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Analyzing land-use change and farmer's behavioral intentions toward wetland conservation: A case study of Iran

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Abstract

Land-use change is a primary driver of global environmental degradation, with wetlands being particularly severely affected—an estimated 30–90% of global wetlands have been lost or significantly altered. Despite their critical ecological importance, wetland land-use dynamics remain understudied, underscoring the urgent need for conservation efforts aligned with three key 2030 global agendas. In Iran, agricultural overexploitation has emerged as the predominant threat to wetland ecosystems, surpassing other factors such as climate change. This study investigates the drivers of land-use change and farmers' conservation behaviors in the Bakhtegan and Tashak wetlands through a two-phase approach. In the first phase, remote sensing and GIS were employed to quantify land- use transformations from 2000 to 2020, revealing a significant expansion of bare lands surrounding these wetlands. In the second phase, local farmers were surveyed to assess the socio- psychological factors shaping their willingness to support wetland conservation. Data were analyzed using ENVI 5.3, ArcGIS 10.3, SPSS 20, and AMOS 20. Results indicate that positive attitudes and subjective norms significantly influence farmers' behavioral intentions toward conservation ($p<0.05$). These findings highlight the need for targeted policy interventions that integrate socio-psychological insights with land-use monitoring to enhance wetland conservation strategies.

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Introduction

Land use is the management of land cover through human intervention in favor of a desired land cover (Lambin et al., 2001). Land use and land cover are key aspects of socio-economic development (Kadoma et al., 2025; Verburg et al., 2006), and directly reflect human activities driven by economic, social, and political goals aimed at generating products and benefits from the environment (Savari et al., 2025; Ahsan et al., 2025; Bentley Brymer et al., 2020; De Groot, 2006). Land-use patterns may change over simultaneously varying scales of time and space, and land-use changes (LUC) are increasingly regarded as primary forces behind global environmental change. These changes affect greenhouse gas emissions, exacerbate global warming, intensify local climatic shifts, and reduce biodiversity and soil resources (Savari et al., 2024; Ghanian et al., 2020; Leip et al., 2015). The drivers of LUC are complex, however, and vary over time and across regions. Understanding the underlying mechanisms has become a central focus of global-change research in recent decades (Meneses et al., 2017). Given the diverse causes of land-use change, such investigations necessarily require interdisciplinary approaches (Li et al., 2016; Qasim et al., 2013). Although LUC typically reflects socioeconomic and political forces, the physical environment also plays a critical role in shaping the trajectories of change (Msofe et al., 2019; Damaneh et al., 2024; Ghoochani et al., 2024).

According to the United Nations Food and Agriculture Organization, the agricultural sector is the source of one-third of global warming due to mismanagement and land-use change (Savari et al., 2022; Balogh, 2020; Dale et al., 2011). Sustainable land use in arid and semi-arid regions is declining due to land degradation caused by human activities (Ghorbani et al., 2021; Eswaran et al., 2019). Crop yields have been falling for decades, forcing people to expand cultivation to more land to meet their needs (Dahimavy et al., 2015; Maitima et al., 2009) and agricultural outputs have increased mainly by spatially expanding production (Weinzettel et al., 2013). Production from grazing lands have also been diminishing due to overgrazing. Natural vegetation has decreased as lands have been converted to cropland and pastures (Nzunda et al., 2013). These changes are fueled by growing demands for agricultural products that are important for achieving food security and generating income (and profit) among both the rural poor and wealthy commercial-farming investors.

The impact of land-use change on wetlands has been overlooked by researchers. Wetlands include lands that remain inundated to some degree, as well as marshes, swamps, peatlands, areas of natural and artificial landscapes that either permanently or temporarily contain stagnant or flowing fresh, brackish, or salt water (Eskandari-Damaneh et al., 2020). Wetlands are ecologically, hydrologically, and biogeochemically unique regions that provide an array of ecosystem services (ESs) (Kaushal et al., 2014; Mintah, Amoako & Adarkwa, 2021). ESs include freshwater supply and storage for human uses like flood control, carbon storage, biological production, wildlife conservation, and prevention of salinization. Wetlands provide secondary benefits to community welfare and livelihood by supporting education, recreation, and tourism (Aryal et al., 2021; Kløve et al., 2011).

There are approximately 1280 million hectares of wetlands worldwide; this includes inland and coastal wetlands in the form of lakes, rivers and swamps, and artificial wetlands like paddy fields and reservoirs (Ahmad et al., 2019; Assessment, 2005). Wetlands occupy 6% of Earth's surface, but environmental pressures from reclamation, dredging, overexploitation of resources, point-source pollution, and desiccation due to global warming threaten wetlands on all continents. An estimated 30-90% of the world's wetlands have already been destroyed or have been significantly altered (M. Finlayson et al., 2005). Iran is home to 24 internationally recognized wetlands, spanning an area of about 1,486,438 hectares, as recorded by the Ramsar Convention on Wetlands (Nasab et al., 2023). However, many of these ecosystems have suffered from severe contamination caused by human activities. Notable examples include the Anzali Wetland, the Hoor al-Azim Wetland, and the Hamoon Wetland (Cheshmvahm et al., 2023; Fakhradini et al., 2021; Ebrahimi-Khusfi et al., 2023).

Despite conservation policies, especially the Ramsar Convention on Wetlands of International Importance Especially as Waterfowl Habitat, there is no evidence that ecological damage has been reduced (Gardner & Davidson, 2011; Graversgaard et al., 2021). The protection and sustainable management of wetlands is a global priority as indicated by the 2030 Agenda for Global Sustainable Development Goals. Three goals (Goal 6.3 “Improvement of Water Quality,” 2.4 “Sustainable Food Production,” and 12.2 “Sustainable Resource Management”) seek to improve wetland management. Wetlands mainly support the provision of ESs, spiritual opportunities, biodiversity, recreation, and educational needs. Despite the importance of ESs, wetlands are still degraded. They have been identified as the most threatened ecosystems in the world (Wood et al., 2013). This is attributed mainly to their drainage and conversion to agricultural lands and to increased withdrawal of water for economic development and food production (Dehnhardt et al., 2019). For example, it is estimated that more than 50% of some wetlands (particularly coastal and inland wetlands and emerging estuaries) were converted to agricultural uses in Europe, Australia, North America, and New Zealand during the 20th century. Elsewhere, there are no reliable data, and therefore many estimates are speculative (Board, 2005; Finlayson et al., 2005; Rebelo et al., 2009). Wetlands tend to have nutrient-rich soils that allow small-scale farmers to produce crops throughout the year (Beuel et al. (2016). They have been increasingly exploited by smallholders to meet demands for food due to economic and demographic growth, global warming, and the reduced yields from traditional agricultural regions. In times of food shortages, wetlands are often the only sources of food for the communities living near them (Schuyt, 2005). Many wetlands in sub-Saharan Africa, however, are slowly deteriorating due to drainage and conversion to enable agricultural expansion (Ayyad et al., 2022; Adekola et al., 2012; Rebelo et al., 2010).

Wetland ESs are shared resources and are essential to human life. In the Islamic Republic of Iran (hereafter Iran), as in many developing countries, the degradation of wetland ecosystems is a significant concern. Iran averages 250 mm of precipitation per year. Water supplies are chronically short and uneven distribution persists (Badamfirooz et al., 2021; Ghanian et al., 2022). Wetlands are important in Iran and are made increasingly vital by global warming.

Iran is an important example of the need for water conservation and management of ESs (Masoompour Samakosh et al., 2024; Eskandari Damaneh et al., 2019; Eskandari Damaneh et al., 2018). Anthropogenic degradation is the main reason for wetland loss. The traditional view of residents of Iran is that wetlands are "wastelands,” which supports the utilitarian belief that "such obvious waste can only be used effectively if it is made cultivable for agriculture and human settlement" (Maltby, 2013). When not considered wasted space, wetlands are generally considered to have minimal value compared to other land uses that provide specific, short-term economic benefits (Palmer-Felgate et al., 2013). Exploitation for agriculture is among the most important causes of wetland destruction in countries like Iran (Masoumi et al., 2024). In their research on 17 villages located near the Tashkent–Bakhtegan Lakes, Masoumi Jashni et al. (2024) assessed the vulnerability of farmers to climate change. The results revealed that over half of the communities (52.93%) were classified as highly vulnerable, while 23.52% of farmers experienced very low vulnerability and another 23.52% were moderately vulnerable. The Iranian government has undertaken several projects aimed at protecting wetlands. In this regard, Sadeghi Pasvisheh et al. (2021) emphasized that preventing further degradation and ensuring effective protection and restoration—aligned with the Sustainable Development Goals—require the integration of scientific insights into a practical framework that provides evidence-based support for policymakers and managers of the

Anzali Wetland. To this end, the Drivers–Pressure–State–Impact–Response (DPSIR) framework was applied as an appropriate tool to connect human pressures with state changes and to offer a comprehensive overview of potential impacts.

It is important to pay closer attention to the role of farmers in wetland management, conservation, and restoration. Despite the importance of local communities' participation in wetland management and conservation in Iran, managers, decision-makers, and policymakers have not paid much attention to the farmers that live near wetlands.

This paper examines the factors that influence farmers' wetland-conservation behavior by focusing on land-use change near the Bakhtegan and Tashak wetland in Iran. The objectives are to determine land-use change in the Bakhtegan and Tashak wetlands and to analyze the determinants of farmers' behaviors toward wetland conservation. Employing a geographic information system (GIS) and remote sensing (RS) enables the tracking of LUC over the period from 2000 to 2020. Farmers' conservation behaviors were revealed in a survey conducted for this purpose. This study is the first of its kind and provides a foundation for studies of the socio-psychological dimensions of wetland conservation. The use of the Theory of Planned Behavior (TPB) as an organizational conceptualization of farmers' behavioral intentions toward wetland conservation is also novel. The combination of the analysis of satellite data to detect land-use change with the survey of behavioral intent toward wetland conservation is also an innovation of this research.

Materials and methods

Study area

The Bakhtegan-Tashak International Wetlands are located west of Neyriz Township in Fars Province at 29°42´42´´N and 53°31´13´ E, 964 km east of the city of Shiraz. This wetland is an important wildlife habitat and is the second-largest inland lake in terms of area in Iran (Masoumi et al., 2024). A wide variety of bird species, mostly overwintering migrants, have been identified. Jackals, foxes, and hyenas are also seen on the wetland's edge. The catchment of the Bakhtegan-Tashak wetlands is almost entirely contained in Fars Province. Rain-fed and irrigated agriculture is performed on 685,186.92 ha of this catchment. Precipitation varies by elevation from 200 mm in the low-lying areas on the southeastern edge of the catchment to 700 mm in the higher elevations on its northwestern edge. The population density within the catchment averages 0.92 people/km^2 (Feizizadeh et al., 2025).

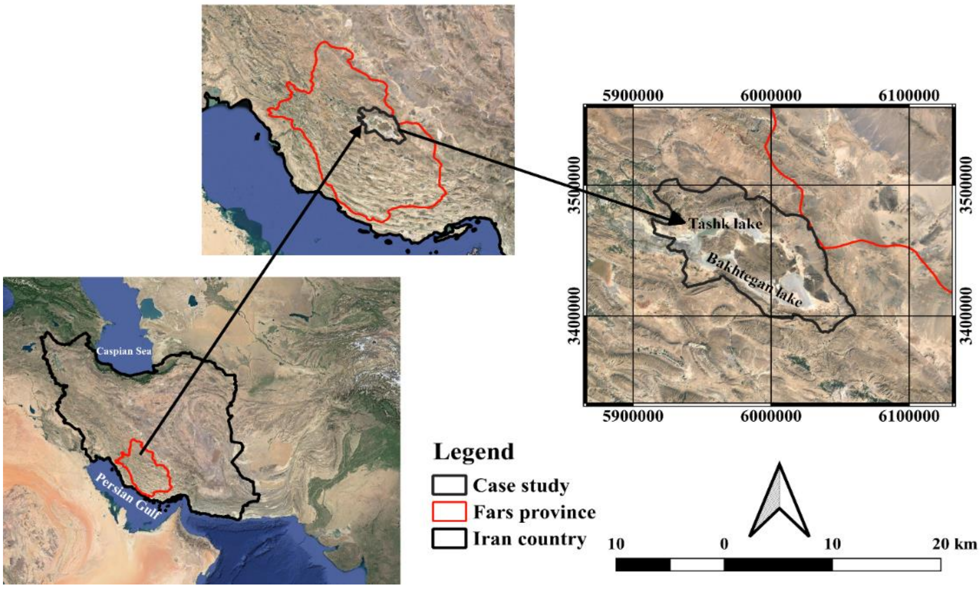

Figure 1. Geographical location of Bakhtegan-Tashk wetlands' catchment

Image processing

Landsat satellite images from the United States Geological Survey were acquired for the years 2000, 2010, and 2020 and analyzed to measure land-use changes. The spatial resolution of the imagery was 30 meters. Each image was clipped to the boundary of the study area (Table 1).

To prepare the images, atmospheric and radiometric corrections were performed using the FLAASH module in ENVI 5.3. The parameters required for atmospheric corrections were extracted from the text file that accompanied the prepared images, and also the required elevation information was obtained from a digital elevation model. All images were corrected to the UTM WGS84 coordinate system, northern zone 39. A supervised maximum likelihood classification method, simple yet powerful, was used to classify land uses across the study area (Gashaw et al., 2017). Six land use classes were used: agriculture, bare lands, forest, rangeland, built-up land, and water body. Training points were determined by combining information from Google Earth, a field survey, a false color composite, and indicators from the images (NDVI, NDBI, and NDWI) (Table 2) (Arekhi et al., 2019; Rugel et al., 2017).

Table 1. Details of Landsat satellite images

Images	Years	Spatial separation	Row/Column
Landsat 5	2000	30	162/39; 162/40; 161/40
Landsat 5	2010	30	162/39; 162/40; 161/40
Landsat 8	2020	30	162/39; 162/40; 161/40

Table 2. Details of the indicators obtained from Landsat satellite images used in the present study

Index	Range	Description
$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$	Between -1 to 1	Normalized index of vegetation difference (Tucker et al., 1986)
$\mathrm{NDWI} = \frac{\mathrm{NIR} - \mathrm{SWR}}{\mathrm{NIR} + \mathrm{SWR}}$	Between -1 to 1	Normalized index of difference in water-covered areas (Gao, 1996)
$\mathrm{NDBI} = \frac{\mathrm{SWR} - \mathrm{NIR}}{\mathrm{SWR} + \mathrm{NIR}}$	Between -1 to 1	Normalized index of differences in urban areas (Zha et al., 2003)

(NIR = Near Infrared, R = Red band, and SWR = Short red band)

The accuracy of the classification of the images from the three dates was evaluated using a confusion matrix. Producer accuracy, User accuracy, overall accuracy, and Kappa index were calculated (Gashaw et al., 2017).

Survey of attitudes

Participants

Empirical survey research was conducted in villages surrounding the wetlands. The target population consisted of households utilizing the wetlands' ecosystem services, totaling 12,328 households. A sample of 450 households was randomly selected using a ratio stratified random sampling method based on the residential directory for each community. Interviews were arranged at mutually convenient times and locations, either in villagers' homes or workplaces, and were administered verbally via questionnaire. Participating villagers were informed of their right to decline answering any question that made them uncomfortable. All responses were anonymous, and no incentives were provided. Completed questionnaires were checked for completeness, yielding 401 valid responses, corresponding to an 89% response rate.

Materials/Procedures

This quantitative study used a non-experimental research design. It involved a cross-sectional survey of farmers in 2020. Data were collected using a researcher-designed questionnaire. The validity and reliability of the survey instrument were tested and confirmed by a panel of experts (either faculty members or field practitioners having extensive experience in socio-ecological interventions for sustainable wetlands management) using Cronbach's alpha coefficients that exceeded the acceptable rates for all components of the questionnaire (Table 3). Three other indicators (composite reliability, convergent validity (CV) (or average variance extracted (AVE)), and divergent validity) were also used to confirm the validity of the indices. The divergent validity of the questionnaire was evaluated by the average shared squared variance (ASV) and the maximum shared squared variance (MSV).

Following the Theory of Planned Behavior (Ajzen (2002), four perceptual variables were created: attitudes, perceived behavior control, subjective norms, and behavioral intention. The data were analyzed using SPSS (version 20) and AMOS (Analysis of Moment Structures, version 20). A Likert seven-point scale (from fully disagree (1) to fully agree (7)) was used for all questions. The summary of the answers was computed as a total score (alpha coefficient) for each variable (Table 3). The values for skewness and kurtosis did not identify any serious violations of normality as all the coefficients were below ±2.

Table 3. The study items included in the study questionnaire and alpha coefficient

Variable	Items	Alpha coefficient
Attitude	A1: I think the conservation campaign is a good initiative to protect the wetland area.	0.86
	A2: I think engaging in the proper management of fertilizers and pesticides in agricultural activity could reduce water pollution.	
	A3: I think participation in wetland conservation and management is useful.	
	A4: I think wetland conservation and management during periods of water shortage is necessary.	
Perceived Behavioral Control	P1: I have the necessary knowledge to participate in wetland conservation and management.	0.87
	P2: I have the time and skills to participate in wetlands management and conservation.	
	P3: I have the necessary economic capacity to participate in wetlands conservation and management activities.	
Subjective norms	S1: I think my friends and acquaintances expect me to be as committed as I can be to participate in the management and conservation of the wetland.	0.74
	S2: My friends and acquaintances think that I should be committed to participating in the management and conservation of the wetland.	
Behavioral intention	B1: I want to learn the necessary skills for wetland conservation and management.	0.75
	B2: I would like to cooperate with the government, experts, and stakeholders involved in the rehabilitation of the wetland.	
	B3: I would like to participate in the management and conservation of wetland.	

Results

Image processing

Classification analysis of 2000, 2010, and 2020 Landsat images

The study area images were classified into six classes (Figure 2). Visual analysis showed that there were significant changes to the proportions of the study area covered by each category. For example, the amount of land covered by water decreased dramatically over the 20-year period. Forested lands disappeared, agriculture diminished, and rangeland and bare lands increased greatly. Built-up areas also grew.

In 2000, rangelands covered 389,202.97 ha or 56.8% of the study area (Table 4). Forest occupied 21,555.3 ha, 3.15% of the area. Bare lands covered 74,441.49 ha (10.86%). Agriculture covered 77119.79 ha (11.26%). Built-up lands accounted for 767.06 ha (0.11%), and water covered 122,100.31 ha (17.82%). By 2010, rangelands, though still occupying a majority of the area declined to 362,142.24 ha (52.85%). Forest decreased to 3,501.38 ha representing only 0.51% of the study area. Bare lands increased nearly three-fold to 201,089.32 ha (29.35%), as did built-up land which grew to cover 2,471.98 ha (0.36%). Agriculture covered only 64,373.41 ha (9.40%) and wetlands decreased to 51,608.59 h (7.53%), less than half of its area in 2000. By 2020, water had decreased to only 179.35 ha (0.03%). Built-up land had grown to 5,856.38 ha (0.85%), nearing 8 times its 2000 extent. Bare lands increased to

277,710.79 ha (40.53%), nearly 4 times its 2000 coverage. Forest decreased to 197.25 ha (0.03%), rangelands to 349,731.62 ha (51.04%), and agriculture to 51511.55 ha (7.52%). Water decreased 17.79% over these 2 decades, and its extent was nearly 0% of the region (Figure 3). Bare lands increased about 29.67% from 2000 to 2020 and agricultural land diminished from 11.26% in 2000 to 7.52% in 2020.

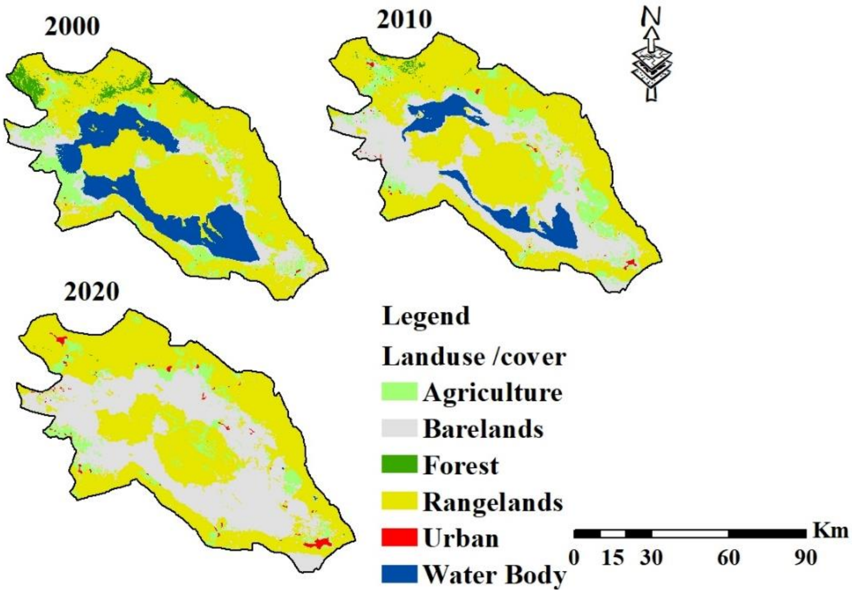

Figure 2. Classified land use / cover maps from 2000 to 2020.

Table 4. Area statistics of the classified images.

LUC class	2000		2010		2020	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Agriculture	77119.79	11.26	64373.41	9.40	51511.55	7.52
Bare lands	74441.49	10.86	201089.32	29.35	277710.79	40.53
Forest	21555.30	3.15	3501.38	0.51	197.25	0.03
Rangelands	389202.97	56.80	362142.24	52.85	349731.62	51.04
Built-up	767.06	0.11	2471.98	0.36	5856.38	0.85
Water Body	122100.31	17.82	51608.59	7.53	179.35	0.03
Total	685186.9229	100	685186.9229	100	685186.9229	100

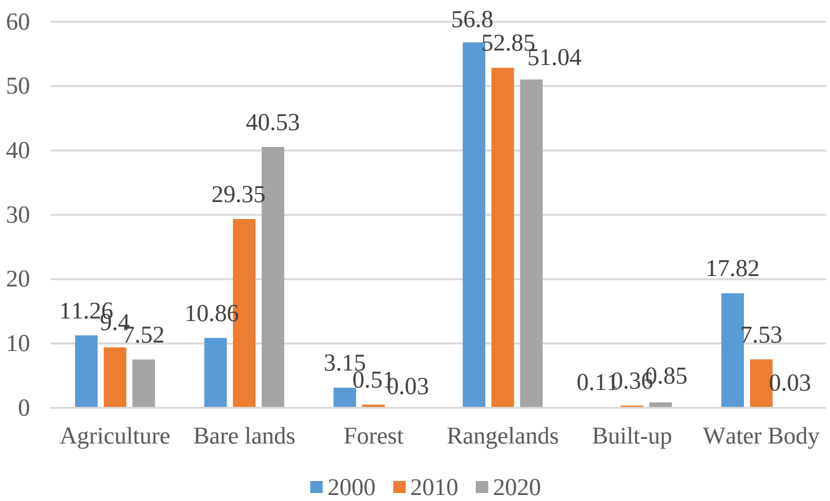

Figure 4. Class statistic of the classified map in percentage from 2000 to 2020 (Percent).

Survey of attitudes

Demographic attributes of respondents

The average age of the survey respondents was 49.4 years (Table 5). The majority of the respondents had primary-level education (53.6%) and about one-fourth (24.5%) were illiterate. Most of the respondents were married (88.9%).

Correlations between Independent and Dependent Variables

A Pearson correlation matrix was constructed to examine the relationships between the variables within the research framework (Table 6). The results reveal that there is a positive association between 'attitude' and 'behavioral intention' ($p<0.05\%$), and positive associations between 'subjective norms' and 'perceived behavioral control' and 'behavioral intention' ($p<0.05\%$).

Table 5. Demographic attributes of the respondents

Demographic attributes	Category	Frequency	Percent
Marital status	Single	45	11.1
	Married	356	88.9
Education	Illiterate	98	24.5
	Elementary	215	53.6
	High school	49	12.3
	Diploma	24	5.8
	B.Sc.	15	3.8
Age (year)	Mean	St.D.	Min-Max
	49.4	12.71	24-75

Table 6. Associations between constructs of the research framework (Pearson correlation)

	Attitude	Subjective norms	Perceived behavioral control	Behavioral intention
Attitude	1			
Subjective Norms	-0.21	1		
Perceived behavioral control	0.12	0.23	1	
Behavioral intention	0.41^{**}	0.52^{*}	0.48^{*}	1

* $P \leq 0.05$ ** $P \leq 0.01$

Confirmatory measurement model

A confirmatory measurement model was tested using AMOS (V20). Confirmatory factor analysis (CFA) was used to ensure the uni-dimensionality of the scales measuring each construct (whether measures of a construct were consistent with the nature of that construct) (cited in (Hall, 2008)). Several commonly-used fit indices were employed to assess the overall model fit (Hu & Bentler, 1999) (Table 7). The comprehensive goodness-of-fit indices produced a Chi-square of 158.26, and Chi-square/DF=2.34 (Schreiber et al., 2006), The comparative fit index (CFI) value of 0.93, incremental fit index (IFI) value of 0.93, and Tucker-Lewis index (TLI) value of 0.90 were deemed good fits to the model (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) value was 0.06 (a value between 0.05 to 0.10 indicates a fair fit) (MacCallum et al., 1996, as cited in (Hooper et al., 2008a, 2008b). The results of the measurement model fit acceptably.

Evaluating Validity and Reliability Results Using Measurement Models

All standardized factor loadings should be at least 0.5 and statistically significant. Such loadings would indicate that observed indicators are strongly related to their associated constructs and contributes to construct validity (Hair et al., 2010). The standardized factor loadings in the model are significant and above 0.5 (Table 8). This indicates a satisfactory fit between the model and the data. Convergent and discriminant validity were also established for all constructs. Composite reliability for all constructs exceeded the threshold of 0.7 (J. J.

Hair et al. (2010). Average variance extracted (AVE) for all constructs exceeded the threshold of 0.5 (Hair et al., 2010). Discriminant validity statistics (MSV and ASV should be less than AVE). All four constructs had good discriminant validity (Table 4). Finally, the skewness and kurtosis did not indicate any serious violations of normality as all coefficients were below ±2 (Table 8).

Table 7. Measures of model fit for the research framework

Items	Chi square	Chi square/DF	IFI	TLI	CFI	RMSEA
Indices	158.26	2.34	0.938	0.901	0.917	0.06

CFI: Comparative Fit Index
IFI: Incremental Fit Index
TLI: Tucker-Lewis Index
CFI: Comparative Fit Index
RMSEA: Root Mean Square Error of Approximation

Table 8. Factor loadings and convergent and discriminant validity in Confirmatory Factor Analysis (CFA)

	Attitudes	Perceived Behavioral Control	Subjective norms	Behavioral intention	Skew	Kurtosis
A1	0.791 [a]				1.302	0.975
A2	0.658**				0.374	0.852
A3	0.825**				1.502	0.531
A4	0.598**				0.881	1.123
P1		0.661 [a]			-1.45	0.741
P2		0.725 **			0.367	0.298
P3		0.798 **			0.811	0.453
S1			0.785 [a]		0.175	0.961
S2			0.718 **		0.728	-0.816
B1				0.685 [a]	0.557	0.691
B2				0.725**	0.472	0.853
B3				0.758**	0.907	0.657
CR	0.81	0.77	0.72	0.70	-	-
AVE	0.52	0.53	0.57	0.54	-	-
MSV	0.28	0.29	0.18	0.19	-	-
ASV	0.23	0.21	0.12	0.13	-	-

a Values were not calculated because loadings were set to 1.0 to control construct variance
** Significant at 1%

Analyzing the Relationships among Variables

Multiple regression was conducted to evaluate how predictive the measures of attitudes, subjective norms, and perceived behavioral control, were toward behavioral intention of wetland conservation. The stepwise method was chosen because it enters the predictor constructs into the equation model until the addition of further constructs produce no significant improvement of the correlation coefficient.

To predict the goodness of fit of the regression model, the multiple correlation coefficient (R), coefficient of determination (R^2), and F ratio were examined (Table 9). The linear combination of the two constructs is significantly related to the behavioral intention of farmers towards wetland conservation (R2=0.31, F = 75.43, p= 0.0001). Only two of the three predictor constructs, attitudes and subjective norms, entered the equation. The other construct did not contribute significantly to the correlation coefficient (0.559). Approximately 0.313 percent of the variance (R^2) in the behavioral intention of farmers towards wetland conservation can be explained by the two predictor constructs. Beta coefficients (or standardized coefficients) can explain the relative contributions of the constructs to the variance in the behavioral intention towards wetland conservation. Assuming that other predictor constructs are held constant, the standardized beta weights indicate attitudes (Beta = 0.39, p = 0.0001) carried the most weight while subjective norms (Beta = 0.28, p = 0.0001) provided less. The other predictor construct does not have a statistically significant effect on behavioral intent.

Table 9. Multiple regression analysis of behavioral intention

Constructs	R	R^2	B	Beta	t statistic	Sig	f statistic	Sig
Constant	-	-	6.17	-	12.59	0.0001**	75.43	0.0001**
Attitudes	0.490[a]	0.241	0.149	0.393	8.05	0.0001**		
Subjective Norms	0.559[b]	0.313	0.288	0.286	5.85	0.0001**		

** $P \leq 0.01$

a: Predictors: (Constant), Attitudes

b: Predictors: (Constant), Attitudes, Subjective Norms

Based on the non-standardized coefficients the regression equation is:

$Y = 6.17 + 0.14X_1 + 0.28X_2$

Y: Behavioral intention

X_1: Attitudes

X_2: Subjective norms

Discussion and Conclusion

Agricultural lands, pastures, gardens, and forests constitute vital ecosystems whose biological performance depends on the behaviors of the communities operating within them. Farmers direct food production activities and continually interact with environmental systems (Van Loon et al., 2020). A precondition for effective environmental policy-making and management planning in farming contexts is an understanding of farmers' behavioral intentions and attitudes toward management activities or goals. Identifying the factors that shape farmers' attitudes provides a strong foundation for management decisions, and this importance further underscores the value of the present research focus.

Landsat images were employed to classify land-use change (LUC) in the Bakhtegan-Tashak wetlands from 2000 to 2020. The analysis revealed a dramatic decrease in water bodies over this period. Built-up lands expanded from 0.11% of the study region in 2000 to 0.85% in 2020, driven by both population growth and the search for new residential areas. Bare land also increased substantially, from 10.86% in 2000 to 40.53% in 2020.

The survey results indicate a high mean age among respondents (49.4 years), which is concerning as it suggests that the majority of farmers are middle-aged or older, while rural youth exhibit little interest in pursuing agricultural livelihoods. This declining interest in agriculture poses significant challenges for Iran and similar countries, given that agricultural activity remains a critical foundation for national economies. Furthermore, most respondents were illiterate or had limited literacy skills (78.1%), representing a major obstacle to improving living standards and complicating environmental management efforts, particularly regarding the provision of extension training to these communities.

According to the survey results, farmers' attitudes toward participation in wetland conservation were positively and significantly associated with their behavioral intentions. Thus, we can conclude that favorable attitudes toward wetland conservation substantially strengthen farmers' intentions to engage in protective actions, a finding consistent with previous research (Mahdavi, 2021). Such favorable attitudes are influenced by prerequisites including prior participation experience, awareness of the consequences of non-participation, and expectations of positive outcomes from involvement in wetland conservation efforts (Eskandari-Damaneh et al., 2020). Ideally, farmers should be fully aware of the consequences of both participation and non-participation in wetland conservation.

The results also revealed that subjective norms had significant positive effects on farmers' intentions toward wetland conservation, highlighting the critical role of farmers' social environments in guiding their behavioral intentions. Similar findings have been reported in other studies (Ghoochani et al., 2017; Sahraii et al., 2019). It can be stated that farmers are more inclined to perform wetland protection behaviors when they perceive and understand the needs and desires of significant others—such as family, friends, acquaintances, and neighbors—to protect wetlands. This phenomenon may reflect a lack of understanding of wetland conservation and insufficient awareness of wetland ecosystem services. This case study underscores the importance of influential groups within communities in facilitating wetland protection. Individuals who hold influence and depend on farmers within farming networks possess significant capacity to encourage farmers' behavioral intentions. Such stakeholders can also be leveraged to explain program elements to farmers, thereby enhancing the likelihood of their participation in wetland preservation. If community leaders are engaged, the need for one-on-one communication to reinforce behavioral intentions may be reduced, and social conditions may be further strengthened through peer pressure. This further underscores that wetland management programs would operate more effectively if they were community- and/or regionally based.

According to Leeuwis and Van den Ban (2004), agricultural extension is conceptualized as a set of communication interventions designed to help resolve problematic situations. Therefore, it is suggested that agricultural extension can contribute to reducing unwise changes in land use and farming activities. To strengthen farmers' intentions through attitudinal change, it is essential to closely examine the social context of the farming community when designing participatory activities. Behavioral and attitudinal alternatives should be developed collaboratively with farmers through participatory packages and projects. It should always be borne in mind that unsuccessful participatory experiences may render farmers reluctant to engage in future initiatives. Future research should also assess the perspectives of other stakeholders, including managers, agricultural extension agents, environmental agency experts, and others, to provide a more comprehensive understanding of wetland conservation challenges and opportunities..

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