5. CONCLUSIONS

In this study, we considered the Mu Us Sandy Land as the research area and used the comprehensive index evaluation and SD model trained on natural-society-economic data for the Mu Us Sandy Land in Inner Mongolia to analyze WRCC from 2000 to 2019 and under six future scenarios out to 2030. Our results found the WRCC has been declining in the region since 2000, and the carrying state has changed from general (0.6786) to poor (0.4235). We found an integrated strategy of industrial restructuring and water conservation measures is the most appropriate development strategy for this area

moving forward. By 2030, WRCC will increase by 1.84 times compared with the situation continuation scheme under this strategy. Our findings provide theoretical guidance on the WRCC situation of the Mu Us Sandy Land and can be used to guide policy implementation to optimize water use. This complements the weaknesses in assessing the WRCC of sandy land, thereby providing an essential contribution to the achievement of rational water resource use and sustainable development in arid and semiarid regions. However, the WRCC is the result of the long-term comprehensive effect on nature and society. This paper focuses on the results of the disturbance of human activities to the water resources system. In the future, it is necessary to combine integrated models and establish a WRCC early warning system platform.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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