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# A fuzzy intelligent system for land consolidation – a case study in Shunde, China

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## Abstract

Traditionally, potential evaluation methods for farmland consolidation have depended mainly on the experts' experiences, statistical computations or subjective adjustments. Some biases usually exist in the results. Thus, computer-aided technology has become essential. In this study, an intelligent evaluation system based on a fuzzy decision tree was established, and this system can deal with numerical data, discrete data and symbolic data. When the original land data are input, the level of potential of the agricultural land for development will be output by this new model. The provision of objective proof for decision making by authorities in rural management is helpful. Agricultural land data characteristically comprise large volumes, complex varieties and more indexes. In land consolidation, it is very important to construct an effective index system. We needed to select a group of indexes useful for land consolidation according to the concrete demand. In this paper, a fuzzy measure, which can describe the importance of a single feature or a group of features, is adopted to accomplish the selection of specific features. A fuzzy integral that is based on a fuzzy measure is a type of fusion tool. We obtained the optimal solution for a fuzzy measure by solving a fuzzy integral. The fuzzy integrals can be transformed to a set of linear equations. We applied the L1-norm regularization method to solve the linear equations, and we found a solution with the fewest nonzero elements for the fuzzy measure; this solution shows the contribution of corresponding features or the combinations of decisions. This algorithm provides a quick and optimal way to identify the land index system when preparing to conduct the research, such as we describe herein, on land consolidation.

Shunde's "Three Old" consolidation project provides the data for this work. Our estimation system was compared with a conventional evaluation system that is still accepted by the public. Our results prove to be consistent, and the new model is more automatic and intelligent. The results of this estimation system are significant for informing decision making in land consolidation.





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## 1 Introduction

Rural conditions have been destroyed in many countries of the world, and these conditions may continue to worsen. Land consolidation (LC) is an effective instrument in rural development. Land consolidation comprises two main components: land reallocation and agrarian spatial planning. Land reallocation can be referred to as land readjustment, which involves the rearrangement of ownership in terms of parcels (size, shape and location) and rights (land exchange). Land reallocation is the core part of the land consolidation approach. Agrarian spatial planning includes the provision of the necessary infrastructure such as roads, irrigation systems, drainage systems, landscaping, environmental management, village renewal, and soil conservation (Thomas, 2006b). LC aims to increase land processing efficiency (Blaikie and Sadeque, 2000; Niroula and Thapa, 2007) and support rural development (Sklenicka, 2006). Thus, LC is very important for rural development. How to proceed with land consolidation and how to evaluate the potential of land for consolidation are crucial problems to be addressed by authorities. The "Three Old" project, which is underway in China, is the typical approach to exploring farmland potential. This "Three Old" reformation can help by returning the entire profit obtained from selling farmland to the farmer. But, all money must be used for reformation of old villages and construction of new villages. Farmers are encouraged to live in a centralized manner in order to free up plenty of farmland to simultaneously achieve large-scale agriculture management and village construction. Land consolidation is the key to the "Three Old" project.

To date, many researchers have focused on the potential for evaluating world land use. The Turkish Statistical Institute (TUIK, 2001) performed a general agricultural census in Turkey. LC projects were developed depending totally on the experiences of those involved (Sonnenberg, 1996; Thomas, 2005, 2006a). A framework for the classification of Peatland Disturbance was proposed (Connolly and Holden, 2013). This model is still subjective. Some scholars proposed statistical method for classifying lands. Quantitative change detection methods was adopted for classifying land





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cover conversions in the eastern Mediterranean coastal wetlands of Turkey (Alphan, 2012). The multivariate statistical approaches was used for determine the criteria of grassland degradation and hierarchical classification highlights two broad classes in the Sanjiangyuan region (Li et al., 2012). Intelligent systems can interpret the professional result and enhance the cognitive performance of decision makers. A fuzzy expert system was proposed for analyzing and solving uncertainty in farmland data (Tayfun and Fatih, 2011). Unsupervised classification of the agricultural area of South Australia was used for severity levels of salt-affected soil based on satellite imagery (Setia et al., 2013). A Spatial Decision Support System (SDSS)-based land reallocation model was developed to reallocate newly created regular-size parcels to landowners in land-consolidation projects (Tayfun and Fatih, 2011). A combined set of digital soil mapping–iterative principal component analysis and sampling design techniques–conditioned Latin hypercube sampling was used to quantify and predict the spatial distribution of soil properties in southern Arizona, USA (Holleran et al., 2015). The models are constructed using computer technology, which is faster and more trustworthy. Still, the results are not intuitive or natural. In this paper, a fuzzy decision tree system for LC is proposed. The characteristics of the decision tree include strong interpretability, high accuracy and rapid implementation, thereby surpassing traditional models.

In agricultural land consolidation, the land index system is important for farmland evaluation. Therefore, the selection of land indexes affects evaluations and decisions. Currently, many researchers have focused on the optimization and selection of a land index system. T. L. Saaty proposed an index-selection method based on an analytic hierarchy process with weights (Saaty and Peniwati, 2008). He proposed the least square method (LSM) and the least logarithm square method (LLSM) for confirming the previous weights (Saaty, 2010). However, land indexes are multiple and very complicated. These indexes may be related to society, economics and ecology. For example, a functional classification index (FCIi) for rangelands combines the productive value (GPi), ecological services value (GEi), ecological sensitivity (ESIi) and seasonal grazing importance (SGIi) (Liu et al., 2011). Traditionally, a land index system was constructed





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according to the experiences of the experts. Due to human factors, however, these evaluations lost objectivity and consistency. Obtaining a set of accurate weights in the analytic hierarchy process is too difficult. The study of soils requires an interdisciplinary approach (Brevik et al., 2015). In this article, a new method based on a computational tool – the fuzzy measure – is proposed for land index selection. This method avoids the human effect and confirms the final index system objectively. A fuzzy measure can describe the importance of the single index and the combination of indexes for decision making (Sugeno, 1974). We can obtain a fuzzy measure with sparse values by using the L1-Norm method. Those indexes with non-zero fuzzy measures are kept in the final index system.

In this paper, the introduction has been given in Sect. 1. Section 2 shows the background and the data drawn from Shunde's "Three Old" project. The next section presents the preliminaries, definitions, and the new system. The results and analysis are shown in Sect. 4. Summaries and policy advice are provided in Sect. 5.

## 2 Materials and data description

For this study, we took the "Three Old" reconstruction project in the Shunde District of Guangdong Province in China as the study case. The "Three Old" refers to old villages, old factories and old towns. The aim of the "Three Old" reformation is to encourage peasants to live in centralized residences and empty large blocks of cultivated land for the development of large-scale agriculture. Therefore, the "Three Old" project mainly is focused on the reconstruction of old villages. Our model is proposed for evaluating the development potential of those reconstructed villages and to provide support for decision making in agricultural development.

Shunde is the pioneer in economic reformation in Guangdong. Its development from an agricultural city to an industrial district spanned 10 years. Shunde is located in southern Guangdong and in the middle of the ZhuJiang River Triangle plain, which extends east to Panyu; north to Foshan; and is contiguous with Shenzhen, Hongkong





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and Macau. The special geographical location, as shown in Fig. 1, dictates the degree of reformation. In this rapidly developing economy, a large amount of cultivated land resources have been destroyed. This extensive pattern of land use is difficult to sustain. The contradiction between supply and demand of cultivated land resources is increasingly becoming acute. These factors restrict rural sustainable development. Thus, the government proposed the "Three Old" consolidation project to strengthen the management of land with construction and to encourage saving land for use in intensive agriculture. The evaluation model can be popularized to these areas, each of which is faced with the same problems.

## 2.1 Pre-process data

The potential evaluation of "Three Old" land consolidation is mainly focused on those land blocks that contain plots and buildings. There are a total of 477 subprojects, of which, 23 subprojects with 5050.86 acres have been completed, 22 are currently being reconstructed, and 432 with 67 134.35 acres have not been started as shown in Table 1. This project is characterized by large areas of land and a large quantity, a wide range and a concentrated distribution of subprojects. The total area reaches to 77 299.77 acres, which is 16.73 % of the land with construction in cities and towns. The ratios of each type of the "Three Old" lands are shown in Figs. 2 and 3.

In this project, the evaluation targets are characterized by multiple features. It is necessary to normalize all feature values to cancel the influence of these variables and values. One general method is 0-1 normalization, which scales the feature by bring all values into the range [0,1]. It is also called unity-based normalization.

Let $X_{\max_{ij}}$ indicates the maximum value and $X_{\min_{ij}}$ indicates the minimum value for the $j^{\text{th}}$ feature of the $i^{\text{th}}$ case. The normalization for each variable can be computed according to the following equations.

For the active index:

$$S_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}};$$

for the negative index:

$$S_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}}.$$

According to the previous formula, the range of $X'$ is between 0 and 1. The distribution of each $X'$ is the same as that of the original value of $X$. The advantage of 0-1 normalization is that the best situation is always 1 and the worst one is always 0, whether the value is negative or active. However, this process disregards the differences among the features' values, which means the relationship among features cannot be determined. However, the 0-1 normalization is still the simplest method.

### 2.2 Land index system

In this study, we began our investigation by collecting materials, using spatial image recognition, conducting field investigations, and assessing results of a questionnaire for the land potential evaluation. All factors, including the land-use state, and economic, social, ecological, environmental and policy factors have been considered. The results will be summarized and analyzed so that the entire contribution of the "Three Old" project can be precisely acknowledged. All indexes being considered are described in Table 2.

We applied a new model to the Shunde data to determine the index system, which is important to the study. Several classical evaluation models were adopted for testing the feature selection results. However, the current number of indexes of the "Three Old" data is too large for use with a fuzzy integral. It takes very long time to acquire the fuzzy measure. Therefore, feature selection is a necessary step. Based on previous





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research, reduction in rough sets is the most effective way to process the data before selecting the indexes and evaluating potential.

## 3 Evaluation method and model

In land consolidation, we must deal with data collected by humans from many locations. These data may be uncertain and noisy. It is necessary to adopt an objective tool to solve the problem of subjectivity. Thus, a fuzzy decision tree was chosen for use in this study. Fuzzy logic was proposed by Zadeh (1965), and this technique can describe and handle vague and ambiguous data. Fuzzy logic is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values) fuzzy logic variables may have a true value that ranges in degree from 0 to 1. Fuzzy logic has been extended to handle the concept of partial truth, where the true value may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Irrationality can be described in terms of what is known as the fuzzjective. Fuzzy logic has been applied to many fields, from control theory to artificial intelligence.

### 3.1 Fuzzy set theory

Fuzzy set theory is primarily concerned with quantifying and reasoning by using natural language in which words can have ambiguous meanings. This can be thought of as an extension of traditional crisp sets, in which each element must either be in or not in a set. Fuzzy sets are defined on a non-fuzzy universe of discourse, which is an ordinary set (Wang and Lee, 2006). A fuzzy set is characterized by a membership function $\mu_F(x)$, which assigns a membership degree $\mu_F(x) \in [0,1]$ to every element. When $\mu_A(x) > 0$, an element $x \in U$ will be in a fuzzy set $F$. That is, $\mu_F(x) = 1$ represents a full member (Zimmermann, 1991). Membership functions can either be chosen based on the user's experience or by using optimization procedures (Jang, 1992; Horikowa et al., 1992). Typically, a fuzzy subset $A$ can be represented as

$$A = \left\{ \frac{\mu_A(x_1)}{x_1}, \frac{\mu_A(x_2)}{x_2}, \cdots, \frac{\mu_A(x_n)}{x_n} \right\}$$

Fuzzification is the process of changing a real scalar value into a fuzzy value (Tsoukalas and Uhrig, 1993). This is achieved with the different types of fuzzifiers. In this paper, we adopted the trapezoidal or triangular fuzzifier. Fuzzification of a real-valued variable is performed with intuition, experience and analysis of the set of rules and conditions associated with the input data variables. There is no fixed set of procedures for fuzzification.

### 3.2 Fuzzy decision tree construction

Fuzzy sets and fuzzy logic are able to deal with language-related uncertainties by fuzzifying, while providing a symbolic framework for increasing knowledge comprehensibility. Fuzzy decision trees (FDT) differ from traditional crisp decision trees in three respects (Janikow, 1998): the splitting of criteria based on fuzzy restrictions, the different inferring procedures and defining the fuzzy sets that represent the data. The heuristic for the fuzzy decision tree is based on minimal ambiguity.

The procedure for constructing FDT is mainly as follows:

1. Place all data into one node as the root;
2. Select one feature with low entropy to divide the cases in the root into different son nodes according to the different feature values.
3. For each son node, repeat the same action until the node cannot be divided, i.e., leaf.

Given that nonleaf node $S$ has $n$ fuzzy features $A^{(1)}, A^{(2)}, \ldots, A^{(n)}$ to be selected, for every $k (1 \leq k \leq n)$, fuzzy feature $A^{(k)}$ takes $m_k$ linguistic values as $T_1^{(k)}, T_2^{(k)}, \ldots, T_{m_k}^{(k)}$. $A^{(n+1)}$





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represents a class that takes values as $T_1^{(n+1)}, T_2^{(n+1)}, \ldots, T_m^{(n+1)}$. In symbolic datasets, the value of features and classes are 0 or 1. For a better description, we define $|S|$ as representing the number of examples of the nonleaf node $S$.

For each value of feature, $T_i^{(k)} (1 \le k \le n, 1 \le i \le m_k)$, the relative frequency about the $j^{\text{th}}$ class $T_i^{(n+1)}$ on nonleaf node $S$ is defined as $p_{ij}^{(k)} = |S_i \cap S_j|/|S_i|$, in which $S_i$ is the subset of $S$ for which feature $A^{(k)}$ has value $T_i^{(k)}$ (i.e., $S_i = \{s \in S | A^{(k)} = T_i^{(k)}\}$) and $S_j$ is the subset of $S$ too, for which $A^{(n+1)}$ takes value $T_j^{(n+1)}$ (i.e., $S_j = \{s \in S | A^{(n+1)} = T_j^{(n+1)}\}$). On nonleaf node $S$, the classification entropy of $T_i^{(k)}$ is defined as $\mathrm{Entr}_i^{(k)} = -\sum_{j=1}^{m} |S_i \cap S_j|/|S_i| \cdot \log_2 |S_i \cap S_j|/|S_i|$.

The average classification entropy of the $k$th feature is defined as $E_k = \sum_{i=1}^{m_k} \omega_i \, \mathrm{Entr}_i^{(k)}$, in which $\omega_i$ represents the weight of the ith value $T_i^{(k)}$, $\omega_i = |S_i|/|S|$. Thus, we can summarize to get the entropy, i.e., $E_k = \sum_{i=1}^{m_k} \frac{|S_i|}{|S|} \, \mathrm{Entr}_i^{(k)}$.

FDT aims to find out one feature that can make the average classification entropy the minimum, i.e., selecting one integer $k_0$, so that $E_{k_0} = \mathrm{Min}_{1 \le k \le n} E_k$.

## 3.3 Land index selection

We are given a data set consisting of $L$ examples, called a training set, where each record contains the value of a decisive feature, $Y$, and the value of predictive features $x_1, x_2, \ldots, x_n$. The positive integer $L$ is the data size. The decisive feature indicates the class to which each example belongs, and it is a categorical feature with values coming from an unordered finite domain. The set of all possible values of the decisive feature is denoted by $Y = y_1, y_2, \ldots, y_m$, where each $y_k$, $k = 1, 2, \ldots, m$, refers to a specified class. The predictive features are numerical, and their values are described by an $n$-dimensional vector, $(f(x_1), f(x_2), \ldots, f(x_n))$. The range of the vector, a subset of $n$-dimensional Euclidean space, is called the feature space. The $j^{\text{th}}$ observation consists of $n$ predictive features and the decisive feature can be denoted by

$(f_j(x_1), f_j(x_2), \ldots, f_j(x_n), Y_j)$, $j = 1, 2, \ldots, L$. Before introducing the model, we give out the fundamental concepts according to the following requirements.

### 3.3.1 Fuzzy measure

Let $X = x_1, x_2, \ldots, x_n$ be a nonempty finite set of features and $P(X)$ be the power set of $X$. To further understand the practical meaning of the fuzzy measure, the elements in a universal set $X$ are considered as a set of predictive features. Then, each value of the fuzzy measure is assigned to describe the influence of each predictive feature or combination of them to the objective. The influences of the predictive features to the objective are dependent due to the nonadditivity of the fuzzy measure. If $\mu(X) = 1$, then $\mu$ is said to be regular. The monotonicity and non-negativity of the fuzzy measure are too restrictive to apply for more problems. Thus, the signed fuzzy measure, which is a generalization of the fuzzy measure, has been defined (Murofushi et al., 1994; Grabisch et al., 2000) and adopted.

A signed fuzzy measure can set its value being negative and free the monotonicity constraint. Thus, it is more flexible to describe the contribution of the individual and combination of the predictive features for some targets. Let $f$ be a real-valued function on $X$. The fuzzy integral of $f$ with respect to $\mu$ is obtained by

$$\int f \mathrm{d}\mu = \int_{-\infty}^{0} [\mu(F_\alpha) - \mu(X)] \mathrm{d}\alpha + \int_{0}^{\infty} \mu(F_\alpha) \mathrm{d}\alpha \tag{1}$$

where $F_\alpha = \{x | f(x) \geq \alpha\}$, for any $\alpha \in (-\infty, \infty)$, is called the $\alpha$-cut of $f$.

Usually, for calculating the value of the fuzzy integral for the given real-valued function $f$, the values of $f$, i.e., $f(x_1), f(x_2), \ldots, f(x_n)$, can be sorted in a nondecreasing order so that $f(x'_1) \leq f(x'_2) \leq \ldots \leq f(x'_n)$, where $(x'_1, x'_2, \ldots x'_n)$ is a certain permutation of





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$(x_1, x_2, \ldots x_n)$. Thus, the value of the fuzzy integral can be computed by

$$\int f\,\mathrm{d}\mu = \sum_{i=1}^{n} [f(x'_i) - f(x'_{i-1})]\mu(\{x'_i, x'_{i+1}, \ldots x'_n\}), \quad \text{where } f(x'_0) = 0 \tag{2}$$

The Fuzzy Integral can deal with nonlinear space based on linear operators.

### 3.3.2 Transformation of the fuzzy integral

To be convenient, Wang (2003) proposed a new scheme to calculate the value of a fuzzy integral by the inner product of two $(2^n - 1)$-dimension vectors as

$$\int f\,\mathrm{d}\mu = \sum_{j=1}^{2^n-1} z_j \mu_j \tag{3}$$

where

$$z_j = \begin{cases} \min\limits_{i:\mathrm{frc}\left(\frac{j}{2^i}\right)\in[\frac{1}{2},1)} f(x_i) - \max\limits_{i:\mathrm{frc}\left(\frac{j}{2^i}\right)\in[0,\frac{1}{2})} f(x_i), & \text{if it is larger than zero or } j \text{ is } 2^n - 1; \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

for $j = 1, 2, \ldots, 2^n - 1$ with a convention, in which the maximum on the empty set is zero. Here, $\mathrm{frc}(\frac{j}{2^i})$ denotes the fractional part of $\frac{j}{2^i}$. In Eq. (4), if $j$ is expressed in the binary form $j_n j_{n-1} \ldots j_1$, then $\{i|\mathrm{frc}(\frac{j}{2^i}) \in [\frac{1}{2}, 1)\} = \{i|j_i = 1\}$ and $\{i|\mathrm{frc}(\frac{j}{2^i}) \in [0, \frac{1}{2})\} = \{i|j_i = 0\}$.

A significant advantage of this new computation scheme is that it can easily discover the coefficient matrix of a system of linear equations with the unknown variables $\mu$. The fuzzy integral can be applied to the further applications, such as regression and classification (Wang, 2003; Wang et al., 1998; Leung et al., 2002). In those practical applications, values of the signed fuzzy measure are to be estimated using the training data sets as unknown parameters. The new scheme makes it more convenient by using an algebraic method, such as the least square method, to estimate the value of $\mu$ and reduce the complexity of computation.

After adopting the transformation, the fuzzy measure for a known dataset can be obtained by using L1-norm regularization.

### 3.3.3 Solution of fuzzy measure

For determining the fuzzy measure, researchers have proposed many methods. In our past work, we used GA to learn the value of the fuzzy measure. In this article, we adopted a new method based on L1-norm regularization.

For solving regression problems, the least square estimation is the most popular function, alternately referred to as the minimum of the residual sum of squared errors (RSS) (Hastie et al., 2001): RSS $= \sum_{i=1}^{n}(y_i - \omega_0 - \sum_{j=1}^{p} x_{ij}\omega_i)^2$. Regularization addresses the numerical instability of the matrix inversion and produces lower variance models. It is obvious that the following penalized RSS function with respect to $\omega$ and $\omega_0$: $\sum_{i=1}^{n}(y_i - \omega_0 - \sum_{j=1}^{p} x_{ij}\omega_i)^2 + \lambda \sum_{j=1}^{p} \omega_j^2$. This is belonged to L2 regularization. For simplifying the notation, we transferred it to the following form (in matrix notation): $\|X\omega - y\|_2^2 + \lambda\|\omega\|_2^2$. Although L2 regularization is an effective means of achieving numerical stability and increasing predictive performance, it cannot address another important problem with least squares estimation, i.e., parsimony of the model and interpretability of the coefficient values. It does not encourage sparsity in some cases (Tibshirani, 1996). Thus, L1-norm has been a trend to replace the L2-norm with an. The L1 regularization has many of the same beneficial properties as L2 regularization; meanwhile, it can obtain a sparse solution, which is more easily interpreted (Hastie et al., 2001) and is what our model needs. With a fuzzy integral, determining the fuzzy measure is the key point. The fuzzy measure represents the importance of features and the interaction degree of the combined features.





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We hope to get a solution of the fuzzy measure with the fewest nonzero values corresponding to the most important features and feature combinations. Using L1-norm regularization, we can minimize the following formula to reduce the number of nonzeroes in the fuzzy measure: $\|\sum_{j=1}^{2^n-1} z_j\mu_j - y\|_2^2 + \lambda\|\mu\|_1$. We can control the compression degree for the fuzzy measure by adjusting the parameter $\lambda$. Shirish and Sathiya (2003) proposed the least absolute selection and shrinkage operator (LASSO) model, which is based on the Gauss–Seidel method. The obvious advantages of the Gauss–Seidel approach are simplicity and low iteration cost. We adopted this type of LASSO to solve the L1-Norm problem. Finally, the optimal fuzzy measure can be obtained and the corresponding land index system is constructed. For example, the fuzzy measure is solved as {0, 0.6, 0, 0, 0, 0.4, 0} for three indexes $\{x_1, x_2, x_3\}$. Then, indexes or index combinations corresponding to non-zero are $\{x_2\}$ and $\{x_2, x_3\}$, which will be important for the final decision.

## 4 Experiments and analysis

Before building the evaluation model, we need finish the feature selection to reduce the complexity of computation by deleting the redundant information. We adopt the WEKA exploit platform to call the feature selection function and develop the evaluation model. After completing the feature selection, the FDT is constructed on the pre-processed data for evaluating the comprehensive potential. The data from the Shunde project contains 477 blocks, 27 of which have completed reformation and can be used as the training set.

The model construction can be presented as shown in Fig. 4.

After applying the L1-norm method to determine the fuzzy measure, the parameter $\lambda$ in the L1-Norm method is used for controlling the degree of compression for reducing the nonzeroes. We set the value of $\lambda$ as 0, 1, 5, 10, 20, 50 and 100. The larger the value of $\lambda$ is, the fewer the number of zeroes in the solution. The compressed fuzzy measure can simplify the computation of the fuzzy integral at the cost of performance. It needs to select an appropriate value for $\lambda$ to balance the complexity and the performance. Finally, the value of $\lambda$ is determined as 100. The binary forms corresponding to the fuzzy measure with values are {10000000} and {1111100} after being compressed by the L1-Norm, which means keeping indexes from x1 to x5. All results with different feature selection methods are listed in Table 3. We can see that the size of the tree is compressed as the number of features is decreased and the performance is improved.

Based on those selected indexes, an evaluation model will be constructed. In this project, those blocks that have been finished and those that are ongoing with transformation present their actual potential and are used as a training set. The remainder, which contains those that have not yet been started, are tested via comparison with the conclusions that have been drawn from these statistics and this analysis. All artificial marks are removed from the original data. The final dataset contains 27 predictive features and 3 levels of potential. Level one means the highest potential, level 2 represents the medium type, and level 3 is the worst grade for transformation. All results are listed in Table 4 to show the situation of the predicted potential of each town.

Assuming that the potential marked by experience is the destination classification, the prediction results of the fuzzy decision tree, which is 89.12 %, shows high consistency with the artificial remarks and the actual land situation of Shunde's "Three Old" project. There is no block with level 1. It illustrates that there are no very old and battered buildings in the Shunde district. In all blocks, levels 2 and 3 exist. Those blocks in the second ranking are characteristic of an effective land-use rate and modest volume rate. However, due to the bad living environment and the ordinary location, the price will not increase greatly. The third level blocks present reasonable volume rate and buildings density and good environmental quality. Some basic facilities need to be improved, so the transformation potential is not so high. Longjiang, Lecong and Ronggui are arranged as the top three towns according to the ratio of level 2, which are key targets that need to be transformed.

## 5 Conclusions

To date the "Three Old" transformation project is just beginning to be developed in Guangdong, China. Study on the "Three Old" project is very useful for the land consolidation field. However, research related to the potential of transformation is sparse. Traditional evaluation of land for potential consolidation mostly depended on statistical methods and experts' experiences. In this article, a soft computing method-the fuzzy decision tree-is induced to evaluate the potential of blocks for transformation. The results are more scientific, explicable and intelligent. The assessment of potential as presented by FDT has reinforced the conclusions drawn using traditional methods. This study can provide supplementary support for decision making.

The "Three Old" transformation is a type of policy problem that is affected by human factors. We need to find better methods to avoid subjectivity. Meanwhile, there are too many indexes for each land project. Some provide noisy information, which is not good for model construction and a final assessment. Thus, index screening is an essential part of land consolidation. Due to the great number of indexes, the computational complexity of determining a fuzzy measure is very high. It is difficult to find each value of the fuzzy measure. In this paper, we used the L1-norm method to solve the problem of complexity. The fuzzy measure with the fewest nonzero values can be obtained by using L1-norm regularization. Experimental results have shown that the selection of indexes can help reduce the complexity and improve performance. Selecting one optimal value of parameter $\lambda$ can maintain a balance between complexity and performance. The values of the fuzzy measure describe the interaction of indexes with respect to contribution for decision making. After selecting the indexes, we built a fuzzy intelligent system based on a fuzzy decision tree for land potential evaluation; this system can be used to divide the consolidated blocks into different levels to facilitate decision making. This system can greatly help those making decisions on how to push farmland reformation.

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## References

Alphan, H.: Classifying land cover conversions in coastal wetlands in the Mediterranean: pair-wise comparisons of Landsat images, Land Degrad. Dev., 23, 278–292, 2012.

Blaikie, P. M. and Sadeque, A. Z.: Policy in the High Himalayas: Environment and Development in the Himalayan Region, ICIMOD, Kathmandu, 2000.

Brevik, E. C., Cerdà, A., Mataix-Solera, J., Pereg, L., Quinton, J. N., Six, J., and Van Oost, K.: The interdisciplinary nature of *SOIL*, SOIL, 1, 117–129, doi:10.5194/soil-1-117-2015, 2015.

Cay, T. and Iscan, F.: Fuzzy expert system for land reallocation in land consolidation, Expert Syst. Appl., 38, 11055–11071, 2011.

Connolly, J. and Holden, N. M.: Classification of peatland disturbance, Land Degrad. Dev., 24, 548–555, 2013.

Grabisch, M., Murofushi, T., and Sugeno, M. (eds.): Fuzzy Measures and Integrals: Theory and Applications, Physica-Verlag, Inc. Secaucus, NJ, USA, 2000.

Hastie, T., Tibshirani, R., and Friedman, J. H.: The Elements of Statistical Learning, Springer, New York, USA, 43–137, 2001.

Holleran, M., Levi, M., and Rasmussen, C.: Quantifying soil and critical zone variability in a forested catchment through digital soil mapping, SOIL, 1, 47–64, doi:10.5194/soil-1-47-2015, 2015.

Horikowa, S., Furahashi, T., and Uchikawa, Y.: On fuzzy modeling using fuzzy neural networks with back-propagation algorithm, IEEE T. Neural Networ., 3, 801–806, 1992.

Jang, J. S. R.: Self-learning fuzzy controllers based on temporal back-propagation, IEEE T. Neural Networ., 3, 714–723, 1992.

Janikow, C. Z.: Fuzzy decision trees: issues and methods, IEEE Trans. on Systems, Man, and Cybernetics-Part B, 28, 1–14, 1998.

Leung, K. S., Wong, M. L., Lam, W., Wang, Z., and Xu, K.: Learning nonlinear multiregression networks based on evolutionary computation, IEEE Trans. on Systems, Man and Cybernetics, Part B, 32, 630–644, 2002.





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Li, X. L., Perry, G. L. W., Brierley, G., Sun, H. Q., Li, C. H., and Lu, G. X.: Quantitative assessment of degradation classifications for degraded alpine meadows (heitutan), Sanjiangyuan, western China, Land Degrad. Dev., 25, 417–427, 2014.
Liu, X. Y., Liang, T. G., Guo, Z. G., and Long, R. J.: A rangeland management pattern based on functional classification in the northern Tibetan region of China, Land Degrad. Dev., 25, 193–201, 2014.
Murofushi, T., Sugeno, M., and Machida, M.: Non monotonic fuzzy measures and the Choquet integral, Fuzzy Set. Syst., 64, 73–86, 1994.
Niroula, G. S. and Thapa, G. B.: Impact of land fragmentation on input use, crop yield and production efficiency in the mountains of Nepal, Land Degrad. Dev., 18, 237–248, 2007.
Saaty, T. L.: Mathematical Principles of Decision Making, RWS Publications, Pittsburgh, Pennsylvania, 2010.
Saaty, T. L. and Peniwati, K.: Group Decision Making: Drawing out and Reconciling Differences, RWS Publications, Pittsburgh, Pennsylvania, 2008.
Setia, R., Lewis, M., Marschner, P., Raja Segaran, R., Summers, D., and Chittleborough, D.: Severity of salinity accurately detected and classified on a paddock scale with high resolution multispectral satellite imagery, Land Degrad. Dev., 24, 375–384, 2013.
Shevade, S. K. and Keerthi, S. S.: A simple and efficient algorithm for gene selection using sparse logistic regression, Bioinformatics, 19, 2246–2253, 2003.
Sklenicka, P.: Applying evaluation criteria for the land consolidation effect to three contrasting study areas in the Czech Republic, Land Use Policy, 23, 502–510, 2006.
Sonnenberg, J.: The European Dimensions and Land Management-Policy Issues (Land Readjustment and Land Consolidation as Tools for Development), FIG Commission 7, Hungary, 1996.
Sugeno, M.: Theory of Fuzzy Integrals and Its Applications, Doctoral thesis, Tokyo Institute of Technology, Tokyo, Japan, 1974.
Thomas, J.: Actual trends concerning land management, land readjustment and land consolidation in Europe, in: Report at the 7th Workshop and 8th MC Meeting of the Action G9 of COST, Greece, 9–11 June, 2005.
Thomas, J.: What's on regarding land consolidation in Europe?, in: Proceedings of the XXIII International FIG Congress, Munich, Germany, 8–13, 8–13 Ocotber, 2006a.





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Thomas, J.: Property rights, land fragmentation and the emerging structure of agriculture in central and eastern European countries, Electronic Journal of Agricultural and Development Economics Food and Agriculture Organization, 3, 225–275, 2006b.
Tibshirani, R.: Regression shrinkage and selection via the lasso, J. Roy. Stat. Soc. B, 58, 267–288, 1996.
Tsoukalas, L. H. and Uhrig, R. E.: Fuzzy and Neural Approaches in Engineering, John Wiley & Sons, Inc., New York, USA, 1993.
TUIK: Tarm Saym Sonuclar, available at: tuik.gov.tr (last access: September 2014), 2001 (in Turkish).
Wang, T.-C. and Lee, H.-D.: Constructing a fuzzy decision tree by integrating fuzzy sets and entropy, WSEAS Transactions on Information Science and Applications, 8, 1547–1552, 2006.
Wang, W., Wang, Z. Y., and Klir, G. J.: Genetic algorithm for determining fuzzy measures from data, J. Intell. Fuzzy Syst., 6, 171–183, 1998.
Wang, Z.: A new genetic algorithm for nonlinear multiregressions based on generalized Choquet integrals, in: Proc. 12th IEEE Intern. Conference on Fuzzy Systems, St. Louis, Missouri, USA, 25–28 May 2003, 2, 819–821, 2003.
Zadeh, L.: Fuzzy sets, Inform. Control, 8, 338–353, 1965.
Zimmermann, H. J.: Fuzzy Set Theory and Its Applications, Kluwer Academic Publishers, Boston, USA, 1991.





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**Table 1.** Statistical data about the types and area of "Three Old" reconstruction.

| State | Old factory | Old town | Old villages | In total |
|---|---|---|---|---|
| Finished | 4437.91 | 568.27 | 44.68 | 5050.86 |
| On-going | 4196.71 | 354.35 | 563.51 | 5114.57 |
| Not starting | 49 634.37 | 9074.25 | 8425.73 | 67 134.35 |
| In total | 58 268.99 | 9996.86 | 9033.92 | 77 299.77 |





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**Table 2.** All indexes of "Three Old" land.

| Criteria layer | Subcriteria layer | Evaluation indexes |
|---|---|---|
| Land-use (A) | Landscapes | Building coordination<br>Block crush degree |
| | Building situation | Building age<br>Building structure |
| | Development strength | Volume ratio<br>changing of building density |
| Economical factors (B) | Basic land price<br>Investment strength<br>Per capita net income<br>Population density | Basic land price<br>changing degree of investment amount<br>Per capita net income<br>Population density |
| Social factors (C) | Social welfare | Medical and sanity<br>Education<br>Public welfares (park, square) |
| | Basic facilities | Traffic connectivity |
| | Green degree | Green ratio |
| Ecological factors (D) | Ecological environment | Noisy pollution<br>Air pollution<br>Water pollution |
| Policy (E) | Compensation and emplacement | Compensation<br>Emplacement |
| | Responding | Responding activity |
| | Management | Public participation |





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**Table 3.** The results with rough set selection and fuzzy measure selection.

| Types<br>Performance | All features | with RS selection | with FM selection |
|---|---|---|---|
| Prediction accuracy | 89.12 % | 93.06 % | **94.34 %** |
| Selected features | all | {4,6,8,9,10,11,15} | {4,6,8,9,10} |
| Number of leaves | 10 | 7 | **4** |
| Size of tree | 19 | 13 | **7** |

**Table 4.** The potential level of each town.

| District | Number of Blocks | Level 1 | Level 2 | Level 3 | Ratio of Level 2 |
|---|---|---|---|---|---|
| Daliang | 55 | 0 | 8 | 47 | 14.55 |
| London | 55 | 0 | 7 | 48 | 12.73 |
| Ronggui | 59 | 0 | 13 | 46 | **22** |
| Leliu | 44 | 0 | 7 | 37 | 15.9 |
| Lecong | 62 | 0 | 14 | 48 | **22.58** |
| Junan | 11 | 0 | 2 | 9 | 18.18 |
| Longjiang | 99 | 0 | 27 | 72 | **27.27** |
| Beijiao | 25 | 0 | 3 | 22 | 12 |
| Chencun | 15 | 0 | 3 | 12 | 20 |
| Xingtan | 26 | 0 | 2 | 24 | 7.69 |





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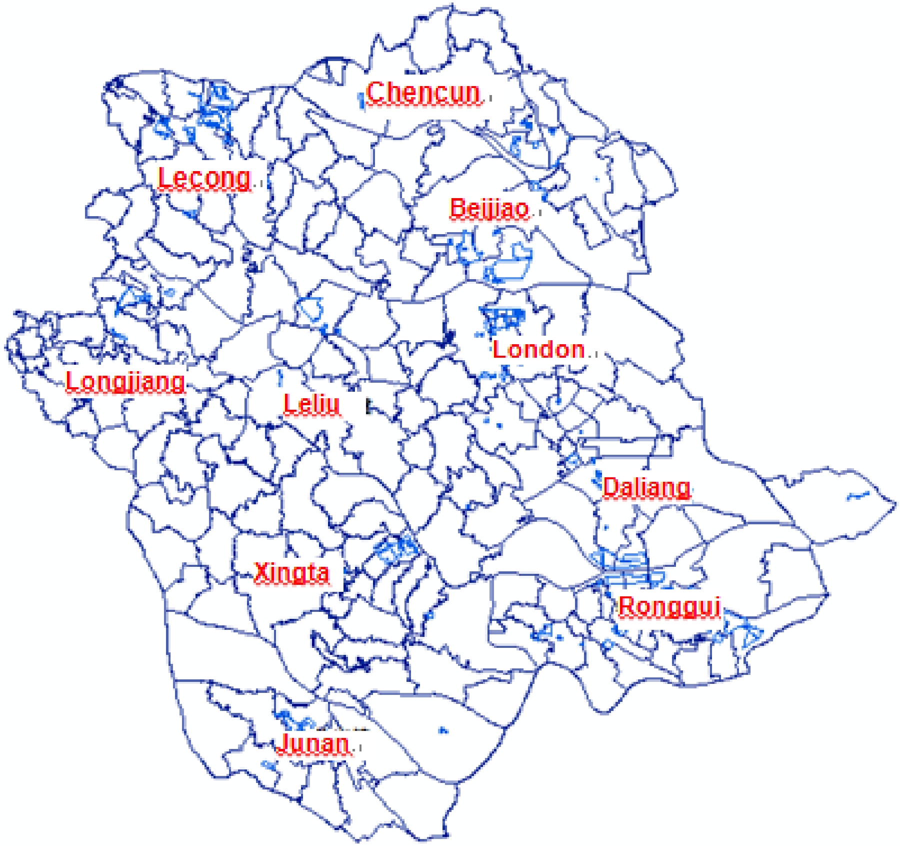


**Figure 1.** The administrative division of the “Three Old” project of Shunde.





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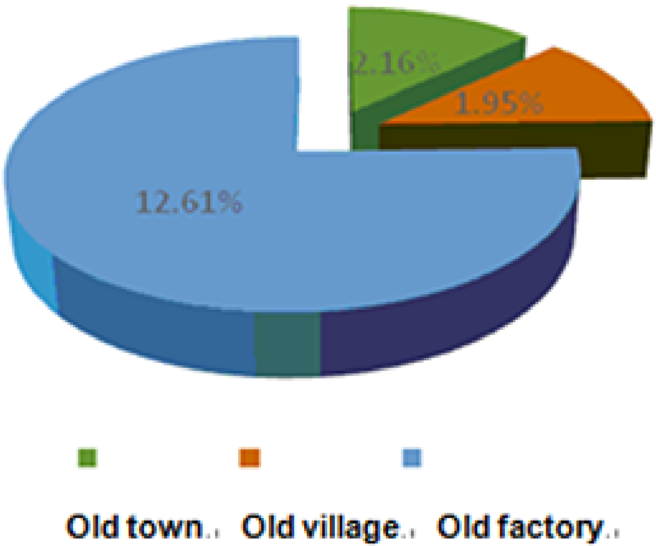


**Figure 2.** The proportion of land, according to construction type, that will be developed by "Three Old" reconstruction.





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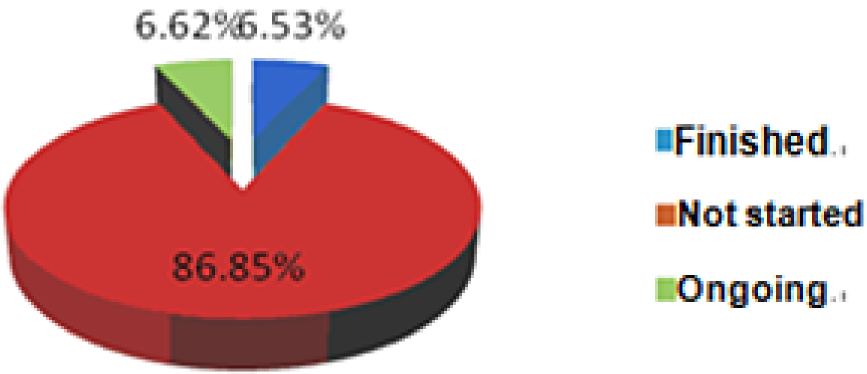


**Figure 3.** The percentages of each state of reconstruction.





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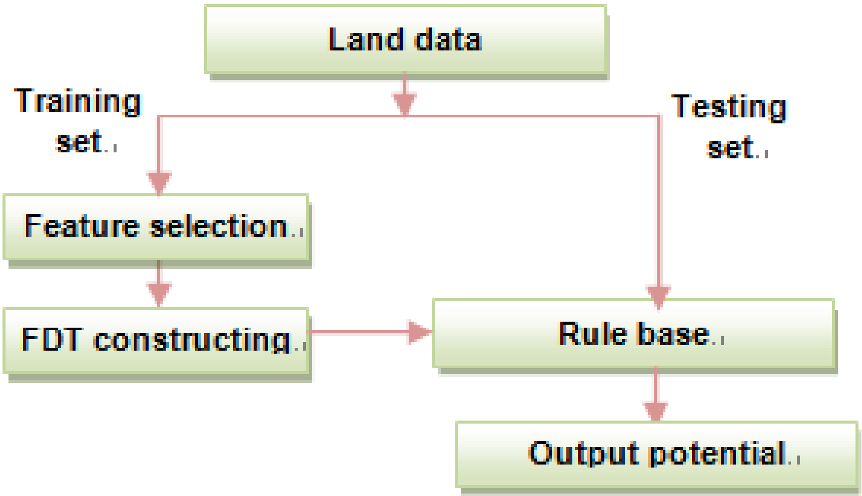


**Figure 4.** Flowchart of the model construction.





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