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# A multi-verse Optimizer Approach Based on a Salp Swarm for Image Feature Selection to Observe Changes in Urban Lands

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**Abstract**. Many changes have occurred in most urban areas, and it is usually governed by many geographical and social factors, the result will be either the expansion or contraction of these cities. In this paper, an optimizer method called salp swarm optimization (SSO) is used to build a driving force model for urban lands according to the changes in the driving force mechanism. The principle of (SSO) is extracting the driving force classification rules corresponding to different types of land use change samples by imitating the behavior of salp. The classification rules are constructed in the form of "IF ... THEN", and three different fitness functions are selected for simulation verification. The data set used in this search represents images from Global Positioning System (GPS) satellites and remote sensing data. The experimental results show that the overall accuracy evaluation of the salp swarm optimization model is superior to other algorithms, indicating that the SSA is feasible for land use change modeling.

**Keywords**. Salp swarm algorithm; Image feature; Urban lands; Driving force model; Fitness function.

## 1. Introduction

Modeling land use change is the focus of scientific research on land change. Many types of research deal with urban land use change mechanisms and the foundation of land to evaluate changes that happened in previous periods. The driving force factors of land are generally used to cover the four aspects of politics, economy, population, and nature based on selecting different elements for the overall analysis, evaluation, and extracting internal logical relationships. It is very important to reveal the driving force mechanism of the natural land changes and explore the dynamic process of land space-time useful [1].

The selection of the driving force model has gone through the development of descriptive models to mechanism prototypes to propose a series of models such as spatial statistical models, system dynamics models, cellular models, and agent models [1,2]. At present, a complete system has been formed and continuously improved in the descriptive model to depend on a logistic regression model that takes the category value of such lands and uses change as the conditional variable and the driving force factor as an impartial variable. The complex relationship of the land use changes is reflected by the multiple coefficient values of the regression equation. This technique has a simple practical and strong scalability [3]. Other models such as embedding cellular automata that are defined as part of the conversion rules have gained wide practicality. For example, the PH CLUE-S model [4] realizes the control of different scales of the land use change model through the variation transfer matrix and total land use allocation module. Iterative simulation can reflect the competitive relationship between different types of land usage. However, the causal paradigm obtained by the linear model is too simple, and it is difficult to express the non-linear change phenomenon of regional land attributes affected by critical value ranges, mutations, or random factors.

## 2. Background and purpose of the research

Consider an excellent example of urbanization important based on converting the terrain from a natural surface to an impervious surface. For many states across the world, swift steps of urbanization lead to endless problems, including noise pollution, traffic jams, and lousy air quality [1]. As a result of the increased compression in certain places, such as (commercial/industrial zones), these forms of transformation are currently applied to a broad spatial extent and at a rapid rate. Additionally, as humanity develops, more green space is consumed, which has a detrimental impact on urban settings [2-4]. A major concern for human health is the worsening living environment brought on by the loss of green space, as (54%) of people worldwide live in urban areas [5].

The principle design of the mechanism model conforms to the objective laws of the earth using a substitute process and can reflect the global-local-individual interaction mechanism throughout the system, which exemplifies the primary focus of present research and development. Several established artificial intelligence techniques, including the genetic algorithm, the ant colony algorithm, and the particle swarm algorithm, are constantly emerging in the field of land use change driving force modeling, which promotes the development of land use change modeling [5, 6]. . Li Xia et al. proposed a geographic cellular automata model to simulate the process of land use change from the bottom up [7]. Material [8] proposed neural networks, decision trees, nuclear learning machines and other methods to obtain (CA) transform rules to improve simulation accuracy. Yang Qingsheng et al. proposed a support vector machine (SVM)– based on land use change analysis models [9]. These models also have certain shortcomings while solving nonlinear changes in land use. In response to the above problems, Liu Xiaoping and others proposed the use of an ant colony algorithm [10], and Cao et al. Proposed a genetic neural network algorithm based on the automatic extraction of conversion rules. The conversion rules do not need to be expressed by mathematical formulas and can be more conveniently and accurately described. The complex relationship of land use change is even more advantageous in practical applications [11].

This study simulates the behavior of salps in natural biomes using salp swarm optimization (SSO), a bionic intelligent computing technology [12] [13]. This technique is very suitable for solving some non-linear complex problems [14]. The key benefit of (SSO) is algorithm simulation, which exposes satisfactory intensification and diversification tendencies, making it desirable for evolving training task division and cooperation mechanisms. The algorithm's iterative procedure can produce local optimum results from vectors that are gradually updated while taking other strains into account in a dynamic cohort of agents, so it has the advantages of simple flexible and easy understanding of the parallel and sequential patterns. Therefore, its application has developed rapidly and applied to many aspects such as optimization of complex problems, multi-variable simulation, and images change detection [15][16].

This paper takes the land use change data of Nineveh, IRAQ in 1977 and 2012 as an example, then introduces the salp swarm optimization into the land use change modeling. The salp algorithm is simulated to verify the relationship between driving force factors and land use change categories. The complicated relationship between changing land use and the forces that drive it is described using classification rules of change [17][18].

## 3. The Artificial Salp Swarm Algorithm's Fundamentals (SSA)

The salp swarm algorithm was developed by academics Mirjalili and Gandomi in 2017 [19]. It is a widely used method for optimization processes. This method models the behavior of the salp swarm group in the oceans using stochastic optimization theory. It is very efficient to solve problems that deal with optimization problems in engineering design fields. This algorithm differs the salp chain into two portions leaders and followers [20]. The leader is only permitted to update his position to the location of the objective (food source), F, in the sea search space. The followers update their position based on the position and information from a leader [20] [21]. The salp chain transfer is expressed obviously in figure (1).

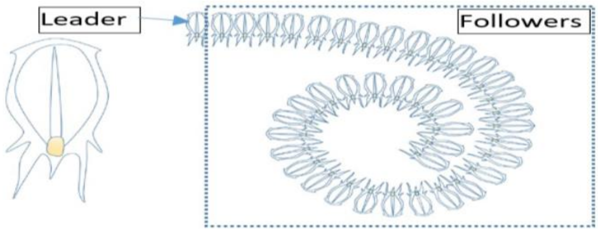

Figure 1: salp's chain movement and the model of leader and follower.

*3.1. Population Initialization*

A significant portion of the search space, known as the Euclidean region, can be expressed as (D*N), where D is the geographic measurement and (N) is the number of populations. The matrix illustration will be constructed individually, as the location of the salp swarm in the space by Xn, the food location by Fn, and ub, lb represent the upper, and lower bounds of the search space as shown in equation (1) [22].

"XD*N = rand (D*N)( ub(D,N) – lb(D,N) + lb(D,N) ……(1)
Where the leader uses $x_d^1$.
The followers use $x_d^i$ i=2, 3, 4, ..., N; d = 1, 2, 3 ...D"

## 4. The Leader's Location Coordination

The leader will update his location using equation (2) when the trout sea squirt chain is foraging during the moving process [13][23].

$$"x_d^i = \begin{cases} F_d + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0.5 \\ F_d - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0.5" \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

"Where: $x_d^1$ represents the location of the leader, while Fd signifies the food at (d-th) dimension; C1, C2, and C3 are the control parameters. Formula (2) shows that the leader's position updates according to the position of the food. (C1) is the convergence element in the optimization process. (C2 and C3) are random amounts of [0, 1], used to improve the predictability and the global search of the chain population" [17][24].

## 5. The Follower's Location Information

In this procedure, helping each other out among those in front and behind, followers move and search for chains like trout ascidian in a sequential manner. Newton's law of motion, as illustrated in equation (3), has an impact on their displacement [5][25]:

X= 0.5 a t2 + v0 t ……………………………………………………………………………..…( 3 )

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This chain behaves by the parameters set forth for regulation and maintains a healthy balance between the processes of investigation and exploitation. Equation (4) illustrates how these parameters depend on the number of iterations that approve high exploratory characteristics [26].

$$c_1 = 2e^{-(\frac{4t}{T_{max}})^2} \qquad (4)$$

Where:

t stands for the number of iterations, whereas (Tmax) denotes the maximum number of iterations. When the iteration count increased, c2 and c3 are decreased by generated at the period [0, 1]. Therefore, it can achieve more acceptance of the variegation tendency for main steps and set more validation on power transferrin at the last stages of optimization. The follower's locations are always corrected based on equation (5) [11] [17].

$$x_j^i = \frac{x_j^i + x_j^{i-1}}{2} \quad \dots\dots\dots\dots (5)$$

Where i ≥ 2 and $x_j^i$ are the positions of the ith follower at the swarm, respectively, for the jth dimension. Figure (2) explains briefly the pseudo-code in (SSA) algorithm.

```
Step1: Intilizaize of salps randomly xi=(i=1,2,.....,n)
          considering ub and lb
Step 2: while (end condition is not met)
         obtain the fitness of all salp
          set F  as leader salp
         update c1 by Eq 3
      For each salps (xi)  in the population do
          {
           If i==1 then
       Update the position of leader by Eq.2
      else
      Update the position of leader by Eq.4
      update the population of salps based on
      upper and lower bounds of variables.
      Update F
          }
Step 3:  Return  F
 END
```

Figure 2: Virtual code of Salp Swarm Algorithm

## 6. Architecture criteria of Land Uses Change Model

SSA has a simple principle, flexible implementation, stability, and strong execution result. In the actual process, it is necessary to define objects for specific problems before they can be applied. The four components of land use change rule included in the core of SSA are extraction of land use change rules, creation of fitness function, surrounding neighborhood search, and prediction, which are described below [11] [27].

1- Extrapolating land-use change regulations: This section examines the connections between various land-use change types' motivating elements. Considering how complicated land use change is, the quantitative mathematical paradigm description is often not accurate enough, so this article describes the rules using "IF… THEN" statements.

2- Fitness function construction: The construction of the fitness function is important for SSO and how to select it. It will directly affect the final result of the SSO algorithm model, for the land classification model. The essence of the land classification model is to use current sample data as accurately as possible to describe the impact of driving factors on land category changes. The most important factor that will be a good indicator called overall accuracy (PPCP ), which is defined as [28]:

$$P_{PCP} = \frac{T_{TN}+T_{TP}}{T_{TN}+T_{TP}+F_{FP}+F_{FN}} \quad \dots\dots\dots\dots (6)$$

Where:

TTN: represents several majority samples that predicted category is consistent with actual.

TTP: is the number of minority samples whose prediction is consistent with the actual.

FFP: refers to several majority samples that are inconsistent with the actual category.

FFN: refers to several minority samples that predict the same majority.

3- Peripheral neighborhood search: Peripheral neighborhood search is an important step to gradually converge the salp swarm algorithm and improve the fitness index. Equation ( 7 ) explain this factor [29]:

$$V_i^j = X_i^j + R_{Random}[-1,1] \times (X_i^j - X_k^j) \quad \ldots \tag{7}$$

Where, $V_i^j$ represents the new position of the salp (i) in the driving force factor j.

The leader salp's initial position interval in the driving force factor j is $X_i^j$ . $X_k^j$ is the position of follow salp k in the driving force factor j.

4- Model prediction: it used extracted land-use change rules to predict and classify sample points according to land type. The rules extracted from the artificial intelligence model differ from the statistical model in the form of valuable periods. Generally, its prediction results exist that the same sample matches multiple rules and multiple categories [30].

## 7. Experiments Results of Real Geographic Data

The experiment uses real geographic data and selects Nineveh city in Iraq as an example. Nineveh is located in the west-north of IRAQ, with an area of about 37,323 km2. Nineveh City is located in the location category at (36° 20' 24.0000" N and (43° 7' 48.0036" E) GPS coordinates. The experimental results depend on data collected for land use change in Nineveh from 1980 to 2012 [5][21].

All data on urban lands and their changes are divided into seven different categories: construction land, commercial land, industrial land, agricultural land, forest, and water body, and desert land. The first three types are merged into urban construction land, agricultural land is used alone as non-urban construction land, and the other three are non-transformable types.

After the elements are combined, two types of maps are generated for urbanization land use change simulation, as shown in Figures (3 and 4). These figures represent real urban land use for two different periods (1980 and 2012).

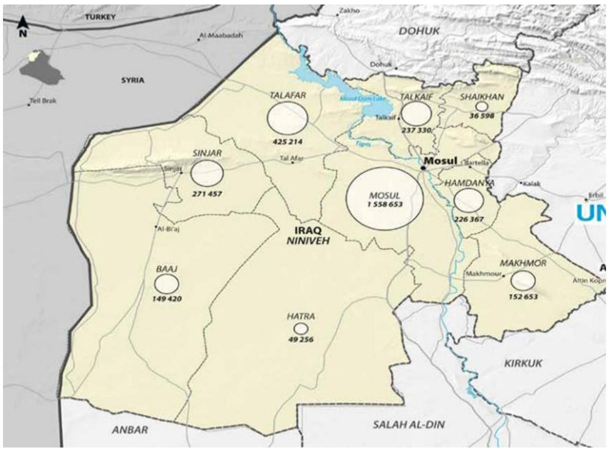


Figure 3: Real urban land use in Nineveh in 1980

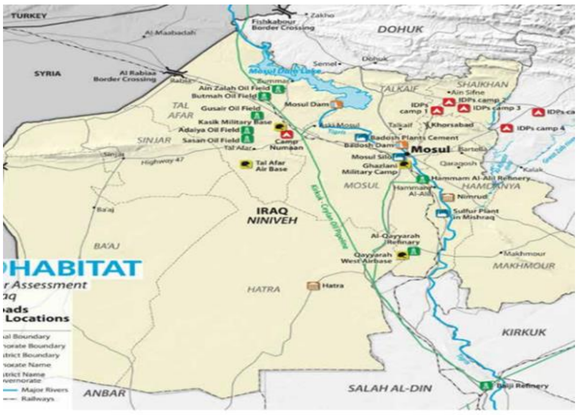


Figure 4: Real urban land use in Nineveh in 2012.

The probability of the change in urban land use is often determined by a series of spatial distance variables, the extent of nearby urban land use, and the surrounding environment, taking into account the research area's real circumstances. Population pressure represents the main driving force for urban construction land growth, so population density is the main influencing factor of the model. Distance variables, including roads, railways, commerce, industry, administrative centers, etc., have a significant role in analyzing the pattern of the spatial distribution of urban growth. The results of the SSA algorithm are highly sensitive to the selection of parameters. The specific parameters include the size of the swarm, and the proportion of salp species, The evaluation of the results is significantly influenced by the number of searches and the maximum number of cycles.

As can be seen from the figure (5), the number of swarms in the range of (50 ~ 160) has a significant effect on the accuracy of the model (PCP). When the swarming number increased over (160), the model results tend to be more stable. The continued increase in the number of the swarm has no obvious effect on the accuracy of the model, but instead increases. The cost is calculated, so the maximum number of cycles can be selected as (500). All these results represent two different periods (1980-1996) and (1997-2012).

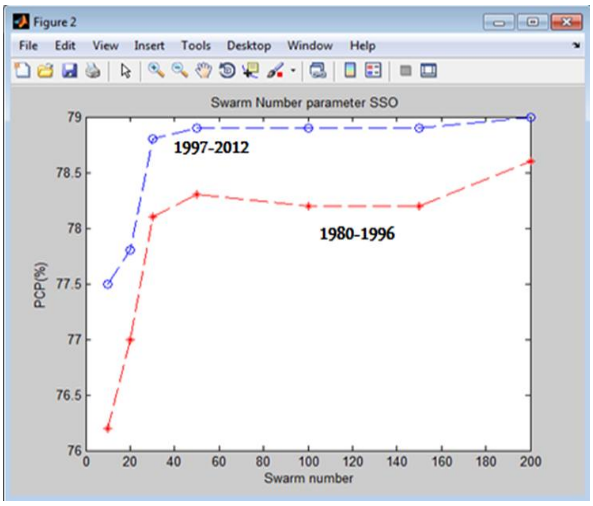


Figure 5: Represent overall accuracy for two different period

Further verifications on the effect of salp size on rule extraction are investigated. The salp swarm size is set to (40, 60, 100, 200, 300, 400, and 500) as shown in figure (6). It can be seen that the salp swarm scale has achieved good results at the value (100) for the effect of different search times on the

SSO algorithm. When the search times are greater than (150), the overall model results tend to stabilize and continue to increase.

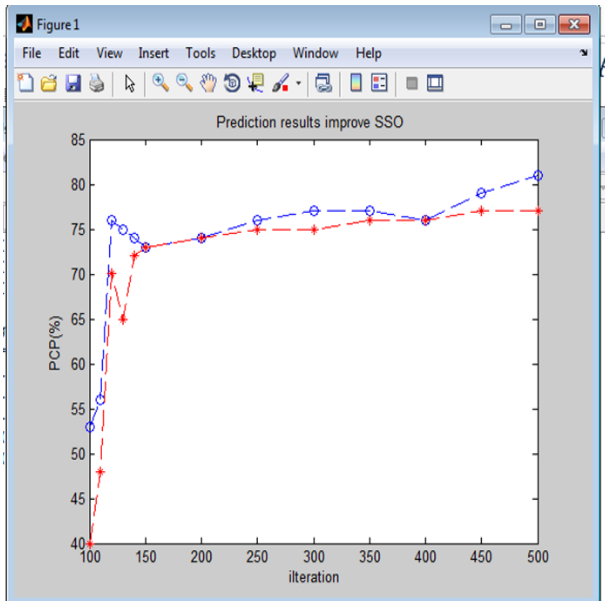


Figure 5: Explain the relationship between iteration time and with (PCP) parameter for two periods

The classification rules of the same driving force, taking this experimental area as an example, are based on the SSA algorithm to perform data mining on the second type of land use change. Table (1) explains a good comparison of different (AI) algorithms with the most important parameters (PCP).

Table 1: The classification results of the land use change of Nineveh based on different (AI) algorithms

| Data Set | SSA | Logistic progre ssion | Neural network | SVM | Ada- Boost |
|---|---|---|---|---|---|
| PCP accuracy(%) | 78.23 | 77.62 | 79.85 | 77.75 | 77.00 |

**8. Conclusions**

This paper used the overall accuracy parameter (PCP) for two different periods to employ it as a good indicator of urban land change use based on the salp swarm algorithm. Table (1) shows that the SSA algorithm used has the best effect among the three different artificial intelligence and is more suitable for land use change simulation. The artificial salp swarm algorithm model can successfully address the global and local optimization of the underlying forces that drive land use change. This paper's model is the first application of the salp swarm algorithm to the study of land use change. Using the SSA model developed in this study, the algorithm is flexible and simple to implement, and the execution efficiency is high. To extend the current model to land allocation and prediction, it is thought that it can be further coupled with the spatial and temporal aspects of land use changes in future studies.

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