

Article

# Study on an AHP-Entropy-ANFIS Model for the Prediction of the Unfrozen Water Content of Sodium-Bicarbonate-Type Salinization Frozen Soil

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Abstract: The development of agriculture and ecology, and the construction of water conservancy facilities are seriously hindered by the salinization of seasonal frozen soil. Unfrozen water exists in the freezing and thawing of frozen soil. This unfrozen water is the core and foundation for studying the process of seasonal frozen soil salinization. However, it is difficult to obtain the unfrozen water content (UW) in routine experiments, and it shows nonlinear characteristics under the action of the main factors contained: salt content, water content, and temperature. In this paper, a new model is proposed to predict the UW of saline soil based on the combined weighting method and the adaptive neuro-fuzzy inference system (ANFIS). Firstly, the distance function was used to combine the analytic hierarchy process (AHP) with the entropy weight method (the combined weighting method) to determine the importance of the influencing factors (temperature, initial water content, and salt content) on UW. On this basis, the AHP, entropy weight method, and adaptive neuro-fuzzy inference system (AHP-entropy-ANFIS) ensemble model was established. Secondly, the five-fold cross-validation method and statistical factors (coefficient of determination, mean squared error, mean absolute percent error, and mean absolute error) were applied to evaluate and compare the AHP-entropy-ANFIS ensemble model, the ANFIS model, the support vector machine (SVM) model, and the AHP, entropy weight method, and support vector machine (AHP-entropy-SVM) ensemble model. In addition, the prediction values of the four models and the experimental values were also compared. The results show that the AHP-entropy-ANFIS model had the strongest prediction capability and the best stability, and so is more suitable for predicting the UW of saline soil. This study provides useful guidance for preventing and mitigating salinization hazards in seasonally frozen areas.

Keywords: unfrozen water; AHP; entropy; SVM; ANFIS; saline soil; frozen soil

# 1. Introduction

Jilin province is one of the major agricultural provinces in China. It has abundant arable land and pasture resources. However, in the west of Jilin province, there is a large area of carbonate saline soil [1,2]. As a result of the influence of factors such as the climatic environment and soil material composition in western Jilin, the saline soil in the area not only has salinization characteristics, but also shows the typical characteristics of seasonal frozen soil [3,4]; therefore, the saline soil in the western area of Jilin province has complex engineering geological properties, which lead to the expansion of



the area of saline soil year by year [5]. The agriculture, the ecological environment and the water conservancy facilities in Jilin province are being eroded increasingly more seriously by the saline soil.

In winter, when the temperature is lower than 0  $^{\circ}$ C, the saline soil freezes. The ground surface freezes first, and in this process, the water in the soil moves towards the ground surface. On the one hand, this leads to frost heaving of the soil, which causes various engineering problems, such as slope instability of the water channels, dykes and dams in hydraulic irrigation engineering [6]. On the other hand, the salt dissolved in the water and the water together converge toward the direction (the ground surface) of the soil freezing, which leads to more and more soil becoming saline soil. Soil salinization causes a lot of agricultural, ecological, and engineering problems, such as grassland and farmland degeneration, and the corrosion of civil engineering [7,8].

The above problems are closely related to the unfrozen water content (UW) of saline soil. During the freezing process of saline soil, the content of unfrozen water determines the amount of water migration in the frozen soil. The amount of the frost heaving of saline soil and the occurrence of salinization are directly determined by the amount of water migration [6,7]. The UW in saline soil is the core and foundation of the soil frost heaving mechanism and the water and salt transport mechanism [9]. Therefore, research into the UW of saline soil in western Jilin is needed.

In the past few decades, in research on UW, scholars have mainly used direct measurement methods—that is, different pieces of testing equipment and methods were used to test the UW of the soil during the freezing process. After many years of research and practice, some macro- and micro methods have been used to study UW, such as the time domain reflection method [10,11], the test box method [12], infrared spectroscopy technology [13], the calorimetry method [14], computed tomography (CT) technology [15], nuclear magnetic resonance technology (NMR) [16,17], etc.

On the basis of experiments, and after analyzing a large amount of experimental data, various scholars have proposed empirical formulas for predicting the UW. For example, a prediction formula based on a calorimetric method experiment was proposed in [18]; for remolded soil, a prediction formula based on the liquid limit of soil was proposed in [19]; and empirical formulas for clay were proposed in [20]. In addition, various scholars have proposed a prediction model based on the theory of thermodynamics of continuous media [21], and a prediction model of UW based on the principle of the electric double layer of soil particles [22].

However, each prediction model has its own applicable conditions and limitations. In addition, because the UW is the result of a process combining multiple factors, such as temperature and water content, it often shows strong nonlinearity. Therefore, traditional empirical models have difficulty in predicting the UW. In recent years, with the continuous progress in science and technology, artificial intelligence technology has developed rapidly. Hybrid models based on machine learning algorithms have received increasingly more attention, research, and applications. Because hybrid models have been shown to perform well at solving nonlinear problems, we expected to be able to build a hybrid model to solve the nonlinear problem caused by the UW.

In this paper, remodeled soil samples of saline soil in the Zhenlai county of western Jilin were selected as the research object, and the UW of saline soil during the freezing process was analyzed and studied. Firstly, the remolded soil samples were measured using NMR equipment in the laboratory, and the UW needed for the study was obtained. Secondly, on the basis of the experimental data, the degree of influence of the influencing factors on the UW was analyzed using the analytic hierarchy process (subjective) and the entropy weight method (objective). Furthermore, we combined subjective and objective methods through a combination with the weighting method, to assign a reasonable weight to each influencing factor. Finally, the analytic hierarchy process, entropy weight method, and adaptive neuro-fuzzy inference system (AHP-entropy-ANFIS) ensemble model was established. This model was compared with the neuro-fuzzy inference system (ANFIS) model, the support vector machine (SVM) model, and the analytic hierarchy process, entropy weight method, and support vector machine (AHP-entropy-SVM) ensemble model. Through comparison, a model suitable for the Zhenlai

area was selected and applied to the prediction of UW. In addition, for the process of model training and testing, a five-fold cross-validation method was adopted.

# 2. Materials

# 2.1. Test Soil Materials

According to an investigation and research into the saline soil in the west of Jilin province, compared with other depth areas, salt is more active at a depth of 40 cm below the ground surface, and the depth of 40 cm is the salt concentration area. In order to study the UW of saline soil, it was planned to collect soil samples from Zhenlai county. These soil samples were collected from below the surface at a depth of 0.4 m. The collected soil samples were remolded to the samples needed for the study. Before remolding the soil samples, the particle size composition (Figure 1) and the clay mineral composition (Figure 2) of the soil were analyzed. As shown in Figure 1, the proportion of clay and silt was the highest. The mass percentages of the clay and silt were 42.5% and 49.5%, respectively. As shown in Figure 2, the clay minerals in the saline soil mainly contained illite and illite/smectite mixed layer. The relative contents of the illite and illite/smectite mixed layer were 23% and 59%, respectively.



Figure 1. The grain size composition of saline soil in Zhenlai.



Figure 2. The clay mineral composition percentage of saline soil in Zhenlai.

# 2.2. Design for the Remodeling Samples

The UW of the saline soil is influenced by multiple factors: salt content, initial water content, temperature, and so on. Therefore, it was necessary to decide upon the salt content, moisture content, and temperature before preparing the remolded soil samples of salinized soil. According to the

definition of saline soil in the specification of the saline soil to be considered, the soluble salt content cannot be less than 0.3%. In addition, the maximum value of soluble salt content in the soil of western Jilin was once higher than 1.5%. Thus, the salt content of the remodeled samples was artificially designed to be 0%, 0.3% and 1.5%. The optimum water content is the corresponding water content when the soil samples reach the maximum dry density. When the collected soil samples were tested, it was found that the optimum moisture content was about 20%. Therefore, 19%, 21%, and 24% were artificially chosen as the initial water content of the reshaped soil samples. Combined with the actual temperature during winter in western Jilin (the lowest value of monthly average temperature was lower than -20 °C), the test temperatures of the samples were artificially designed to have seven temperature points: -1, -3, -5, -7, -10, -15 and -20 °C. During the test, the UW corresponding to each temperature point was tested. Moreover, western Jilin province is a concentrated area of sodium bicarbonate type saline soil. This soil has a high content of sodium ions, so when remodeling the soil sample, a certain amount of sodium bicarbonate was added. Table 1 shows the design parameters of the samples. The salt content, water content, and test temperatures of the remodeled soil samples were used as the input variables of the models.

Salt Content/%	Temperature/°C	Initial Water Content/%
	-1	
	-3	
0	-5	19
0.3	-7	21
1.5	-10	24
	-15	
	-20	
Type of salt	Sodiun	n bicarbonate

Table 1. The parameter design of the samples.

# 2.3. Test Remodeling Samples

After the design of the remolded soil samples was completed, remolded soil samples with a diameter of 2.5 cm and a height of 5 cm were obtained. In this paper, the nuclear magnetic resonance (NMR) method was selected to study the remolded soil samples, with the expectation of obtaining the UW of the soil samples in the process of freezing. During the test, the soil samples were placed in the NMR experimental equipment. The temperature was controlled and gradually reduced from -1 to -20 °C. At each temperature point, the UW of the soil sample was obtained. A total of 35 groups of UW data were obtained from the NMR experiment, as shown in Table 2. The UW data were then used as the output variables of the models.

Table 2. The unfrozen water content (UW) of the samples in nuclear magnetic resonance experiment.

Initial Water Content/%	Salt Contont/%		Temperature Reduction Process/°C						
	San Conteny /8	-1	-3	-5	-7	-10	-15	-20	-
19	0	16.92	14.96	9.58	8.90	8.33	7.78	7.49	
19	0.3	16.12	14.86	9.78	8.64	8.24	7.48	7.22	
19	1.5	18.31	18.85	11.47	10.65	9.09	7.91	7.63	The UW/%
21	1.5	20.40	20.79	12.12	10.56	9.05	8.31	7.42	
24	1.5	23.23	23.15	11.79	10.32	9.45	7.94	7.72	

# 3. Methodology

# 3.1. Predictive Model Development

This paper intends to establish a hybrid model based on the combination weighting method and machine learning algorithm. In the model, temperature, salt content and initial water content were selected as the input factors, and the output was the UW. The previous showed that the UW can be obtained under the control of three factors: temperature, salt content, and initial water content. However, the degree of influence of the three influencing factors on the UW is not clear.

Therefore, in order to establish a combined model, it was necessary to clarify the degree of influence of the three influencing factors on the UW—that is, to determine reasonable weights for the three influencing factors. To prevent the results from being too subjective or objective, and analytical method combining both subjective and objective methods, was applied to provide more reasonable weights for the influencing factors. This helped to improve the prediction accuracy of the model.

#### 3.1.1. Weighting Method

Subjective Evaluation Method

In the mid-1970s, the American scholar Saaty [23] proposed a method for subjective decision-making: the analytic hierarchy process (AHP). This method can quantitatively analyze and solve problems. The analytic hierarchy process is good at dealing with complex problems featuring multiple levels and factors, and offers good applicability. For solving practical problems, the AHP method can be based on the following process [24,25]:

1. According to the needs of the practical problem, construct a hierarchical structure model to achieve the purpose of decomposing the target layer. The impact factors are then compared and evaluated for selecting suitable candidate objects;

2. According to the method described by Saaty, the values from 1 to 9 and their reciprocals are used as scoring criteria to assess the relative importance of the influencing factors [23–25]. The importance of the influencing factors is evaluated for the target factors. The degree of importance of any two influencing factors on the target factors is determined by comparing them. The degree of importance is scored by experts, and a judgment matrix is built using the obtained scores. The judgment matrix is shown in Equation (1):

$$A = (E_{ij}) = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1m} \\ e_{21} & e_{22} & \cdots & e_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mm} \end{bmatrix},$$
(1)

where m is the number of influencing factors.

The judgment matrix and its maximum eigenvalue, as well as the eigenvector corresponding to the maximum eigenvalue need to satisfy the following relationship:

$$Aw = \lambda_{max}w,\tag{2}$$

where  $\lambda max$  is the maximum eigenvalue and *w* is the eigenvector.

3. When the AHP is used to deal with practical problems, it is necessary to determine whether the judgment matrix meets the consistency principle. The consistency of the judgment matrix can be measured using the consistency ratio. In general, when the consistency ratio is less than 0.1, the matrix passes the consistency test. This proves that the results obtained from the matrix are reliable. The consistency ratio can be obtained by Equation (3):

$$CR = CI/RI,$$
(3)

where *CR* is the consistency ratio, *RI* is the average random consistency index, and *CI* is the consistency index.

The average random consistency index can be obtained as shown in Table 3 [25].

 Table 3. The value of the random consistency index (RI).

т	2	3	4	5	6	7	8	9	10
RI	0	0.52	0.90	1.12	1.26	1.36	1.41	1.46	1.49

The consistency index can be determined by the maximum characteristic root corresponding to the discrimination matrix, as shown in Equation (4):

$$CI = \frac{\lambda_{max} - m}{m - 1},\tag{4}$$

• Objective Evaluation Methods

The entropy weight method uses the entropy values of the influencing factors to determine the weights of the influencing factors [26,27]. It is an objective evaluation method. This method mainly determines the importance (weight) of each factor by evaluating the discrete degree of each factor in the system. The higher the degree of dispersion, the smaller the entropy and the greater the importance of the factor. The process that the entropy weight method uses to deal with the problem is as follows [26,27]:

1. Assuming that the system contains *n* samples and *m* influence factors, and construct them to matrix *B*, as shown in Equation (5). In addition, the matrix *B* is normalized according to Equation (6), thus obtaining  $C_{ij}$ .

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nm} \end{bmatrix} (i = 1, 2, 3, \cdots, n; j = 1, 2, 3, \cdots, m),$$
(5)

$$C_{ij} = \frac{b_{ij} - \min\{b_{1j}, \cdots, b_{nj}\}}{\max\{b_{1j}, \cdots, b_{nj}\} - \min\{b_{1j}, \cdots, b_{nj}\}},$$
(6)

where  $b_{ij}$  is the *j*th influencing factor of the *i*th sample;  $min\{b_{1j}, \dots, b_{nj}\}$  is the minimum value of the *j*th influencing factor; and  $max\{b_{1j}, \dots, b_{nj}\}$  is the maximum value of the jth influencing factor.

After the data are normalized, the entropy value can be determined using Equation (7):

$$E_{j} = -k \sum_{i=1}^{n} u_{ij} \ln u_{ij},$$
 (7)

where *k* is related to the sample size *n*, as shown in Equation (8); and  $u_{ij}$  is the frequency of the *j*th factor, which can be calculated by Equation (9):

$$k = \frac{1}{\ln(n)} , \tag{8}$$

$$u_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} \,, \tag{9}$$

where  $C_{ij}$  is the value obtained after normalizing matrix *B*.

2. The difference coefficient of the entropy can be determined by the entropy value, as shown in Equation (10):

$$R_j = 1 - E_j av{10}$$

where  $R_i$  is the difference coefficient of the entropy.

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3. According to the difference coefficient, the weight of the factor can be calculated, as shown in Equation (11):

$$w_j = \frac{R_j}{\sum_{j=1}^m R_j}, (0 \le w_j \le 1, \sum_{j=1}^m w_j = 1)$$
(11)

where  $w_i$  is the weight of the factor.

Comprehensive Evaluation Methods

When the subjective method (AHP) or the objective method (entropy weight method) are used to analyze the degree of influence of the influencing factors on UW, the weights obtained are too subjective or too objective, respectively. Reasonable weights will help to build a model with better performance. Therefore, in order to get reasonable weights, the subjective method (AHP) and the objective method (entropy weight method) should be used in combination when weighting the influence factors. In this paper, the concept of the distance function is introduced, and the distance function is used to combine the subjective and objective methods, and to construct a combined weighting method. Using the combination weighting method to evaluate the importance of influencing factors and obtain reasonable weights of influencing factors [28], the subjective weight coefficient and the objective weight coefficient can be determined by the Equation (12) related to the distance function, and the combination weight can be determined by Equation (13).

$$\begin{cases} D\left(w_{j}^{1}, w_{j}^{2}\right) = \sqrt{\frac{1}{2} \sum_{j=1}^{n} \left(w_{j}^{1} - w_{j}^{2}\right)^{2}} \\ D\left(w_{j}^{1}, w_{j}^{2}\right)^{2} = (a - b)^{2} \\ a + b = 1(a, b > 0) \end{cases}$$
(12)

where  $w_j^1$  and  $w_j^2$  are the weights, they should be calculated by the subjective method (AHP) and the objective method (the entropy weight method), respectively;  $D(w_j^1, w_j^2)$  is the distance function of the subjective weight ( $w_j^1$ ) and objective weight ( $w_j^2$ ); and *a* and *b* are the weight coefficients of the subjective weight and objective weight coefficients, respectively, *a* and *b* are real numbers.

By substituting the weighting coefficients (*a* and *b*) into Equation (13), the combination weight of the subjective and objective weights can be obtained:

$$w_{cj} = aw_j^1 + bw_j^2, (0 \le w_{cj} \le 1)$$
(13)

where  $w_{ci}$  is the combination weight.

#### 3.1.2. The Adaptive Network-Based Fuzzy Inference System

In the early 1990s, a new algorithm, the adaptive neuro-fuzzy inference system (ANFIS), was proposed [29]. It applies the back-gradient method and the least squares algorithm, and uses the "If–Then" rule for management and constraints. In addition, with the help of the membership function, it completes nonlinear mapping of the data from the input to the output [30,31]. The structure of the ANFIS model is shown in Figure 3. ANFIS inherited the advantages of neural networks and fuzzy reasoning theory, and is good at solving nonlinear and other related complex problems. Therefore, ANFIS has been applied to practical engineering, for example, to evaluate concrete performance [32], and to study soil chemical properties [33]. In this paper, the process of establishing ANFIS for the UW prediction model is shown in Figure 4.



**Figure 3.** The structure of the adaptive neuro-fuzzy inference system (ANFIS) model: (1) p and q represent input variables; (2) nodes containing fuzzy sets  $X_i$  (i = 1,2) and  $Y_j$  (j = 1,2) need to determine their membership functions and perform fuzzy operations on input variables; (3) the function of the node with the Greek letter  $\prod$  is to multiply the output data of the previous layer, and the output data of the node represents the credibility of the fuzzy rules; (4) the neuron labeled N indicates that the output data of the previous layer is normalized and then output from this node; (5) the function of the node with  $u_i$  (i = 1,2,...,6) is to multiply the output data of the previous layer with the related function to calculate the output of fuzzy rules; (6) the function of the node with symbol  $\Sigma$  is to sum all the input data of this node, and get the output result u.



Figure 4. The process of establishing ANFIS for the unfrozen water content (UW) model.

#### 3.1.3. The Support Vector Machine

The Support Vector Machine (SVM) algorithm was created in the mid-1990s [34]. The most prominent feature of the support vector machine is that it has a strong generalization adaptability [35–37], and it can deal with complex problems caused by nonlinearities. When encountering a nonlinear problem, it first processes the complex nonlinear data. After these data are transformed, they are projected into a high-dimensional space, and then a suitable linear function is found to solve the complex nonlinear problem [35,36]. As a result of the excellent performance of the SVM, it has been applied to deal with matters of landslide sensitivity analysis [37], slope stability research [38], and surrounding rock deformations estimation [39]. The principle of the SVM to deal with problems is as follows [35,40,41]:

Assuming that the input data is  $x_i$  (i = 1, 2, ..., k) and the output data is  $y_i$  (i = 1, 2, ..., k), then the data set consisting of input data and output data is  $x_i, y_i$ .

Assuming  $\mu(x)$  is a nonlinear mapping, it can map the input data from low-dimensional space to high-dimensional space. Turn complex nonlinear problems into simple linear problems of high-dimensional space. It can be expressed by Equation (14):

$$g(x) = w\mu(x) + b, \tag{14}$$

where w is weight vector, as shown in Equation (15); and b is bias value.

$$w = \sum_{i=1}^{k} (\alpha_i - \alpha_i^*) x_i, \tag{15}$$

where  $\alpha_i$  and  $\alpha_i^*$  are Lagrange multipliers, which can be calculated by Equation (16):

$$\begin{pmatrix}
\max -\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}(\alpha_{i}-\alpha_{i}^{*})(\alpha_{j}-\alpha_{j}^{*})k(x_{i},x_{j})-\varepsilon\sum_{i=1}^{k}(\alpha_{i}+\alpha_{i}^{*})+\sum_{i=1}^{k}y_{i}(\alpha_{i}-\alpha_{i}^{*})\\
s.t.\sum_{i=1}^{k}y_{i}(\alpha_{i}-\alpha_{i}^{*})=0, , \quad (16)\\
0 \le \alpha_{i}, \alpha_{i}^{*} \le C,
\end{cases}$$

According to Equations (14)–(16), the regression function can be determined as shown in Equation (17):

$$H(x) = \sum_{i=1}^{k} (\alpha_i - \alpha_i^*) K(x_i, x) + b,$$
(17)

where  $K(x_i, x)$  represents kernel function that meets Mercer's conditions.

#### 3.2. Data Collection and Collation

The UW prediction model not only needs to determine the intelligent algorithm for establishing the model, but also needs to obtain a certain amount of reasonable data as support. Therefore, before the prediction model was established, it was necessary to achieve the collection and arrangement of data. In this paper, the inputs of the models are temperature, salinity and water content, and the output of the models are the unfrozen water content. After the UW test experiment was completed, a total of 35 sets of experimental data were obtained, as shown in Table 2. The data were divided as follows: about 80% of the experimental data were taken out and applied as training data; about 20% of the remaining experimental data were allocated as testing prediction model data [42]. In other words, out of the 35 sets of experimental data, 28 sets of experimental data were randomly taken for training, and the remaining seven sets of experimental data. Furthermore, the model was trained and tested using the five-fold cross-validation method.

#### 3.3. Models Comparison Method

In order to accurately predict the UW of the soil samples, it was necessary to compare the predictive ability of the models. In this paper, four statistical factors were introduced to assess the predictive power of the two models. The four evaluation factors are the coefficient of determination ( $R^2$ ), the mean squared error (MSE), the mean absolute percent error (MAPE) and the mean absolute error (MAE) [31,43]. These factors can be calculated using Equations (18)–(21).

The coefficient of determination is:

$$R^{2} = 1 - \frac{\sum_{i=1}^{M} (UW_{\text{predict}} - UW_{\text{experiment}})^{2}}{\sum_{i=1}^{M} (UW_{\text{predict}} - UW_{\text{experiment-a}})^{2}},$$
(18)

The mean squared error is:

$$MSE = \frac{1}{M} \sum_{i=1}^{M} \left( UW_{\text{predict}} - UW_{\text{experiment}} \right)^2, \tag{19}$$

The mean absolute percent error is:

$$MAPE = \frac{1}{M} \sum_{i=1}^{M} \frac{|UW_{\text{predict}} - UW_{\text{experiment}}|}{UW_{\text{experiment}}} \times 100\%,$$
(20)

The mean absolute error is:

$$MAE = \frac{1}{M} \sum_{i=1}^{M} |UW_{\text{predict}} - UW_{\text{experiment}}|, \qquad (21)$$

where  $UW_{\text{predict}}$  is the prediction data of the model,  $UW_{\text{experiment}}$  is the result of the NMR experiment, and  $UW_{\text{experiment-a}}$  is the average of the experimental results.

The MAPE, MSE and MAE reflect the predictive capabilities of the model for the expected values, where the value range is from 0 to positive infinity. The smaller the values are, the closer the prediction result of the model is to the experimental values, which indicates that the predictive ability of the model is better. The value range of  $R^2$  is between 0 and 1. This reflects the degree of closeness between the predicted result of the model and the test value. The larger the value of  $R^2$  is, the better the data fit. At the same time, this also shows that the model has a better predictive ability.

# 4. Results and Discussion

# 4.1. Mechanisms Affecting Unfrozen Water Content

The relatively high clay content in the soil, close to 50% (Figure 1), showed that the specific surface area of the soil was relatively large, and the soil particles had a strong adsorption capacity for the water molecules. The water molecules were gathered around the soil particles through the adsorption capacity of the soil particles, thus forming a water film. The higher the initial water content was, the thicker the water film. At the same temperature, this phenomenon led to higher initial water content, a higher UW, and the same change trend for UW and water content, as shown in Figure 5a. In Figure 5a, the green bar, blue bar, and red bar represent the UW of the soil samples with water content of 19%, 21%, and 24%.



**Figure 5.** At -3 °C, the relationship between water content, salt content, and UW; (**a**) at -3 °C, the relationship between water content and UW; (**b**) at -3 °C, the relationship between salt content and UW.

The soil mainly contained sodium bicarbonate, so the content of sodium ions was relatively high. The clay minerals in the soil contained some highly hydrophilic minerals, such as illite and illite/smectite mixed layer minerals (Figure 2). When the highly hydrophilic minerals interacted with the sodium ions in the sodium salt, a large amount of thin film water (weakly bound water) gathered around the soil particles. With an increase in sodium ions, the water film gradually thickened (Figure 6), showing the UW to increase as with the water film thickened. Therefore, at the same temperature, the salt content increased, which indirectly inhibited the freezing of the soil, resulting in an increased UW. The UW and the salt content also maintained the same change trend, as shown in Figure 5b. In the Figure 5b, the green bar and red bar represent the UW of the soil sample with salt content of 0.3% and 1.5%.



Figure 6. The relationship between the sodium ions and water film.

When the outside temperature is less than 0 °C and continues to decrease, unfrozen water appears in the soil, and as a whole, the UW decreases as the temperature decreases [44]. Therefore, it is self-evident that temperature is the main factor affecting changes in UW.

## 4.2. Analysis of the Degree of Importance of the Factors Affecting the Unfrozen Water Content

In this paper, the AHP and entropy weight methods were used to study the influencing factors of UW, and the subjective and objective weights of the influencing factors were thus determined. The distance function was introduced to combine the subjective weights with the objective weights, and reasonable weights were thereby redetermined.

## 4.2.1. The Analytic Hierarchy Process

The UW is mainly controlled by three influencing factors: temperature, salt content and initial water content. Before applying the AHP to determine the weights of the three influencing factors, the judgment matrix should be constructed first. By comparing the three factors, the importance of each influencing factor relative to the other influencing factors was obtained. In Table 4, the first three columns of data present the results of the comparison. According to Formula (2), the weights of the three influencing factors can thus be calculated. The fourth column in Table 4 shows the weights of the three influencing factors.

Factors	Factors Temperature Initial Water Conte		Salt Content	Weights
Temperature	1	3	5	0.6483
Water Content	1/3	1	2	0.2297
Salt Content	1/5	1/2	1	0.1220

In Table 4, the weight values of temperature, water content and salt content are 0.6483, 0.2297 and 0.1220, respectively. This shows that the temperature weight was the highest, while the salt content weight was the lowest. The subjective analysis method tends to consider temperature as the main factor affecting the UW. At the same time, the average consistency index (CR) and consistency index (CI) were determined according to Equations (3) and (4), respectively. The CI value was 0.002, the CR value was 0.0036, and the CR value was less than 0.1. These comparison results were consistent with the rule of consistency, and the weights of the influencing factors determined by the AHP method were reasonable.

# 4.2.2. The Entropy Weight Method

The entropy weight method (the objective method) was used to evaluate the degree of importance of the three influencing factors of temperature, salt content, and initial water content. According to Formula (6), the matrix of the three factors was normalized. The entropy value, difference coefficient, and weight of influencing factors were determined by Equations (7)–(11), as shown in Table 5.

<b>Fable 5.</b> The evaluation result	s of the entro	opy weight m	ethod
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Heading	Temperature	Salt Content	Initial Water Content	
Entropy	0.94	0.90	0.72	
Difference coefficient	0.06	0.10	0.28	
Weights	0.1416	0.2187	0.6397	

In Table 5, the weights of the temperature, salt content and initial water content are 0.1416, 0.2187 and 0.6397 respectively. It can be seen that the weight of the initial water content is the largest, while

the weight of the temperature is the smallest. The objective analysis method tends to consider the initial water content as the main factor affecting the UW.

### 4.2.3. The Combined Weighting Method

In order to obtain a reasonable weight, and prevent the weights determined by the AHP and entropy weight method from being too subjective or objective, thereby ensuring that the obtained prediction model offers better performance, it is necessary to combine the AHP (subjective) with the entropy weight method (objective) evaluation methods. Using Equations (12) and (13), the weight coefficient and combination weight of the combination weighting method can be determined, as shown in Table 6.

Heading	Temperature	Salt Content	Initial Water Content
AHP weight coefficient		0.7330	
Entropy weight coefficient		0.2670	
Combination weight	0.5130	0.1478	0.3392

Table 6. The evaluation results of the combined weighting method.

In Table 6, the weight coefficient of AHP is 0.7330, and the weight coefficient of entropy is 0.2670. The combined weights of temperature, salt content and initial water content are 0.5130, 0.1478 and 0.3392, respectively. Among them, the weight of temperature is the largest, and the weight of salt content is the smallest. This shows that temperature had the strongest influence on UW, salt content had the weakest influence on UW, and the initial water content was between both.

#### 4.3. Compare and Select the Model

After determining the weights of the influencing factors, the AHP-entropy-ANFIS model was established in combination with ANFIS. This model was compared with the ANFIS model, the SVM model and the AHP-entropy-SVM model, and the model with the strongest predictive ability was selected to predict the UW. In this paper, temperature, salt content, and initial water content were input into the models, and the UW of saline soil was the output factor of the models. The training and testing of the models were realized on the MATLAB software platform. In the ANFIS prediction model, according to actual needs, a total of 27 different "If-Then" rules were formulated, and the "trimf"-type function, with an improved training effect, was selected as the membership function [31,43]. In the SVM prediction model, the "radial basis" function is an important part of the model. It is the main method for the model to process data. The SVM model applies the grid search method, and combines the penalty parameter and radial basis kernel factor to train the model [36].

In addition, in the process of training and testing, a five-fold cross-validation method was used to avoid the problem of overfitting the model. Through this five-fold cross-validation, the coefficient of determination, the mean squared error, and the *p*-value of each model was obtained, as shown in Table 7.

The data in Table 7 were then analyzed. In the process of training, the mean  $R^2$  values of the four models (AHP-entropy-ANFIS, ANFIS, SVM, and AHP-entropy-SVM models) were all greater than 0.8, and the mean  $R^2$  of the AHP-entropy-ANFIS model was the highest, reaching 0.9935. The mean MSEs of the four models were 0.14, 0.19, 2.99, and 2.78, respectively. Clearly AHP-entropy-ANFIS (0.14) was the smallest. For the stability of the model, the order from high to low was as follows: the AHP-entropy-ANFIS model, the ANFIS model, the AHP-entropy-SVM model, and the SVM model.

In the process of testing, the four models were compared. The mean R<sup>2</sup> the of the AHP-entropy-ANFIS model was the largest, at 0.9692. The mean MSE of this model was 0.86, making it the smallest. Compared to the training process, the stability of the AHP-entropy-ANFIS model, the AHP-entropy-SVM model and the SVM model were slightly reduced, but the AHP-entropy-ANFIS model remained the most stable. The AHP-entropy-ANFIS model thus

performed the best. In addition, in the process of training and testing, the *p*-values of the models were less than 0.05.

Mathad	Demonsterne	Coss-Validation					Maar	Standard
Method	Parameters	k = 1	<i>k</i> = 2	<i>k</i> = 3	k = 4	k = 5	wiean	Deviation
AHP-entropy-ANFIS	R <sup>2</sup>	0.9962	0.9960	0.9922	0.9919	0.9914	0.9935	0.002
ANFIS	(Training)	0.9873	0.9960	0.9923	0.9920	0.9917	0.9919	0.003
SVM		0.8867	0.8501	0.8693	0.8545	0.9248	0.8771	0.030
AHP-entropy-SVM		0.8813	0.8864	0.8721	0.8653	0.9236	0.8857	0.023
AHP-entropy-ANFIS	MSE	0.10	0.10	0.17	0.18	0.17	0.14	0.040
ANFIS	(Training)	0.33	0.10	0.17	0.18	0.17	0.19	0.085
SVM		3.00	3.95	3.00	3.41	1.59	2.99	0.874
AHP-entropy-SVM		3.15	2.97	2.94	3.28	1.58	2.78	0.687
AHP-entropy-ANFIS	<i>p</i> -Value	$6.20 \times 10^{-33}$	$1.06 \times 10^{-32}$	$6.51 \times 10^{-29}$	$9.61 \times 10^{-29}$	$2.07 \times 10^{-28}$	-	-
ANFIS	(Training)	$3.53 \times 10^{-26}$	$1.00 \times 10^{-32}$	$4.94 \times 10^{-29}$	$9.10 \times 10^{-29}$	$1.46 \times 10^{-28}$	-	-
SVM		$8.26 \times 10^{-14}$	$3.22 \times 10^{-12}$	$5.39 \times 10^{-13}$	$2.19 \times 10^{-12}$	$3.96 \times 10^{-16}$	-	-
AHP-entropy-SVM		$1.52\times10^{-13}$	$8.63\times10^{-14}$	$4.03\times10^{-13}$	$7.97\times10^{-13}$	$4.82\times10^{-16}$	-	-
AHP-entropy-ANFIS	R <sup>2</sup>	0.9642	0.9236	0.9864	0.9881	0.9837	0.9692	0.027
ANFIS	(Testing)	0.8488	0.9238	0.9819	0.9896	0.9857	0.9460	0.061
SVM		0.8685	0.7034	0.8817	0.9311	0.7786	0.8327	0.091
AHP-entropy-SVM		0.8706	0.5961	0.8964	0.9131	0.8001	0.8153	0.130
AHP-entropy-ANFIS	MSE	1.18	0.96	0.91	0.42	0.83	0.86	0.278
ANFIS	(Testing)	2.00	0.96	0.99	0.49	0.84	1.05	0.564
SVM		2.15	2.95	3.66	4.25	12.06	5.02	4.016
AHP-entropy-SVM		2.04	3.27	2.78	5.24	10.38	4.74	3.367
AHP-entropy-ANFIS	<i>p</i> -Value	$8.33 \times 10^{-5}$	$5.64 \times 10^{-4}$	$7.31 \times 10^{-6}$	$5.30 \times 10^{-6}$	$1.15 \times 10^{-5}$	-	-
ANFIS	(Testing)	$3.20 \times 10^{-3}$	$5.60 \times 10^{-4}$	$1.50 \times 10^{-5}$	$3.76 \times 10^{-6}$	$8.40 \times 10^{-6}$	-	-
SVM	-	$2.24 \times 10^{-3}$	$1.84 \times 10^{-2}$	$1.71 \times 10^{-3}$	$4.34 \times 10^{-4}$	$8.54 \times 10^{-3}$	-	-
AHP-entropy-SVM		$2.15\times10^{-3}$	$4.20\times 10^{-2}$	$1.22 \times 10^{-3}$	$7.80\times10^{-4}$	$6.56\times10^{-3}$	-	-

Table 7. The coefficient of determination, the mean squared error, and the *p*-value of each model.

Figure 7 describes the mean absolute percent errors (MAPEs) of the different models. Among them, legend A is the AHP-entropy-ANFIS model, legend B is the ANFIS model, legend C is the SVM model, and legend D is the AHP-entropy-SVM model. It can be seen from Figure 7 that in both the training process and the testing process, the MAPE of the AHP-entropy-ANFIS model was less than that of the other three models, and the MAPE of the AHP-entropy-ANFIS model was less than 10. In the training process, the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the ANFIS model, and the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the ANFIS model. In the testing process, the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the ANFIS model. In the testing process, the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the ANFIS model. In the testing process, the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the SVM model. In the testing process, the MAPE of the AHP-entropy-ANFIS model was about 1/1.5 that of the SVM model, and about 1/2 that of the ANFIS model.



Figure 7. The mean absolute percent error of the different models.

Figure 8 describes the mean absolute errors (MAEs) of the different models: legend A is the AHP-entropy-ANFIS model, legend B is the ANFIS model, legend C is the SVM model, and legend D is the AHP-entropy-SVM model. As shown in Figure 8, compared with the other three models, the MAE of the AHP-entropy-ANFIS model was the smallest, at less than 1. During the training process, the MAE of the AHP-entropy-ANFIS model was about 1/1.6 that of the ANFIS model, and about 1/6 that of the AHP-entropy-SVM model. During the testing process, the MAE of the AHP-entropy-ANFIS model was about 1/1.6 that of the AHP-entropy-ANFIS model.



Figure 8. The mean absolute error of the different models.

In addition, the predicted values and test values of the different models were compared, and the models' ability to predict the UW of saline soil was judged by the conclusions obtained.

Figure 9 describes the relationship between the data output by the different models during the training process and the real (experimental) data. As shown in Figure 9, compared with the ANFIS model, the prediction result of the AHP-entropy-ANFIS model was closest to the real experimental value. The changes in the blue curve and red curve are very similar; the difference between the two curves is very small, and the two curves basically coincide. The performance of the SVM and AHP-entropy-SVM models was slightly worse, as the blue and red curves are not completely coincident. Although the changes in the two curves are similar, they present some differences. This result reveals that, compared with the other three models, the AHP-entropy-ANFIS model provided a stronger fitting capability and better performance during the training process.





**Figure 9.** The predicted data of the different models during the training process and the real (experimental) data.

Figure 10 describes the relationship between the data output by the different models during the testing process and the real data. As described in Figure 10a, the variations in the blue and red curves are similar, and there is only a small difference. In the two curves, the curve corresponding to data points 2 to 6 basically coincides. Thus, the error of the AHP-entropy-ANFIS model is smaller. In Figure 10b–d, the data point corresponding to the red curve becomes larger or smaller, resulting in a large difference between the red and blue curves. This shows that during the test process, compared with the AHP-entropy-ANFIS model, the other three models provided a weaker fitting ability and poorer performance.



Figure 10. Cont.



**Figure 10.** The relationship between the predicted data of the different models during the test process and the real data: (**a**) the predicted data of the AHP-entropy-ANFIS model during the test process and the real data; (**b**) the predicted data of the ANFIS model during the test process and the real data; (**c**) the predicted data of the SVM model during the test process and the real data; (**d**) the predicted data of the AHP-entropy-SVM model during the test process and the real data.

Xu [45], Anderson and Tice [46] studied the unfrozen water content. They built empirical models on the basis of experiments to predict the unfrozen water content. The unfrozen water content is obtained through empirical formulas, but only the unfrozen water content corresponding to the freezing temperature can be obtained, and the complete unfrozen water content change characteristic curve cannot be obtained. So, the models established in this paper can better predict the unfrozen water content.

In short, through the comparative analysis of the statistical factors, the predicted values, and the experimental values of the different models, it was found that, compared with the ANFIS, SVM and AHP-entropy-SVM models, the AHP-entropy-ANFIS model can produce smaller prediction errors and have a stronger fitting ability. Therefore, the AHP-entropy-ANFIS model offers better prediction capability. Consequently, the AHP-entropy-ANFIS model is the best choice for predicting the UW of saline soil in Zhenlai.

#### 5. Conclusions

This article mainly focused on the UW of sodium-bicarbonate-type salinization frozen soil in Zhenlai county, western Jilin province. The UW of the remodeled samples was obtained using a nuclear magnetic resonance experiment. The combined weighting method was used to study the influence of temperature, salinity and initial water content on the UW. On the basis of these results, combined with the fuzzy neural inference system, the UW prediction model was established. The five-fold cross-validation method was used to train and test the model. The following conclusions can be drawn:

1. The soil contains a great deal of clay and highly hydrophilic clay minerals, so a thick water film forms around the soil particles. In addition, as the water content or salt content increase, the water film around the soil particles becomes thicker. Therefore, under the same temperature, the higher the water content or salt content is, the higher the UW;

2. The AHP (subjective) and entropy weight method (objective) were used to evaluate the degree of influence of temperature, salt content, and water content on UW, and thus determine the subjective and objective weights of temperature, salt content, and water content. The distance function was introduced and applied to combine the subjective weight and objective weight, and the combined weight of the three influencing factors was obtained.

3. On the basis of the combined weighting method and the ANFIS method, the AHPentropy-ANFIS ensemble model was proposed. In addition, this model was compared with the ANFIS model, the SVM model and the AHP-entropy-SVM model. It was found that the *p*-values of all models were less than 0.05. Compared with the other three models, the R<sup>2</sup> of the AHP-entropy-ANFIS model was the largest, its MSE, MAPE, and MAE were the smallest; and its stability was the best. Moreover, the difference between the predicted value and the experimental value of the AHP-entropy-ANFIS model was relatively small. Therefore, the AHP-entropy-ANFIS model had the strongest prediction capability, and thus is more suitable for predicting the UW of saline soil in the Zhenlai area than other methods.

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