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Identifying and managing risk factors for salt-affected soils: a case study in a semi-arid region in China

De Zhou · Jianchun Xu · Li Wang · Zhulu Lin · Liming Liu

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Abstract Soil salinization and desalinization are complex processes caused by natural conditions and human-induced risk factors. Conventional salinity risk identification and management methods have limitations in spatial data analysis and often provide an inadequate description of the problem. The objectives of this study were to identify controllable risk factors, to provide response measures, and to design management strategies for salt-affected soils. We proposed to integrate spatial autoregressive (SAR) model, multi-attribute decision making (MADM), and analytic hierarchy process (AHP) for these purposes. Our proposed method was demonstrated through a case study of managing soil salinization in a semi-arid region in China. The results clearly indicated that the SAR model is superior to the OLS model in terms of risk factor identification. These factors include groundwater salinity, paddy area, corn area, aquaculture (i.e., ponds and lakes) area, distance to drainage ditches and irrigation channels, organic fertilizer input, and cropping index, among which the factors related to human land use activities are dominant risk factors that drive the soil salinization processes. We also showed that ecological irrigation and sustainable land use are acceptable strategies for soil salinity management.

Keywords Soil salinization · Risk factor identification · Spatial autoregressive model · Hierarchical framework · Multi-attribute decision making · Yinchuan Plain

D. Zhou · J. Xu (✉) · L. Wang
Department of Land Resources Management, Zhejiang Gongshang University, 18 Xuezheng St., Xiasha University Town, Hangzhou 310018, China
e-mail: xujc2002@sina.com

D. Zhou
e-mail: zhoude520@163.com

Z. Lin
Department of Agricultural and Biosystems Engineering, North Dakota State University, NDSU Dept.7620, PO Box 6050, Fargo, ND 58108, USA

L. Liu
Department of Land Resources Management, China Agricultural University, 2 Yuanmingyuan West Rd., Beijing 100193, China

Introduction

Soil salinization as a result of environmental changes and land use activities is a major form of soil degradation in arid and semi-arid regions (Dumanskia and Pierib 2000; Li et al. 2007). *Primary soil salinization* (PSS) is caused by environmental conditions such as climate, topography and landforms, soil types, and hydrology, while *secondary soil salinization* (SSS) is mainly caused by land use activities such as excessive irrigation and/or lack of adequate salt leaching (Pereira et al. 2007; Zhou et al. 2013). Environmental conditions are mostly uncontrollable risk factors, whereas land use activities are controllable risk factors. The interactions between these two types of risk factors make the identification of the key controllable risk factors a difficult task. We define the key controllable risk factors as the factors that mainly cause the soil salinization problem in

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a region, and effective soil salinity management strategies should be targeted at controlling these factors.

Many studies in the past had already tried to identify risk factors for soil salinization (e.g., Florinsky et al. 2000; Bennett and Virtue 2004; Poulton et al. 2005; Grundy et al. 2007; Smith 2008; Holland et al. 2009; Caccetta et al. 2010; Acosta et al. 2011; Bilgili 2013). Darwish et al. (2005) found that poor quality irrigation water and excessive uses of water and fertilizers had resulted in soil salinization in an irrigation area in Lebanon. Wiebe et al. (2007) reported that summer fallow had increased soil salinity in Canadian Prairies. He also suggested that uninterrupted land use with more surface cover, especially permanent plant cover, would keep water from becoming redistributed within soils hence reducing soil salinization. These studies had contributed to our understanding of soil salinization and its risk factors, but the process of identifying risk factors for soil salinization is still subject to stochastic and subjective limitations.

Statistical and neural networks models have been used for soil salinity risk identification and for further exploration of the relationship between soil salinization and its risk factors (Bradd et al. 1997; Patel et al. 2002; Triantafilis et al. 2004; Wang et al. 2008; Akramkhanov and Vlek 2012). However, traditional statistical techniques such as linear regression model (Zhang et al. 2010b), multiple gray relation model (Rao and Yadava 2009), and system dynamic model (Ali Kerem and Yaman 2001) are limited when they are used to analyze spatial data due to spatial autocorrelations in geographic variables (Overmars et al. 2003; Merckx et al. 2011; Naimi et al. 2011). Spatial autoregressive (SAR) model (Anselin and Griffith 1988) is a powerful tool for spatial analysis (Kissling and Carl 2008; see also Aguiar et al. 2007; Kissling and Carl 2008), and it can be used to examine the relationship between soil salinity and its risk factors (Akramkhanov et al. 2011).

Once key controllable risk factors are identified, the multi-attribute decision making (MADM) analysis (Hatami-Marbini et al. 2013) can be used to help land owners, resource managers, and policymakers to develop strategies for soil salinization management. By integrating simple additive weighting (SAW) (Chou et al. 2008), analytic hierarchy process (AHP) (Ludovic-Alexandre et al. 2011), elimination and choice expressing translating reality (ELECTRE) (Vahdani et al. 2013), and the technique for order preference by similarity to ideal solution (TOPSIS) (Vahdani et al. 2011), the MADM is normally used to develop multi-principle strategies for soil salinity control and management (Hatami-Marbini et al. 2013).

The objective of this study is twofold: (1) identifying key controllable risk factors for soil salinization processes using a SAR model and (2) developing soil salinity management strategies using the MADM analysis. The attainment of the research objective is demonstrated through a case study of managing the salt-affected soils in a semi-arid region in northwest China. The work flow of our study is presented in Fig. 1.

Study area

The Yinchuan Plain (YCP) of Ningxia Hui Autonomous Region (37° 44′–39° 20′ N, 105° 45′–106° 54′ E) covers an area of 7790 km^2 in a typical semi-arid region in northwest China (Fig. 2). The YCP is influenced by a continental climate with an average annual temperature of 9 °C and an average annual precipitation of 185 mm. The average annual evaporation is 1825 mm, as much as 10 times higher than the average annual precipitation (Zhang et al. 2010a). The YCP has three major landforms, i.e., the Yellow River alluvial-lacustrine plain, the Yellow River floodplain, and the Helan piedmont alluvial plain (Fig. 2). Soils are alkaline and calcareous with medium to fine textures, altered significantly by more than 2000 years of irrigated land use (Xiong et al. 1996).

The YCP has been traversed by the Yellow River which irrigates vast stretches of arable land along its course and has been undergoing extensive grain production to meet the demand of the rapid population growth and socio-economic development. The region has a modern irrigation agriculture system that was converted from natural prairie system more than 2000 years ago. Most grassland and forest land had been cultivated for paddy production with approximately 30×10^4 ha of agricultural land. The irrigated land increased from 20.07×10^4 ha in 1990 to 27.64×10^4 ha in 2000 (Guo 2009; Jia et al. 2002). The principal crops are corn, wheat, and rice. The cash crops are Lycium chinense, rape, benne, and soybean (Zhang et al. 2010a).

Due to the poor environmental condition (intense evaporation and low-lying terrain), the plain has been suffering serious soil salinization. Human activities are the main driving factors of the SSS, including unreasonable agricultural irrigation practice (e.g., flooding irrigation), high groundwater table, poor drainage, and

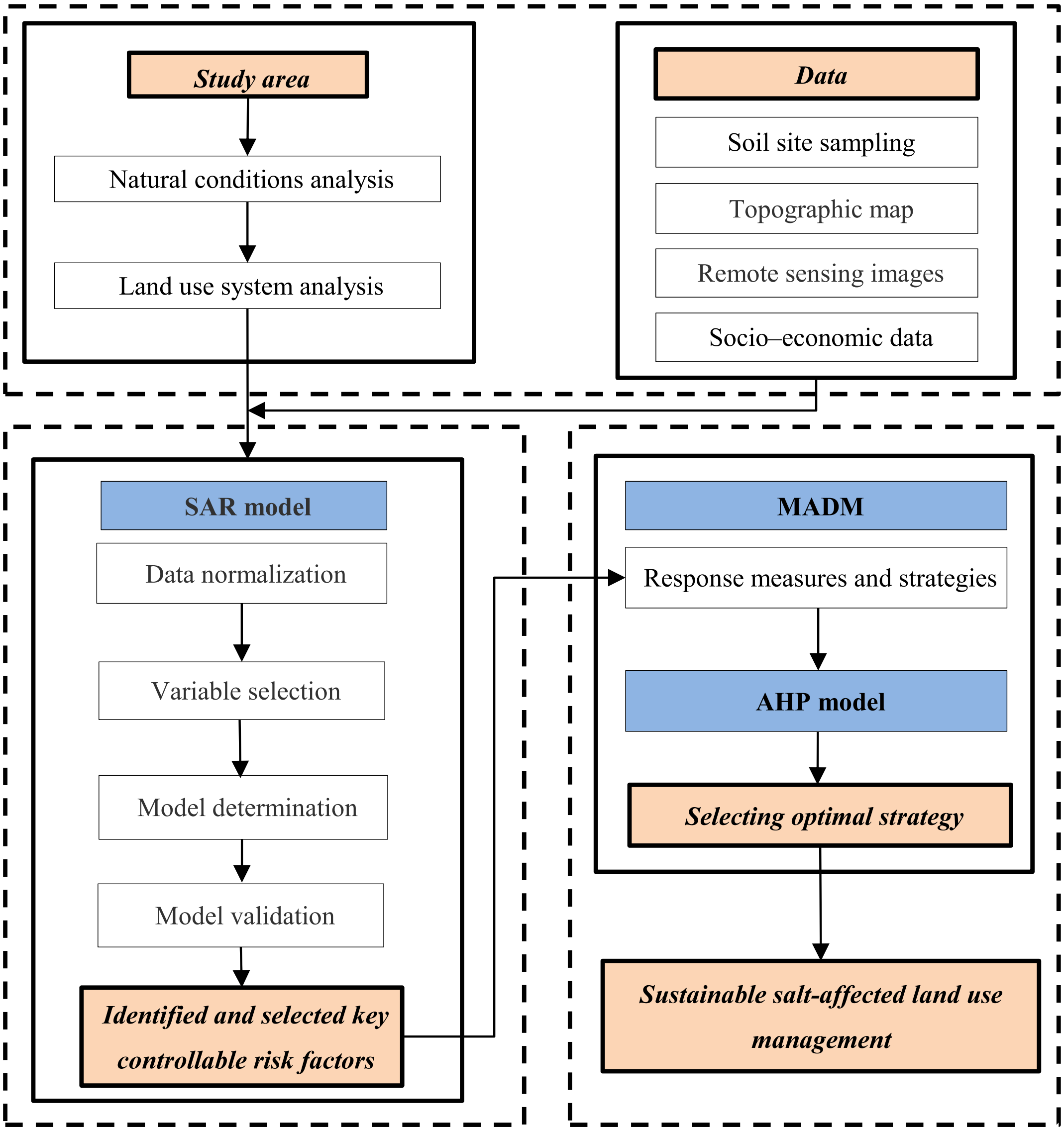


Fig. 1 The work flow diagram of identifying and managing risk factors for soil salinization

intensive agricultural land use (Zhang et al. 2010a). In the history of the plain, the alternate process between soil salinization and desalinization has gone through three stages, i.e., 1958–1962, 1962–2000, and 2000-present (Zhang et al. 2010a). Fortunately, the SSS in the plain has been controlled through the improvement of the land use (the adjustment of agricultural infrastructure) and the enhancement of the land use awareness of farmers and policy-makers, especially the establishment of the irrigation-drainage system with about 3000 major-minor channels of a total length of more than 7000 km (Cai et al. 2010). Currently, soil salinization in the plain has been mitigated and further stabilized because of implementing a consistent series of rational agricultural practices.

Material and methods

Data and pre-processing

Total soluble salts in topsoils (1–20 cm) (i.e., SAL_TOPSOIL in Table 1) were measured at 101 sampling sites in cultivated lands in Spring 2005 (Zhang et al. 2010a). Total soluble salts in soils were measured using the method described in Dehaan and Taylor (2002).

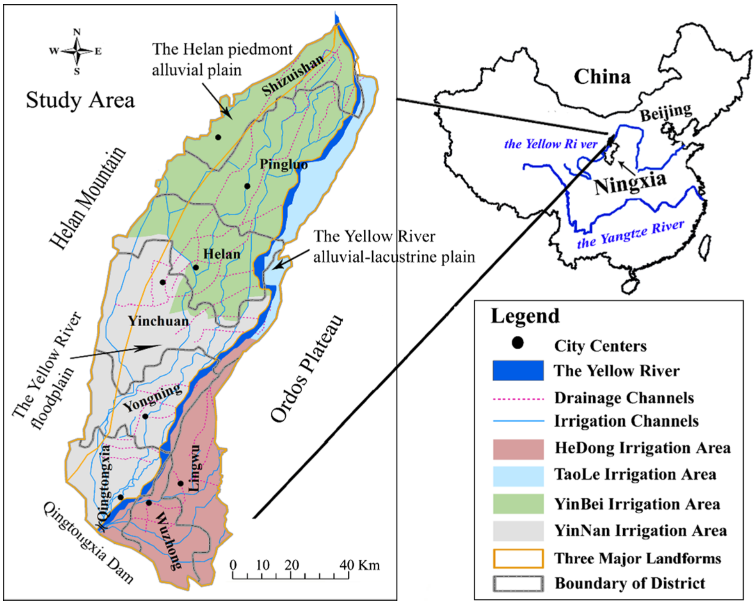


Fig. 2 Study area, sampling sites, and irrigation-drainage systems

Data for a total of 16 variables classified in terms of eight aspects (i.e., climate, topography, groundwater regulation, agricultural structure, land cover, infrastructure, agricultural technology, and demography, see Table 1) were collected for key controllable risk factor identification. These variables were further grouped as natural factors and human factors (see Table 1).

The natural factors include evaporation to precipitation ratio (RATE_ER) and relative relief (REL_RELIEF). The RATE_ER was obtained from Ningxia weather service, and the REL_RELIEF was calculated using a secondary (computed) Digital Elevation Model (DEM) map at a scale of 1:10, 000 in GIS software ArcGIS 10.0 (ESRI Inc., USA).

Human factors include fourteen variables. Depth to groundwater (GROU_DEPTH) and groundwater salt content (GROU_SAL) were recorded at 253 groundwater monitoring wells (Zhang et al. 2010a). Normalized difference vegetation indices (NDVI) and three distance variables, including the distance to irrigation channels (DIS_IRRIG), distance to drainage channels (DIS_DRAIN) and distance to road (DIS_ROAD), were extracted from remote sensing images (Landsat-7 ETM$^+$) with 30×30 m resolution taken on April 27, 2004. The main distance variables were calculated using Euclidean distance tool in ArcGIS 10.0 (ESRI Inc., USA). Other data were collected from the *Ningxia Statistical Yearbook* (NSB Ningxia Statistical Bureau 2000–2010). Household surveys were conducted in 2010 and the survey data were stored in a geo-database. Socio-economic data were collected at the county level.

All data were subsequently transformed into spatial variables and interpolated using ordinary Kriging technique. These data were further standardized and stored in relational database using ArcGIS 10.0 platform (ESRI Inc., USA) (Wang et al. 2010).

Soil salinization, especially soil secondary salinization, is an outcome of both natural conditions and land use activities. Zhou et al. (2013) reviewed the risk factors for soil salinization. Among those studies reviewed, only a few studies (e.g., Lamble and Fraser 2004; Biggs et al. 2009) included geological risk factors when developing soil salinity risk maps, mainly because of lack of geological data. In this study, risk factors such as lithologic unit texture, soil texture, and water stagnation were not considered due to lack of data. For example, the seepage effect and deep percolation from the vast network of irrigation and drainage channels on soil salinity were simply represented by the distance to irrigation channels and the distance to drainage ditches (see also Zhou et al. 2012; 2013). The irrigation canals are not lined and the canal efficiency is about 0.44 (Jia et al. 2006).

Spatial autoregression model

Spatial statistical models include spatial relationships among geographic variables, that is, positive and negative spatial correlations, spatial clusters, and spatial

Table 1 Soil salinization risk factors in Yinchuan Plain

Categories	Spatial variables		Abbreviation[a]	Sources[b]	Main references
Dependent variables					
Soil salinity	Y	Salinity content in topsoil (g kg^{-1})	SAL_TOPSOIL	1	
Explanatory variables					
Natural factors					
Climate	X_1	Evaporation to precipitation ratio (-)	RATE_ER	2	Biggs et al. 2009; Wiebe et al. 2007
Topography	X_2	Relative relief (m)	*REL_RELIEF*	3	Grundy et al. 2007; Wiebe et al. 2007
Human factors (dominated by socio-economic development)					
Groundwater regulation	X_3	Depth to groundwater (m)	GROU_DEPTH	1	Holland et al. 2009; Smith 2008
	X_4	Salinity content in groundwater (g L^{-1})	*GROU_SAL*	1	Arslan and Demir 2013; Rina et al. 2013; Lamble and Fraser 2004
Agricultural structure	X_5	Percentage of paddy area in every county (%)	*PER_PADDY*	4	Biggs et al. 2009; Sugimori et al. 2008
	X_6	Percentage of wheat area in every county (%)	PER_WHEAT	4	Biggs et al. 2009; Sugimori et al. 2008
	X_7	Percentage of corn area in every county (%)	*PER_CORN*	4	Biggs et al. 2009; Sugimori et al. 2008
	X_8	Percentage of aquaculture area in every county (%)	*PER_AQUA*	4	Phong et al. 2003
	X_9	Percentage of animal husbandry in every county (%)	*PER_ANIMAL*	4	Di Bella et al. 2014
Land cover	X_{10}	Normalized difference vegetation indices (−)	NDVI	5	Ding et al. 2011; Lobell et al. 2010
Infrastructure	X_{11}	Distance to road (m)	DIS_ROAD	3 and 5	Biggs et al. 2009; Lamble and Fraser 2004
	X_{12}	Distance to drainage ditches (m)	*DIS_DRAIN*	3 and 5	Benz et al. 1976; Pannell and Ewing 2006
	X_{13}	Distance to irrigation channels (m)	*DIS_IRRIG*	3 and 5	Pereira et al. 2007
Agricultural technology	X_{14}	Organic fertilizer input per county (t km^{-2})	*INPU_FERTILI*	4	Tejada et al. 2006
	X_{15}	Cropping index (−)	*INDEX_CROP*	4	Benz et al. 1976; Li et al. 2007
Demography	X_{16}	Population density (people km^{-2})	DEN_POP	4	Li et al. 2007

[a] In italics, variables included in the SAR model

[b] Sources: *1* sample survey, *2* Ningxia weather service, *3* topography map, *4* Ningxia statistical yearbook, *5* ETM (remote sensing image was produced form Landsat ETM or Landsat ETM+).

outliners (Overmars et al. 2003; Aguiar et al. 2007; Huo et al. 2011). Global Moran's I is a commonly used statistical measure for spatial autocorrelation, and it is computed as follows (Huo et al. 2011):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})\left(y_j - \overline{y}\right)}{\sum_{i=1}^{n}(y_i - \overline{y})^2} i \neq j \quad (1)$$

where n is the number of variables; y_i and y_j are the observations at locations i and j; $\overline{y}$ is the average value of y; and w_{ij}, is an element of spatial weight matrix W, is the spatial weight between locations of i and j. The weight matrix describes the relationship between an element and its surrounding elements and is normally computed based on distance (Huo et al. 2011).

In this study, the spatial correlation analysis was conducted using distance-based weight matrix. Global Moran's I values range from −1 (indicating perfect dispersion) to +1 (perfect correlation). Negative (positive) values indicate negative (positive) spatial autocorrelation. A zero or near zero value indicates a random spatial pattern, and there is no spatial autocorrelation (Overmars et al. 2003; Huo et al. 2011; Slavik et al. 2011).

The SAR model is a natural extension to ordinary least squares regression models for land use modeling. It is also easy to interpret the model's coefficients (Kanaroglou et al. 2013). The SAR model normally includes two sub-models, spatial lag model (SLM), and spatial error model (SEM) (Geoda 2005; Wulder et al. 2007). The spatial lag model is described as follows:

$$Y = \rho \mathrm{W} y + X\beta + \varepsilon, \quad \varepsilon \sim N\left(0, \sigma^2\right) \quad (2)$$

where ρ is the spatial autoregressive coefficient, Y is a vector of observations on the dependent variable, Wy is a spatially lagged dependent variable for weight matrix W, X is a matrix of observations of explanatory variables, and ε is error term. ρ and β are model parameters.

The spatial error model is expressed as follows:

$$Y = X\beta + \varepsilon \quad \varepsilon = \lambda \mathrm{W}\varepsilon + u \quad (3)$$

where Y is a vector of observations of the dependent variable, W is the spatial weight matrix, X is a matrix of observations of explanatory variables, ε is a vector of spatial autocorrelation error terms, and u is a vector of random error. λ and β are parameters.

Pseudo R^2 should be used to test the goodness of fit for the SAR models since R^2 is not an unbiased measure in this case. The pseudo R^2 is defined as the ratio of the variance of the predicted values over the variance of the observed values for the dependent variable (Anselin 1990; Overmars et al. 2003). Maximized log likelihood (LIK), Akaike information criterion (AIC), and Schwartz criterion (SC) can also be used. The higher value of LIK or the lower values of AIC and SC indicate good fit for the SAR models. The standardized regression coefficient (β) and associated significance level (p value) can be used to compare the relative importance and positive or negative correlations among risk factors in a SAR model.

Ten variables (or risk factors) were selected using stepwise regression analysis to be included as explanatory variables in the final SAR model (see Table 1). SAS 9.2 (SAS Inc., USA) was used for stepwise regression analysis, and GeoDa™ 0.95i (Geoda 2005) was used for SAR modeling.

MADM techniques using the AHP method

The MADM were developed to find the best strategy from a set of alternatives for organizational decision making (Zhang and Lu 2009). The best alternative has the highest degree of satisfaction for all of the relevant attributes and can be made through evaluation and comparison of these feasible alternatives which are characterized by trade-off among constraints (Zare Mehrjerdi 2014). The MADM has been widely used to facilitate decision making in evaluating complex projects (Cakir and Canbolat 2008; Javanbarg et al. 2012), including wind farm siting (Leda-Ioanna et al. 2010), prioritization of operator selection (Yuen 2010), and re-vegetation policy options (Qureshi and Harrison 2001).

The AHP by Saaty (1980) can be applied to rank strategies and ultimately select the optimal strategy. The AHP model addresses the complex decision problem using a hierarchical framework, consists of an overall goal, of a group of options or alternatives for reaching the goal, and of a group of factors or criteria that relate the alternatives to the goal (Ludovic-Alexandre et al. 2011). The hierarchy of the AHP can be visualized in a diagram as in Fig. 3. The procedure can be summarized as follows: structuring the decision problem, making pairwise comparisons and getting the judgmental matrix, checking the consistency of the judgments, aggregating weights across varieties of levels, and obtaining a

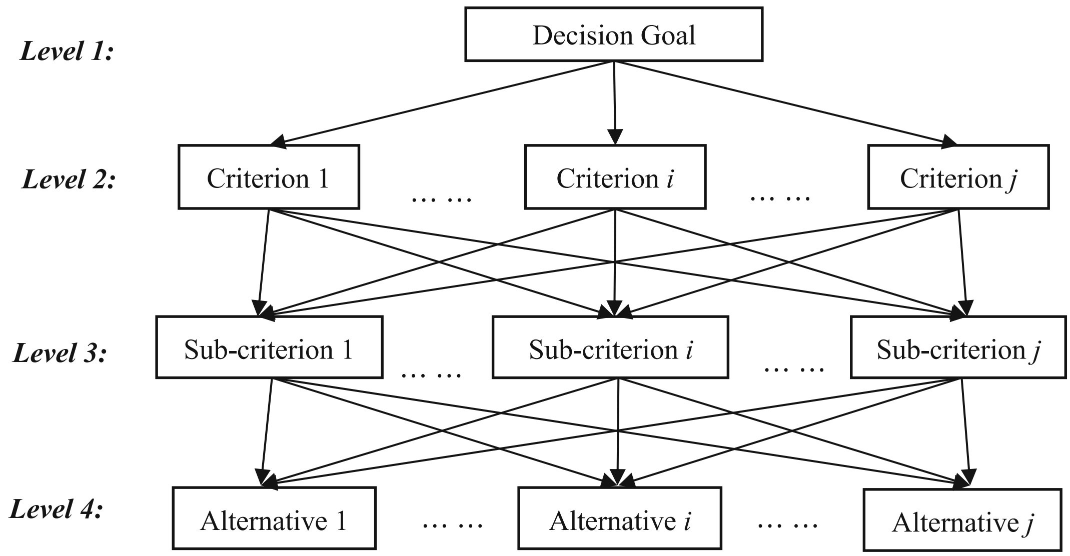


Fig. 3 The AHP methodology

final decision (Mattiussi et al. 2014; Zhou et al. 2013). More details about the AHP methodology can be found in the literatures (Leda-Ioanna et al. 2010; Qureshi and Harrison 2001; Saaty 1980; Vaidya and Kumar 2006; Wang et al. 2010; see also Zhou et al. 2013).

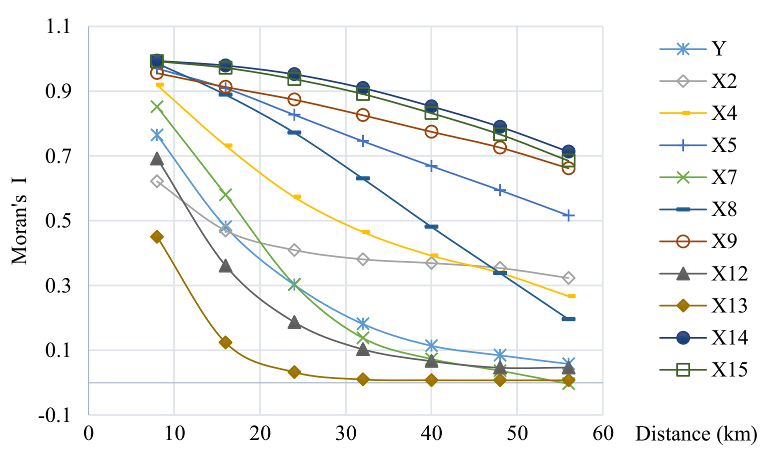
Results and discussion

Spatial autocorrelation of soil salinity and risk factors

Global Moran's *I* values were calculated for soil salinity and ten risk factors that were included in the SAR model using stepwise regression analysis (see Fig. 4). The distance-based weight matrices were computed using a lag distance of 8 km (i.e., 0–8, 8–16 and 16–32 km, etc). Figure 4 shows positive spatial autocorrelations for soil salinity and risk factors within about 32 km. The spatial autocorrelations decrease gradually as distance increases, which is consistent with the findings by Wang et al. (2007). Therefore, the spatial autocorrelations of these variables should be considered in the SAR model (Overmars et al. 2003; Wulder et al. 2007).

A pattern can be found in Fig. 4 for the global Moran's *I* values for the ten risk factors. The global Moran's *I* values are higher for the risk factors related to frequent human activities (e.g., X14, organic fertilizer input per county; X15, cropping index) than those

Fig. 4 Moran's *I* values of soil salinity and its risk factors



related to natural conditions (e.g., *X*2, relative relief). Higher global Moran's *I* values for human factors suggest that the influences of land use presented a regionalized pattern in the YCP, whereas the natural factors became a more localized phenomena. Although the global Moran's *I* values can explain continuous variation over space well, it ignores local instability of geographical variables (Anselin 1995). Thus, the Local Indicators of Spatial Association (LISA, see Anselin 1995) for a sensitivity analysis (outliers) may be analyzed in the future.

SAR modeling

Table 2 presents the differences between the OLS model and two SLM models. Both OLS and SLM1 include all ten risk factors as explanatory variables. SLM2 only include eight explanatory variables, minus REL_RELIEF and PER_ANIMAL.

The OLS model has the lowest R^2 value (0.517) among all models while the SLM1 has the highest Pseudo R^2 value of 0.885. Both SAR models (SLM1 and SLM2) are better than OLS, having lower values of AIC and SC or a higher value of LIK.

For natural factors, Table 2(b) shows that REL_RELIEF is not significant (p=0.015>0.01), which means that REL_RELIEF is not a main risk factor contributing to the YCP's SSS problem. This is not consistent with other studies that reported that topography was a predominant factor for primary soil salinization in local areas (Grundy et al. 2007; Wiebe et al. 2007). The plausible explanation may be that the YCP consists of three major landforms which are the Yellow River alluviale−lacustrine plain, the Yellow River floodplain, and the Helan piedmont alluvial plain (Zhou et al. 2013). So, topography is not a direct risk factor for regional soil salinization but a direct risk factor for local soil salinization. Therefore, REL_RELIEF was removed from SLM2 (Table 2(c)).

For human factors, Table 2(b) shows that PER_ANIMAL is not significant (p=0.753>0.05). Li et al. (2007) have reported that improper land use such as overgrazing (PER_ANIMAL) is a main risk factor for salinized wasteland expansion and aggravates the conversion from grassland to saline and alkaline land. Although the animal husbandry was one of the pillar industries in the YCP, the situation is different now (Li et al. 2012). Another reason is that the policy of returning farmland to woodland and grassland has been launched by the local government. Compared with farmland, woodland and grassland were more salt-tolerant and more effective in curbing salinization than the ordinary grain (e.g., wheat and corn) (Zhou et al.

Table 2 Three different models for soil salinization in the YCP

Variable	Coefficient (β)	S.D.	*t* value	Probability (*p*)
(a) Ordinary least squares model (OLS)				
R^2=0.517; LIK=–889.603; AIC=1801.21; SC=1850.07				
CONSTANT	2.804	0.041	68.692	0.000
REL_RELIEF	0.215	0.057	3.766	0.000
GROU_SAL	1.077	0.059	18.414	0.000
PER_PADDY	–0.011	0.103	–0.109	0.913
PER_CORN	0.607	0.174	3.494	0.001
PER_AQUA	0.240	0.109	2.208	0.028
PER_ANIMAL	–0.187	0.120	–1.557	0.120
DIS_DRAIN	–0.331	0.050	–6.669	0.000
DIS_IRRIG	0.275	0.042	6.544	0.000
INPU_FERTI	–0.877	0.454	–1.931	0.054
INDEX_CROP	1.200	0.525	2.287	0.023
Variable	Coefficient (β)	S.D.	Z–value	Probability (p)
(b) Spatial statistic model 1 (SLM1)				
Pseudo R^2=0.885; LIK=–502.321; AIC=1028.64; SC=1081.95				
ρ	0.774	0.020	39.082	0.000
CONSTANT	0.651	0.059	11.037	0.000
REL_RELIEF	0.067	0.028	2.424	0.015
GROU_SAL	0.290	0.035	8.327	0.000
PER_PADDY	–0.115	0.050	–2.304	0.021
PER_CORN	0.231	0.085	2.719	0.007
PER_AQUA	0.173	0.053	3.270	0.001
PER_ANIMAL	0.018	0.058	0.314	0.753
DIS_DRAIN	–0.086	0.025	–3.490	0.000
DIS_IRRIG	0.114	0.021	5.489	0.000
INPU_FERTI	–0.501	0.220	–2.273	0.023
INDEX_CROP	0.674	0.255	2.645	0.008
Variable	Coefficient (β)	S.D.	*Z*–value	Probability (*p*)
(c) Spatial statistic model 2 (SLM2)				
Pseudo R^2=0.884; LIK=–505.324; AIC=1030.67; SC=1075.09				
ρ	0.778	0.020	39.521	0.000
CONSTANT	0.640	0.059	10.878	0.000
GROU_SAL	0.276	0.034	8.145	0.000
PER_PADDY	–0.126	0.048	–2.634	0.008
PER_CORN	0.184	0.077	2.387	0.017
PER_AQUA	0.174	0.051	3.413	0.001
DIS_DRAIN	–0.065	0.023	–2.834	0.005
DIS_IRRIG	0.121	0.021	5.845	0.000
INPU_FERTI	–0.515	0.215	–2.394	0.017
INDEX_CROP	0.746	0.253	2.944	0.003

2013). So PER_ANIMAL was also removed from the SLM2. After removing these two risk factors, there is no significant improvement from SLM1 to SLM2 in terms of LIK, AIC, and SC. But both PER_PADDY and INPU_FERTI have a smaller *p* value in SLM2.

For all regression models in Table 2, positive β of a factor means that the soil salinity increases as the value of that factor increases. In contrast, negative β means that the soil salinity decreases as the value of that factor increases. Table 2(a) shows that the three risk factors including PER_PADDY, PER_ANIMAL, and INPU_FERTI are not positive significant ($p>0.05$), while the factor PER_PADDY has the lowest negative contribution to soil salinity ($\beta=-0.011$).

All eight remaining factors in SLM 2 have significant effect on soil salinization ($p<0.01$ or $p<0.05$) (Table 2(c)). Controllable factors of human activities including GROU_SAL, PER_CORN, PER_AQUA, DIS_IRRIG, and INDEX_CROP aggravate soil salinization, while other factors including PER_PADDY, DIS_DRAIN, and INPU_FERTI alleviate soil salinization. In general, soil salinization and desalinization are a lengthy and complex processes affected by natural conditions (such as climate, hydrology, topography, and geology) and human-induced risk factors (such as land use patterns, irrigation systems, and farmer's economic behaviors). Zhou et al. (2013) reported that GROU_SAL was a main risk factor in the YCP. The northwestern region of the YCP had the highest groundwater salinity, and the southern region had the low groundwater salinity. PER_CORN contributed to soil salinization because of excessive irrigation and the lack of adequate leaching and removal of salts (Corwin and Lesch 2003). PER_AQUA is positive significant means that increasing fish-farming would increase soil salinity (Hamed 2008). Since the late 1980s, the previously abandoned (unused) low-lying lands have been converted to aquaculture lakes and ponds in the YCP (Xiong et al. 1996) and were constructed for fish farming (Yao 1995) to improve the regional economic development. DIS_IRRIG is also a key risk factor, which makes the following negative effects in the region: (1) high groundwater tables caused by over irrigation, (2) carrying saline irrigation water to areas where irrigation is needed, and (3) moving salts from deep geological storage to the rooting zone and surface soils by the raised water level (Zhou et al. 2013). INDEX_CROP represents the land use intensity for agricultural production as well as the irrigation frequency and irrigation amount in the YCP where irrigation agriculture is dominant. INDEX_CROP is also one of the main causes of salinity expansion (Li et al. 2007).

For negative risk factors that alleviate soil salinity, the percentage of cultivated areas for paddy rice (PER_PADDY) is a double-edged sword to salinization process (negative or positive). On the one hand, paddy rice increases irrigation demand and causes higher groundwater table. On the other hand, paddy rice, by high quality irrigation water, meets the leaching requirement for salt removal. Therefore, different irrigation practices for paddy rice may lead to difference in salinity risk. Land consolidation and converting paddy rice cultivation into rotations between paddy rice and other dryland crops may result in improved groundwater table, reduced irrigation demand, and less uncontrolled drainage (Sato 2001; Mao et al. 2004). Organic fertilizer inputs (INPU_FERTI) can alleviate soil salinization. The result is consistent with the previous findings by Zhou et al. (2013). Finally, the eight risk factors included in SLM2 can be selected to develop measures to control SSS in the following MADM analysis.

Multi-attribute decision making analysis using a hierarchal framework

The structure of the hierarchal framework (i.e., an AHP model) is organized as shown in Fig. 5, including the overall goal, the criteria, the sub-criteria (i.e., a group of factors or measures), and the alternatives. The weight vector of normalized relative importance of each risk factor is developed by experts' knowledge (Saaty 1980; Zare Mehrjerdi 2014). The first layer is named as the overall layer (A), i.e., the overall goal of decision making aiming at preventing the secondary soil salinization and developing sustainable land uses.

The second layer is called the criterion layer (B), consisting of three criteria, i.e., the economic feasibility (B1), the ecological feasibility (B2), and the societal feasibility (B3). In order to achieve the overall goal, three fundamental principles of sustainability (i.e., economic, ecological, and social feasibilities) should be considered in the MADM analysis. In terms of economic feasibility, the purpose is to determine positive economic benefits for the salt-affected land uses, which the proposed projects will lead to, through a typical cost and benefit model (Young 1970). For example, land consolidation (or leveling) and/or irrigation and drainage system improvement not only mitigate soil salinization, but

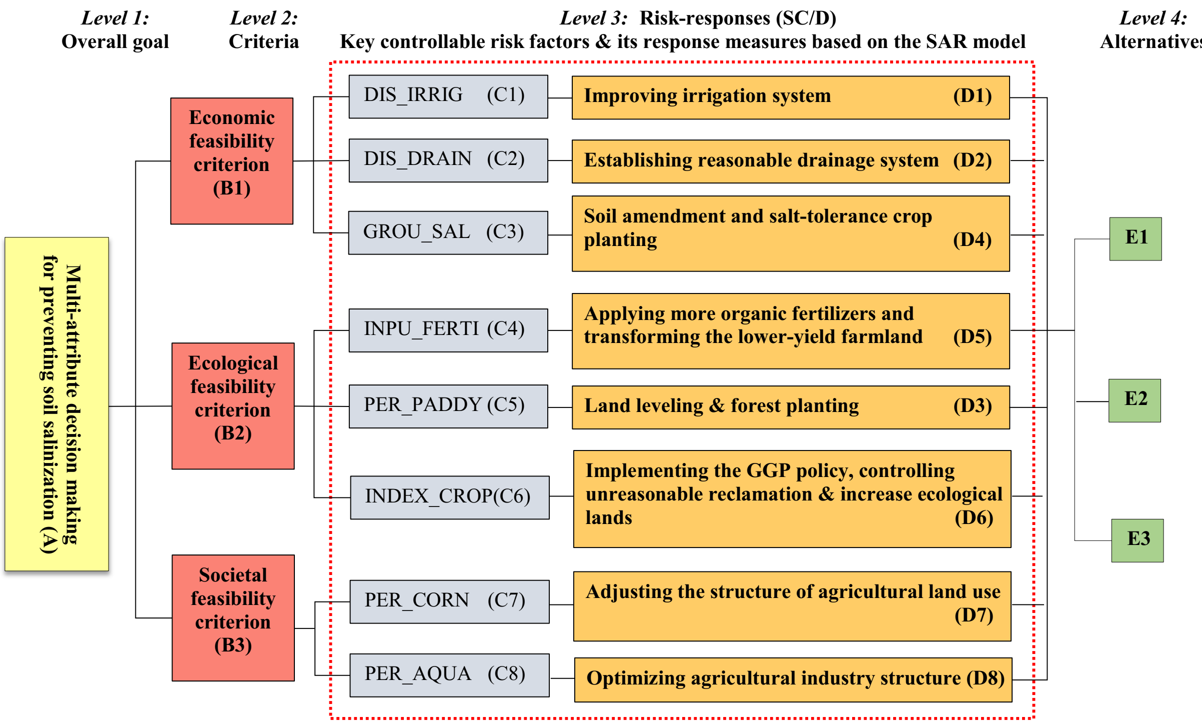


Fig. 5 The hierarchy framework for managing risk factors of soil salinization in the YCP

also increase large economic consumption. These types of projects should have highest funding priority. In contrast, increasing paddy rice and irrigation water for salt-leaching may be able to decrease surface soil salinity, but it may be not economical in certain areas. On the other hand, ecological and social feasibilities are also important. For example, increasing cropping index may produce more agricultural products and generate higher farm revenue; it may also intensify the land use, which may eventually lead to pollution and destruction to the environment and the society.

The third layer is defined as the key controllable risk factors layer (C). The eight key controllable risk factors (C1–C8) were selected based on the previous SAR analysis. The fourth layer is named as the response measures layer (D). These eight measures (D1–D8) were derived from both quantitative SAR analysis and qualitative experts' assessment. Researchers, land users, and resource managers have experimented a set of measures to alleviate the YCP's soil salinization. These measures include drainage, planting paddy, colmatage, reasonable irrigation, land consolidation (leveling), organic fertilizer application, paddy-upland rotation, and salt-tolerant crops (Lu 2004). Additionally, since 1999, the Yellow River Conservancy Commission (YRCC) started to reallocate the Yellow River's water resources among the nine provinces along its course (Zhang et al. 2010a; Zhou et al. 2013). Water resources conservation plans are being implemented to achieve sustainable use of land and water resources (Pereira et al. 2007). In this case study, we merged the C and D layers into one layer and called it risk-response layer (SC/D).

The bottom layer in the hierarchy is called the alternative layer (E). It includes three strategies (E1, E2 and E3) through expert elicitation (Table 3) to regulate land uses for the purpose of sustainable use of land and water resources. The soil salinity in the YCP is irrigation-induced salinity (Xie et al. 2002; Zhou et al. 2013). Therefore, these three strategies include rice field-upland field rotation between paddy rice and other dry-land crops (E1), high efficiency water resources utilization (E2), and ecological irrigation and sustainable land use (E3).

Element's relative importance in each decision layer and the relative importance of each key controllable risk factor in the AHP framework have been compared using paired comparison judgment matrices (Saaty 1980; Zare Mehrjerdi 2014). The consistency ratio (CR) of judgment matrices and the largest eigenvalue (λ_{max}) were also calculated. The three judgment matrices of A-B, B-

Table 3 The Multi-attribute decision making strategies for managing risk factors of soil salinization

Strategies Land use patterns	Description of strategies
Strategy 1 (E1) − promoting the rice field-upland field rotation between paddy rice and other dryland crops	– Keeping current land use pattern and structure for solving contradictions between population growth and food security – Improving current irrigation and drainage system, and more funding for farmland infrastructure – Changing current unreasonable irrigation schedules and irrigation practices
Strategy 2 (E2) − High efficiency water resources utilization	– Using water resources conservation as a guide to promote the water-saving agriculture practices – Updating the irrigation and drainage system and developing the agricultural water-saving projects – Combining the use of both groundwater and surface water of irrigated agriculture for risk aversion of soil salinization – Adjusting the water price of agricultural irrigation at a reasonable level for enhancing the efficiency of water resources use
Strategy 3 (E3) − Ecological irrigation and sustainable land use	– Aiming at the use of water-saving, rearranging the limited agricultural water based on the land use difference between north area and south area of the YCP – Combination of transforming the lower-yield farmland and the Grain for Green Project (GGP) in heavily salt-affected areas; implementing sustainable ecological restoration projects for the purpose of protecting and restoring soil fertility – In the premise of guaranteeing food production, adjusting agricultural land use structure for developing cash crops and salt-tolerant crops that have been characterized as water-saving in the YCP – Optimizing agricultural industry structure and establishing the sustainable rural eco-economic pattern based on the all-round development of in farming, forestry, animal husbandry, sideline occupation, and aquaculture.

SC/D, and SC/D-E were calculated based on the constructed AHP framework, and the results are presented in Tables 4, 5, and 6. The key controllable risk factors in each decision layer were also ranked. As a result, the consistency tests of all judgment matrices are acceptable (all CRs<0.10).

Tables 4 and 5 show that the economic feasibility criterion (B1, weight value=0.472) dominates the decision making process, followed by the societal feasibility criterion (B3, weight value=0.316), and the ecological feasibility criterion (B2, weight value=0.212). Table 6 shows that response measures, such as improving irrigation system (SC/D1, weight value=0.210), establishing reasonable drainage system (SC/D2, weight value=0.161), adjusting the structure of agricultural land use (SC/D7, weight value=0.127), and optimizing agricultural industry structure (SC/D8, weight value=0.189), should have priorities over other measures to control soil salinization risk. The weights for three alternatives are also given in Table 7, including improvement of the paddy-upland rotation in rice paddy field (E1, weight value=0.214), high efficiency water resources use (E2, weight value=0.298), and ecological irrigation and sustainable land use (E3, weight value=0.488). The weights suggest that E3 has the highest priority in preventing soil secondary salinization risk.

Table 4 The judgment matrix and weight values for A–B

A	B1	B2	B3	Weights
B1	1.000	2.226	1.492	*0.472*
B2		1.000	0.670	*0.212*
B3			1.000	*0.316*

CR=0.0000<0.10, λmax: 3.0000

Implications of the proposed methodology

Through integrating SAR modeling, MADM analysis, and AHP method, we proposed an approach to identifying and managing risk factors for the salt-affected soils in a semi-arid region of Northwest China. The

Table 5 The judgment matrix and weight values for B-SC/D

B1	SC/D1	SC/D2	SC/D3	Weights	CR[a]	λmax	Total weights
SC/D1	1.000	1.221	2.226	*0.445*	0.0043	3.0044	*0.472*
SC/D2		1.000	1.492	*0.341*			
SC/D3			1.000	*0.214*			
B2	SC/D4	SC/D5	SC/D6	Weights	CR[a]	λmax	Total weights
SC/D4	1.000	1.492	2.718	*0.498*	0.0171	3.0178	*0.212*
SC/D5		1.000	1.221	*0.292*			
SC/D6			1.000	*0.209*			
B3	SC/D7	SC/D8		Weights	CR[a]	λmax	Total weights
SC/D7	1.000	0.670		*0.401*	0.0000	2.0000	*0.316*
SC/D8		1.000		*0.599*			

[a]All CRs <0.10

results are substantial and will be able to help us develop more consistent management tools to manage soil salinization and its risk factors in the region. Firstly, the integrated quantitative and qualitative method was able to identify key controllable risk factors of natural and human environment variables related to soil salinization. Particularly, this method provides an evidence-based selection process for the construction of multi-attribute decision making strategies. Secondly, the proposed methodology also has a great advantage in avoiding the subjectivity of soil salinization risk management.

We also like to emphasize that the main objective of our paper was to propose an analysis framework based on the integrated approach of the SAR modeling, the MADM analysis, and the AHP, which was

Table 6 The judgment matrix and weight values for SC-E

	Total weights		E1	E2	E3	Weights	CR [a]	λmax
SC/D1	*0.210*	E1	1.000	0.819	0.449	*0.228*	0.004	3.004
		E2		1.000	0.670	*0.298*		
		E3			1.000	*0.475*		
SC/D2	*0.161*	E1	1.000	0.670	0.301	*0.172*	0.000	3.000
		E2		1.000	0.449	*0.257*		
		E3			1.000	*0.571*		
SC/D3	*0.101*	E1	1.000	0.670	0.449	*0.212*	0.000	3.000
		E2		1.000	0.670	*0.316*		
		E3			1.000	*0.472*		
SC/D4	*0.106*	E1	1.000	1.000	0.670	*0.286*	0.000	3.000
		E2		1.000	0.670	*0.286*		
		E3			1.000	*0.427*		
SC/D5	*0.062*	E1	1.000	0.670	0.301	*0.172*	0.000	3.000
		E2		1.000	0.449	*0.257*		
		E3			1.000	*0.571*		
SC/D6	*0.004*	E1	1.000	1.221	0.670	*0.298*	0.004	3.004
		E2		1.000	0.449	*0.228*		
		E3			1.000	*0.475*		
SC/D7	*0.127*	E1	1.000	0.819	0.449	*0.228*	0.004	3.004
		E2		1.000	0.670	*0.298*		
		E3			1.000	*0.475*		
SC/D8	*0.189*	E1	1.000	0.670	0.301	*0.178*	0.017	3.018
		E2		1.000	0.670	*0.304*		
		E3			1.000	*0.518*		

[a]All CRs < 0.10

Table 7 The weight values of three alternatives of managing soil salinization in the YCP

Strategies	Weights
Strategy 1 (E1)	*0.214*
Strategy 2 (E2)	*0.298*
Strategy 3 (E3)	*0.488*

demonstrated through the Yinchuan Plain case study. The results for the plain can be improved as more high quality data become available in the future. This was the case for the Canadian SRI, which was originally proposed by Eilers et al. (1995) and later modified and updated by Florinsky et al. (2000) and Wiebe et al. (2007) when a better soil map became available for the region. In addition, when the improved high quality data and the data for these environmental qualities (or ecological risk receptors) become available in the future, approaching soil salinization and its risk factors as a problem of sustainability also empowers us to shift our focus of risk factor identification and management from the response measures of salinity to its broad impact on agricultural productivity, biodiversity, infrastructure, and other ecosystem services.

Our analysis also showed that human land use activities have greater contributions (alleviation or aggravation) to soil salinization than the natural environment conditions in the YCP. The study suggests that land users and managers should carefully implement the policies as they would cause soil salinization in any areas with poor environmental conditions. More land use policies and measures should be carried out to maintain salt-water balance, including land cover regulations and hydrologic condition adjustments (George et al. 1997). That is the reason why the principles of the MADM analysis were guided by the water and land resource conservation in this study.

In order to achieve the study's overall goal, more supporting measures or management practices are needed in the future. These mainly include the following:

- Establishing a long-term early warning system for soil salinization, including population change early warning subsystem, water safety and use early-warning subsystem, and cultivated land resource security early warning subsystem.
- Developing land suitability assessment system for salt-affected land uses.
- Integrating risk prevention mechanism into land and water resources use planning.
- Strengthening farmers' risk prevention awareness of soil salinization through education.

Conclusions

Through a case study in the Yinchuan Plain in a semi-arid region of northwest China, we tested the applicability of the integrated approach of SAR modeling, MADM analysis, and AHP process as an alternative tool for identifying and managing the soil salinization and the key controllable risk factors.

The results of this study show that spatial autocorrelation of soil salinization and its risk factors decrease gradually with the increasing of distance in the YCP. Comparison of the goodness of fit clearly indicates that the SAR model is superior to the OLS model. The SAR model is a robust tool for identifying the key risk factors related to soil salinization. Our analysis also shows that PER_PADDY, DIS_DRAIN, and INPU_FERTI are important SSS alleviators, while GROU_SAL, PER_CORN, PER_AQUA, DIS_IRRIG, and INDEX_CROP are important SSS aggravators.

This study also shows that the constructed hierarchy framework can be used to decompose the overall goal of secondary soil salinity risk management. The AHP model incorporates both quantitative information (e.g., SAR model) and qualitative information (e.g., experts' opinions) to reduce the subjectivity of selecting the key controllable risk factors, to update preventive measures, and to develop multi-attribute decision making strategies. The MADM analysis relates to the overall management goal through a hierarchy framework for organizing and analyzing complex decisions, structuring a decision problem, quantifying controllable risk factors, and evaluating alternative strategies. The obtained optimal alternatives, i.e., ecological irrigation and sustainable land use, are generally acceptable by experts.

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