Assessing the Impact of Land Circulation Policy in China using Object-Oriented Methods

Sida Zhuang
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by

Sida Zhuang

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Specialisation: Environmental Modelling and Management

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Abstract

In China, rural land circulation has been considered as the new fundamental land policy to improve land-use efficiency, to rationalize farm size and to achieve modern agriculture. It would desirably lead to more rationalized and moderate scale of agricultural operation, which will help to introduce technology and enhance grain production. However, there is little literature on assessing changes in farm field size in terms of land circulation. By extracting fields from Google earth high resolution images in 2004 and 2015 and comparing, this study examines the field size changes in three study area in Anhui, one of the main grain production provinces. Object-oriented image analysis based on *eCognition software* was adopted to extract the field information. Methods of multi-resolution segmentation and fuzzy membership function classifier were employed, a satisfying extraction of fields were then exported to ArcGIS and validated by digitized sample area. An accuracy of 89% was achieved. The result reveals that in all three study area the number of farm fields and total area of farm land has dropped down, however, the mean size of fields has increased remarkably. Changes tend to be more active in flat area and suburb, with both achieving more than doubling in average field size. Meanwhile the agriculture land in this study has managed to observe the real progress of rural land circulation in China, provided a way to understand the possible cause for variation of implementation and its impact on rural land reform.

Keywords: Rural land circulation, farm field size, object-oriented classification, Google earth, eCognition

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1 Introduction

1.1 Background

In China, sustainable agricultural intensification has been considered as major priority due to decreasing farmland and the large population(Zhou et al., 2012). Since the onset of the economic reform in 1970s, China has expedited its process of urbanization, resulting in a significant loss of farmland to non-agricultural use. Fischer (2007) analysed the land monitoring data from MLR for the period 1987–2000, showing that an annually 0.3 million hectares net loss of farmland. Then, in the beginning of the new century, ecological recovery programs, like Sloping Land Conversion Program(Bennett, 2008), have greatly accelerated the decline in cultivated area. In the meanwhile, along with the population growth, a rising demand for agricultural products has caused China serious challenges in food supply given the declining farmland, with the aim of ensuring food self-sufficiency and a fair living standard for people(Verburg et al., 2000)

Under this circumstance, field size has been a central concern to governments because it plays a major role in determining the efficiency of agricultural production and the income levels of farmers (Thapa, 2007;Chen et al.,2010). However, in less developed provinces like Anhui, traditional farming with rather small field size is still the prevailing situation. Therefore, an increase in farm size, by concentration and annexation of field, seems to be an imperative and inevitable demand in the evolution of Chinese agriculture. It will help to introduce technology and attract capital investment in land, to develop high-efficiency and high-yield agriculture and accentuate the positive effects of urbanization and industrialization (Fan & Chan-Kang, 2005; Yuneng & Bo, 2011 ; Li,2010; Shang,2011) .

On the other hand, in China, rural land is normally under collective ownership. For a long time, although farmers are endowed with land use rights and contract management rights, they cannot directly trade or mortgage the collective land to expand their farmland. Hence Rural Land Circulation, the activity of the rural household contract land keeping contract right in legal way, transferring the right of management to other farmers or other economic organization (Kerselaers et al., 2013), is a milestone of Chinese agriculture gradually evolving into modern agricultural mode. However, due to the defect of supporting system, the development of rural land circulation has remained stagnant until recent years. Therefore, it is of great significance to study how well and to what extent the rural land circulation has carried out in China, in terms of farm field size changes.

Remote sensing has been proved to be an efficient way to monitor and quantify agricultural fields (Barbosa et al., 2015). Conventional methods of information extraction from remote sensing are usually based on visual interpretation or pixel-based method. However, both of them barely suffice to handle fine resolution images. Visual interpretation is too objective and time-consuming while pixel-based methods tend to end up with “salt and pepper” noise. To address the challenges of classifying high resolution remote sensed images, researchers are switching from them to object-oriented approach (Hay et al., 2005 ;Baatz & Schäpe, 2000). The initial step of an object-oriented approach is segmentation, which makes fully use of colour, shape, texture, spatial information and their interrelation to group pixels into meaningful objects. Then classification will be based on the segmentation result.

1.2 Research Problem

Although there are many studies about Rural Land Circulation in China, most of them focused on policy, system or number of household involved. Little attention has been paid to changes in field size after the implementation of rural land circulation. Consequently, neither comprehensive evaluation nor clear conclusion can be established towards the impact of this policy. This gap may be caused by the fact that there is no available data recording field size, which is reasonable because, normally, data like this will be acquired through ground survey and land registration, which is too time-and-money-consuming.

In this case, remote sensing can be a good substitute to help us have a general picture of what is going on. This study is mainly interested in the land circulation situation in less developed area where improvements are considered more needed. Meanwhile, these area are more likely to have hilly land and thus small field size, sometimes even terraced fields. As a result, it requires very fine resolution remote sensed images and appropriate field extraction methods considering the trade-offs among the complexity of classification, computational time, and classification accuracy (Li & Shao, 2014).

Therefore, object-oriented information extraction strategy was applied on Google Earth high resolution images in time series. Usually high resolution images like Quick-Bird can be expensive. By using high resolution images on Google Earth pro for free our method is more cost-effective. However, this would lead to another limitation in spectral information since Google earth images only contains three visible bands-RGB. In this case, water mask and vegetation index like NDVI, requiring information from infrared bands, won't be applicable. As a result, to extract field information using only three bands can be quite challenging.

In eCognition software, by error and trial, with a serial of rule sets and threshold classification algorithm, fields within the study area has been extracted, calculated and compared. Finally, this study shall shed some light on the distribution and change of field size under the impact of rural land circulation in less developed areas in China.

1.3 Research Objectives

1.1.1 General Objective

The overall aim of this study is to have a better understanding of distribution and changes in field size, to evaluate the role of Rural Land Circulation in these changes, and to find possible trend or correlation between field size and other factors like landscape/slope.

1.1.2 Specific Objectives

1. To extract fields from Google Earth high resolution images for the sample area pre- and post- Land Circulation policy in eCognition
2. To calculate and present the distribution and changes of field size in ArcMap
3. To assess the accuracy by validating the result with digitized sample area
4. To find possible trend or correlation between field size and other factors.

1.1.3 Research Questions

Objective1

- How to select sample area?
- How to select images from time series?
- What is the appropriate rule sets and algorithm for segmentation and classification?

Objective2

- Did field size or the number of fields change before and after the implementation of Rural Land Circulation policy?
- If so, where did these change occur and to what extent?
- Is there any change in shape pattern? If so, how?

Objective3

- How reliable is the result?

Objective4

- Is it likely that Land Circulation policy has an impact on field size?
- How does Rural Land Circulation influence the farmlands and what are the possible impact?

2 Literature Review

2.1 Land Circulation in China

2.1.1 Background and Significance

There is widespread recognition that with its huge population, China plays a critical role in international food market. According to Schade and Pimentel (2010), due to loss of arable land, China will impose unbearable pressure on global grain market with its current grain importing rate. The international agricultural commodities trade balance in China has dropped to deficit in 2004, and the amount has been increasing, with a $49.19 billion trade deficit in 2012(Hong, 2014). Firdaus et al. (2010) predicted that China may face a 14 percent deficit of the expected food demand by 2030 and a food deficit of 18 percent by 2050. The increasing trade deficit stalls the whole economic development and poses a serious threat to global food security.

On the other hand, Chinese farmers has been haunted with three major problems for years: the scale of contractual operation is small, the cultivation fields are distributed fragmentally, and the efficiency of operation is rather low (Feng et al., 2009). The main issue lies in the irrational size and distribution of fields, which could be dated back to former rural reform policy. For the purposes of equality, each households are assigned with plots of varying quality that often are geographically separated. As a consequence, average farm size in China is rather low compared to other countries (Table 1) and the farms are tend to be fragmented. This situation is reinforced by constraints on trading or transferring farmland use right, since it stops productive farmers to enlarge their farm and up-scale their operation.

Although dispute over the relationship between farm size and agricultural efficiency(Fan & Chan-Kang, 2005; Shang, 2011; Thapa, 2007; Zhang et al., 2006) has been continuing since Sen (1962) first discovered an inverse relationship between these two in India, there is no denying that fragmented farmlands will inevitably cause the loss of technical efficiency of modern agriculture (Rahman, 2009;Tan et al., 2010). Van den Berg et al.(2007) studied the impact of increasing farming size and mechanization in Zhejiang province, reaching the conclusion that it will lead to rising rural incomes and rice production.

Table 1: Average farm size is small in China

Country	Average farm size(hectares)
China	0.6
Indonesia	0.8
Japan	1.2
India	1.3
Thailand	3.2
Turkey	3.2
Colombia	25
Brazil	73
Chile	84
South Africa	288

(*Source*: 2000FAO World Census of Agriculture)

In this case, land circulation policy allows field rationalization, boosts the moderate scale operation and facilitates the application of modern agricultural technologies, which will significantly improve the agricultural efficiency and thus ensuring food safety. Besides, it not only provides strong support for realizing agricultural modernization, but also rich raw materials and workforces for the industrialization (Zhu, 2013). Circulation of land sources generates big enterprises, specialized cooperatives and big farming households which will absorb the migrant labours released from the rural area and increase rural income. Therefore, how to further emancipate the rural productive forces and make full utilization of limited land resources by accelerating the circulation of the rural contracted land use rights is vital to the development of rural economy and constitutes the top priority of governments at all levels(Hong, 2014).

2.1.2 History and Development

Since the 1980s, gradual reforms saw drastic changes in rural labor movement, agricultural land use conversion, rural industrialization, and technology popularization, which make agriculture in China enter a critical transformation and upgrade stage(Tao Yang, 1997; Xu & Tan, 2001;Long et al., 2011; Mullan et al., 2011). Rural Land Circulation, allowing rural household to transfer, rent or trade their land contract management right, namely the land use right, is an important approach to large-scale, intensive, modern agricultural management mode (Zhu, 2014). Therefore, the Chinese government has been making efforts towards the steady development of rural land circulation.

It could be dated back to 1984 that the No.1 files of central government, for the first time, permitted agricultural land transfer under certain circumstances. However, it was not until 1988 did the amendment of the Constitution acknowledge the legitimacy of agricultural land transfer(Yuneng & Bo, 2011). Since then, the Chinese government gradually issued a series of files to legalize agricultural land circulation and improve its system(Wang & Jiang, 2009). In spite of the support from central government, rural land in China has remained largely static due to land-tenure insecurity and poorly-developed market (Krusekopf, 2002).

The year 2003 witnessed the initial establishment of Rural Land Contracting Law came into being. It clearly stated that farmland contract management right can be transferred on a voluntary and compensatory basis in the form of subcontracting, leasing, assignment, exchanging, joint-stock partnership, etc.(Du & Sun, 2011). However, the collective ownership and the use of farmland cannot be changed. The real watershed took place in 2008 when circulation policy was further established and emphasized on the third plenary session of the 17th CPC Central Committee (Yuan, 2015). From then on, the circulation scale has been continuously enlarging and the circulation speed has been continually quickening(Chen & Du, 2014).

However, due to some unique features of Chinese agricultural system and the defect of land circulation supporting system, the development of rural land circulation has been faced with many obstacles. Many (Lou & Zhang, 2002; Li, 2010; Lu & Chen, 2015)have studied this issue from different angles. For instance, it is the collectives who have the land ownership in rural area, farmers only have the land use right. In this case, during the circulating, farmers' interest could easily be harmed since there is no interest expression channel for farmers and the collectives tend to welder farmers power in this process(Chen & Du, 2014). Besides, the household registration system restrain farmers from working and living in the cities, and there is no sound social security system for rural population, so many off-farming farmers would still keep their lands as their fail-safe, which largely constrains the reallocation of labour and hinders the promotion of rural land circulation(Chen et al., 2010).

Recently, the No.1 files of central government in 2014, clearly encourages rural land circulation with diversified agricultural business models and aims to accelerate the perfection of rural land circulation market(Lu & Chen, 2015). The issue of poorly defined land contract rights and the deficiency of institutional structures for the trading has been attended to and big progress in rural land circulation is expected. With the rapid development of land circulation in China and the increasingly mature circulation system, it is time to evaluate the current situation and draw lessons from strengths and weakness.

2.1.3 Current Situation

Rural land circulation in China has come a long way from its very beginning three decades ago and has proved itself to be the new guiding principle in rural reform(Hong, 2014). Concerns over the current development of rural land circulation in China has been discussed(Lu & Chen, 2015; Tan et al., 2013; Yi & Lin, 2015; Yuneng & Bo, 2011). The main characteristics of current situation can be concluded from the following aspects.

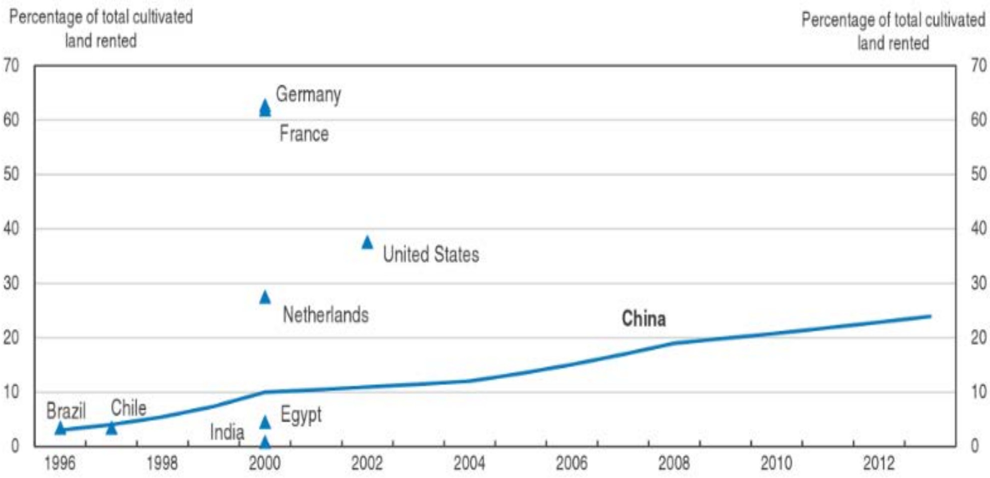
Acceleration and scale enlargement of rural land circulation

According to the Ministry of Agriculture, the total contracting circulation area of rural household is 26.9 million ha at national level by 2014, with an increase of 18.3% over 2013 and 256% over 2008. Circulation area accounts for 30.4 % of household contract management area, while it only accounts for 26.7% by 2013 and 8.9% by 2008. 25.3%. Thus, it cannot be denied that the scale of rural land circulation has been rapidly enlarging since 2008 and would likely to continue. By 2014, 25.3% of the rural households were involved in land circulation, which are 58.33 million households, with a 2.4 percent point growth from 2013. Among them, more than 2.87 million households have contract management area more than 3.3 ha. There are more than 0.87 million family farms, running area more than 11.3 million ha with average farm size around 13.3 ha, and more than 1.3 million farmers' specialized cooperatives.

In short, with the increasing encouragement from the central government, the scope of rural land circulation has steadily risen over the past years. Nevertheless, the frequency of land rental is still rather low compared to developed countries (Figure 1).

Uneven development of rural land circulation across provinces

By 2014, there still remains obvious uneven distribution of contracting circulation land among different provinces/cities. The provinces/cities with top rural land circulation ratio are Shanghai 71.5%, Jiangsu 58.4%, Beijing 52%, Heilongjiang 50.3%, Zhejiang 48%, Anhui 41%, Chongqing 39.7%, Henan 37.1%. It was found that in the provinces with a higher level of urbanization and economic development, land circulation is more active. For example, for province/cities with high



(OECD, 2015)

Figure 1: The proportion of farmland has been increasing but remains below developed countries

circulation rate like Jiangsu, Zhejiang, Chongqing, Shanghai, they have rather limited land resources but they are more urbanized and industrialized. On the other hand, provinces (cities) with rather large land resources like Heilongjiang, Henan and Anhui, which are the main grain production regions in China, also have relatively high proportion of rural circulation land. In these provinces, rural land resources per capita are more or less above the national average level, which means farmers have more at their disposal, in this case, to transfer.

Although thriving of rural land circulation is the overall trend in all provinces, the speed and pace of development varies. By 2013, these provinces (cities) experienced largest increase in circulated area compared to last year: Gansu 89%, Henan 52%, Shanxi 51.1%, Hebei 47%, Ningxia 43.3%, Liaoning 41.1%, Hubei 37% and Guizhou 37.1%. The high increase rate of rural land circulation in less developed provinces like Gansu, Ningxia and Guizhou may be accredited to their largely static rural land before.

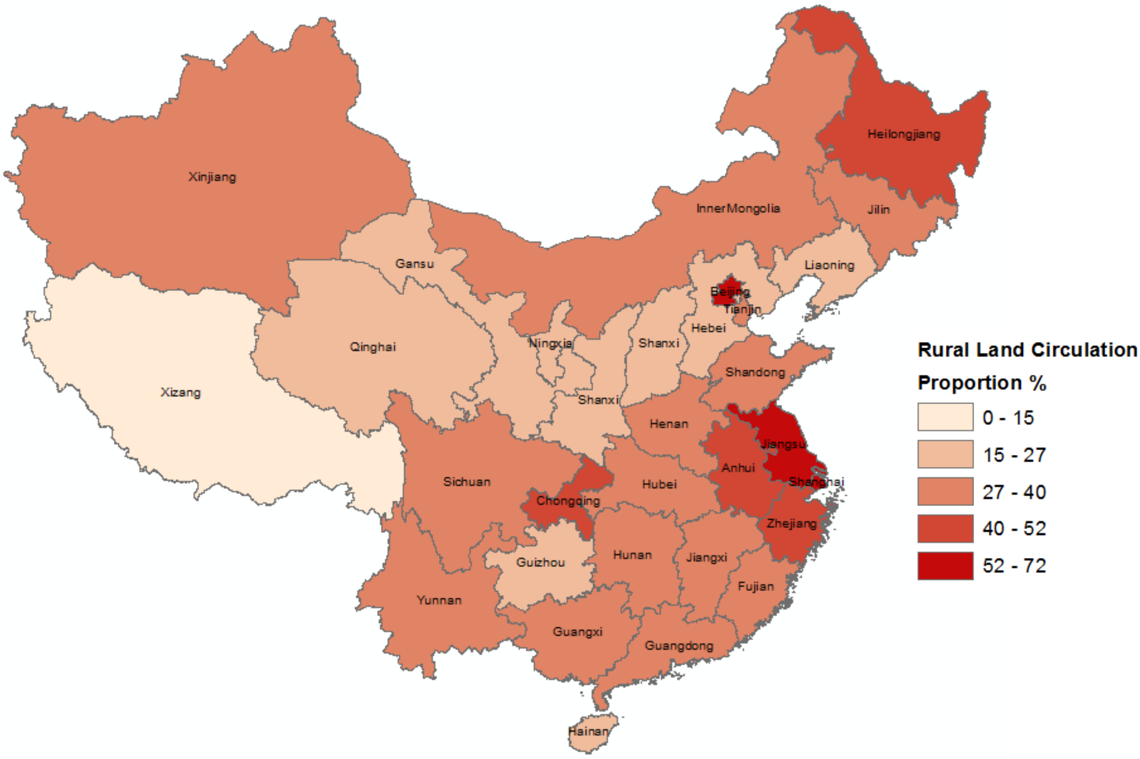


Figure 2: The rural land circulation proportion across country

Diverse forms of rural land circulation

According to the Rural Land Contracting Law, Land circulation can take forms of lease, exchange, subcontract, share, inheritance and other means. With the ever-growing development of rural land circulation in China, there are now more diversified circulation mode like, swaps, professional investors, family farms, farmers' cooperatives and other professional main-scale operation. However, subcontract and lease still remain as the main forms of rural land circulation. 51% of the area is circulated through subcontract while 27% through lease. As shown in Figure1, land circulated through these two mode altogether account for the majority of rural circulation area while other forms only take up small proportion. On the other hand, among all the circulated rural land, 58.4% of them were transferred to other farmers, 21.9% to farmer specialized cooperatives. In the meanwhile, land transferred to enterprise only makes up 9% of all rural circulation area and others 10%. Therefore, subtracting or leasing land to other farmers and cooperatives are the main stream of land circulation mode.

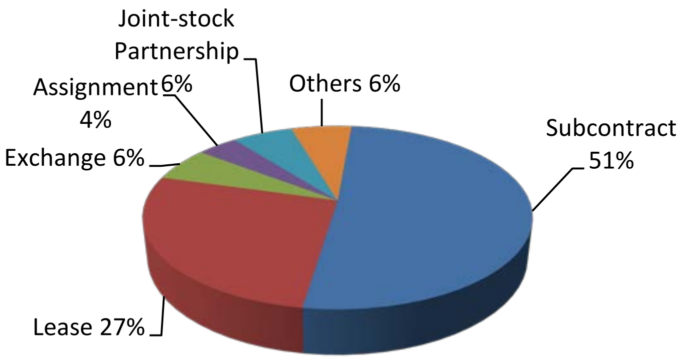


Figure 3: Transaction form in rural land circulation

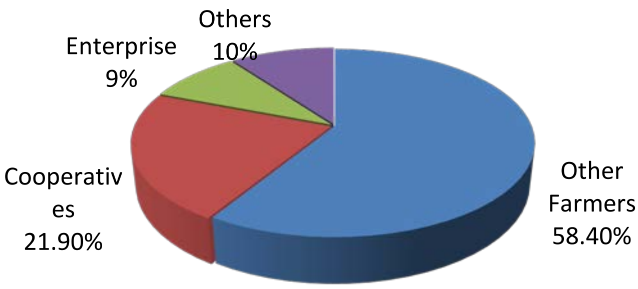


Figure 4: Transaction objects in rural land circulation

More contractual transaction system

The contract rate of rural land circulation has been steadily increased. In the past, Farmers, who are temporarily unable or unwilling to cultivate land, can entrust the contracted land to others after consultation, and people entrusted are often their friends or relatives (Du & Sun, 2011). In this case, they usually just have oral agreement instead of legally binding contract. However under this transaction mode, land circulation is largely confined to friends, relatives and other people one can trust. Farmers with high productive techniques may still lack opportunities to expand their farm. Recently, with the improvement of management and market, the process of rural land circulation has become more normalized and the contractual rate has been constantly increasing. According to the Ministry of Agriculture, there were 18 million ha out of total 26.9 million ha circulated rural contracting area having formal transfer contracts, which means 8.7 million ha rural land has been transferred only under oral agreement. With the reinforced policy propaganda of contract land circulation and more legalized transaction system, farmers will gradually understand their rights and their anxiety over losing their land could be largely relieved, thereby arousing farmers' initiative in land circulation.

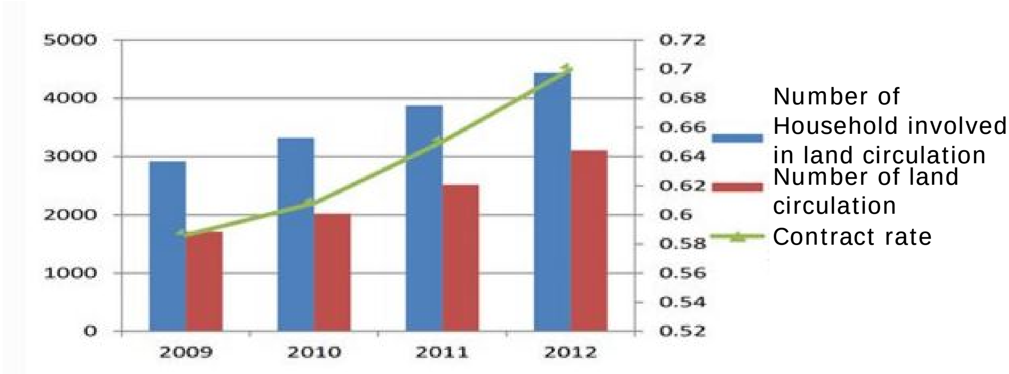


Figure 5: Number of households involved in land circulation and its contract rate

Small-scale scattered management

Although rural land circulation has been thriving, the main agricultural mode remains fragmented, small-scale and scattered. The researcher from Development Research Centre of State Council pointed out that more than 220 million rural households still run farmland under 2 ha, which takes up 96.1% of the total rural households all over the country. The general small farm size roots in the household responsibility system(HRS), which requires the village collective to divide farmland according to household size in a fair and equitable way(W. Hu, 1997). As a result, a household may have a combination of high-yield land parcels and low-yield ones, ones far from home and ones easily accessible. The fairness in allocation of farmland once greatly stimulated agricultural production and rural development (Lin, 1991; Skinner et al., 2001), but it also led to the fragmentation of farmland and thereby the low efficiency on labour productivity(Ding, 2003). Therefore, rural land circulation still needs to be encouraged and promoted in the course of achieving moderate-scale and intensive agricultural mode.

2.2 Information Extraction from High Resolution Remote Sensing Images

Remote sensing provides rich data at varying spatial and temporal resolutions for all kinds of applications including mapping, environmental monitoring, disaster management and urban planning, etc.(Benz et al., 2004) To make full use of these data, certain features need to be extracted and analysed based on different research interest. Batistella (1998) studied the different roles of different sensors and their applications. However, with the emergence of new technology, more sophisticated products with high resolution like WorldView, Quickbird are available nowadays, which have opened up new possibility for more detailed and precise information extraction (Wojtaszek & Ronczyk, 2011).

2.2.1 Farm Fields Extraction

Information extraction from remote sensing imagery has wide applications in various fields. Xu et al.(2012) summarized the existing methods of urban vegetation extraction based on remote sensing images. Lu & Weng (2007) presented a new approach to ship detection Road in remote sensing. Giada et al.(2003) tested and compared different methods to address information extraction from IKONOS imagery over refugee campus. There also has been numerous discussion about river extraction from remote sensed images (Hecher et al., 2013; Yang, 2015), automated building extraction (Ezhili & Akshaya, 2013; Zeng, 2014) as well as road extraction (Ziems et al., 2007). Remote sensing has contributed extensively to our understanding of the environmental and social interaction. In this study, farm fields are of our primary interest. Literature (See Table 2) has introduced various way of extracting farm fields.

Table 2: Tabular representation of study of field extraction procedures

Study Area	Data	Approach	Accuracy/Result
Texas, California and South Dakota (Yan & Roy, 2014)	2006-2010 30m Weekly Web Enabled Landsat Data(WELD)	Object-based; watershed algorithm;	90.1% overall accuracy with field class user's and producer's accuracies of 83.0% and 93.8%
Tongzhou, Beijing,China (Hu et al., 2009)	2.4m Quickbird Imagery on 2/5/2006	1.Wavelet transform and watershed segmentation 2.Improved region merger algorithm 3.Inverse wavelet transform 4.Canny operator	This method can extract large area of farmland parcels accurately and effectively. By using improved region merger algorithm, it also solved the problem of over-segmentation and improved extraction accuracy
Coastal New England, United States (Zhu & Woodcock, 2014)	All available Level 1 Terrain (corrected) (L1T) Landsat TM/ETM+ images for Worldwide Reference System (WRS) Path 12 and Row 31 with cloud cover less than 80%	A new algorithm for Continuous Change Detection and Classification (CCDC) 1.a threshold derived from all seven Landsat bands. 2. Random Forest Classifier (RFC)	producer's accuracy of 97.72% and user's accuracy of 85.60% for changed pixels, and overall accuracy of 91.80%
Turkey (Turker & Kok, 2013)	SPOT4 multispectral (XS) and SPOT5 XS images; Trusty land parcels	1.Canny edge detector 2.graph-based vectorization method to detect line segment 3.perceptual grouping	The accuracy is 82.6% and 76.2% for the SPOT5 and SPOT4 images respectively

Sharifabad region in the north-west of Iran (Esfahani, 2014)	Landsat 5 Thematic Mapper (TM) acquired on 1th August 2011	1.Image segmentation based on threshold(NDVI) approach 2.Random sets generation 3. Douglas-Peuker Algorithm	Google Earth image overall accuracy of 91% with a Kappa coefficient of 0.8360
Hilly area in Wuhan, Hubei, China size 300*300pixel (Chen et al., 2014)	0.61m QuickBird on 10/2009 300*300pixel	1.Sobel gradient operator 2.Entropy difference analysis 3.A marker driven watershed transform	Accuracy of the proposed method is 73.06% which is 22.40% higher than the Mean-shift segmentation method with a better performance in farmland extraction in hilly area.
(Rydberg& Borgefors, 2001)	N\A	1.Edge detection by gradient-based method 2.Segementation based on region growing	N\A
Northern Thailand, mainly crop fields Test area1&2 Size 500*500pixel (Susaki & Shibasaki, 1999)	Landsat TM NDVI image acquired on 20/1/1989 (path 129, row 49,)	1.Wavelet transform to extract textual information 2.Scale-space filtering methods to determine NDVI threshold 3.Level slicing to images with the threshold value	The extraction ratio of area 1 is 93.5%, area 2 is 81.4%. If the crop fields are isolated without clear boundaries, it was found that they cannot be extracted.

Farm field extraction has been an interesting topic in remote sensing. As shown in the table, different segmentation methods and innovations have been made to improve the accuracy of extraction. The general accuracy of these extraction is above 70 percent. However, there is little discussion about adopting an object-based multi-resolution segmentation to extract field boundaries. This study would fill this gap by studying the effect of this approach. Additionally, in most cases field extraction would use high resolution remote sensing data unless the general field size is large enough for moderate resolution image analysis. However, due to the limitation of spectral bands in Google Earth imagery, it has seldom been applied to information extraction despite the high resolution and free availability. This study will take up the challenge to use Google Earth high resolution images, which is of great significance to the feasibility and accessibility of field information extraction from earth observation data.

2.2.2 Object-Oriented Classification

Classification is the process of assigning pixels into meaningful classes (Campbell & Wynne, 2011), which makes it essentially a consequential information extraction process. Jawak et al.(2015) reviewed the state-of-the-art classifiers for their potential usage in urban remote sensing and concluded classification methods are broadly based on Pixel-based classification (PBC) or Object-oriented classification (OOC). Due to the fact that traditional pixel-based classification may have difficulties dealing with high resolution and thus high heterogeneity imagery, the development of Object-oriented classification came along with the increasing availability of high-resolution imagery, which has the potential to capture highly-detailed and accurate information.

Many researchers(Gholoobi et al., 2010; Repaka et al., 2004; Sun et al., 2005; Whiteside et al., 2011) compared and contrasted Pixel-based classification and Object-oriented classification, and claimed that object-based classification has better performance for classifying higher resolution imagery. The most important difference between these two methods lies in the fact that object oriented information extraction is to interpret an image and the relevant semantic information by meaningful image objects and their mutual relationship rather than individual pixels. To be specific, compared to conventional pixel-based classification approaches, utilizing only the spectral reflectance, image objects incorporate more information such as texture, shape, relations to adjacent regions (Sun et al., 2005). To extract the certain features from high resolution images, not only spatial information but also contextual information of an object will be needed(Gupta & Bhadauria, 2014). Therefore, Object-oriented classification could result in much more reasonable classification, effectively avoid resulting in speckle like “salt & pepper effect”, which is typical in pixel-based approaches, and greatly improve the accuracy of classification(Kelly et al., 2011).

Object-oriented classification has been a very active research area in remote sensing since 2000. Zhang & Feng (2005)employed object-oriented classification to obtain tree and grass in urban area using IKONOS data, achieving over 97% overall accuracy. Li & Shao (2014)conducted land-cover mapping at fine resolution based on object-oriented approach in Midwestern USA resulting in richer information classes and a higher accuracy than pixel-based methods. Wojtaszek & Ronczyk (2011) examined the application of object-oriented methods in urban land-cover mapping, and concluded that the additional information provided by object-oriented approach is necessary to improve the outcome. Geneletti and Gorte (2003) proposed a method for integrating object-oriented classification with pixel-based supervised classification using images of different resolution, and they found the accuracy of classification much improved than traditional pixel-based approaches. At the same time, many new multi-scale object-based models such as MOSS for land cover mapping, change detection and etc. have been developed(Hall & Hay, 2003; Hay et al., 2005; Mitri, 2002). Hay et al. (2003) examined the potential of three object-based multi-scale models for landscape structure in high-resolution images and provided a comparison of each approach.

In general, the object-oriented classification process can be divided into the two main workflow steps: segmentation and knowledge-based classification of the segments(Sun et al., 2005).

Image Segmentation

The crucial initial step of object-oriented classification is image segmentation. A meaningful segmentation is a necessary prerequisite for a successful object-oriented image processing(Baatz & Schäpe, 2000). The process starts by segmenting the image into meaningful objects, which will be classified in the later step. Image segmentation has been an active field in remote sensing as well as computer vision(Zhang, 2006). Many segmentation algorithms, like watersheds and region growing algorithms have been developed(Singh & Singh, 2010). In this study, the eCognition Developer software provides top-down and bottom-up strategy of segmentation.

Top-down segmentation means segmenting objects into smaller objects from large objects or the entire image as one object. eCognition Developer offers several top-down segmentation methods. Chessboard segmentation and quadtree-based segmentation are the most representative ones. They are usually useful for tiling and piding objects into equal regions in a preliminary segmentation. Chessboard segmentation cuts the dedicated image objects into equal squares of a given size in a straightforward manner while quadtree segmentation creates squares of differing sizes.

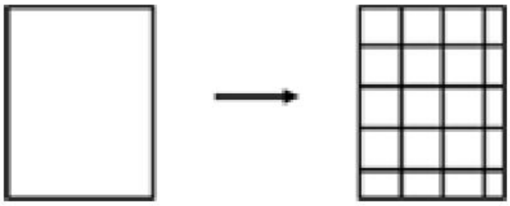
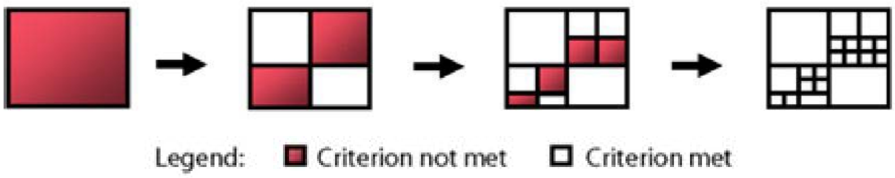


Figure 6： Chessboard Segmentation



(Trimble Documentation, 2013)

Figure 7： Quadtree Segmentation

Bottom-up segmentation refers to assembling objects to create larger objects. It can but not necessarily start with the pixels of the image.
Multi-resolution segmentation offered by eCognition software is the most widely used bottom-up algorithm in object-oriented image analysis. It is a region-merging approach, which means it begins with treating each pixel as a separate object and then allows adjacent image objects merge into larger segments until meaningful objects are created. The decision of merging pixels is based on homogeneity criteria, describing the similarity between adjacent image objects(Griffith, 2005). It is calculated as a combination of the color and shape properties of the initial and resulting image objects of the intended merging. Color homogeneity is based on the relative importance of the standard deviation of the spectral colors. The shape homogeneity is based on the deviation of a compact or smooth shape(Trimble Documentation, 2013).

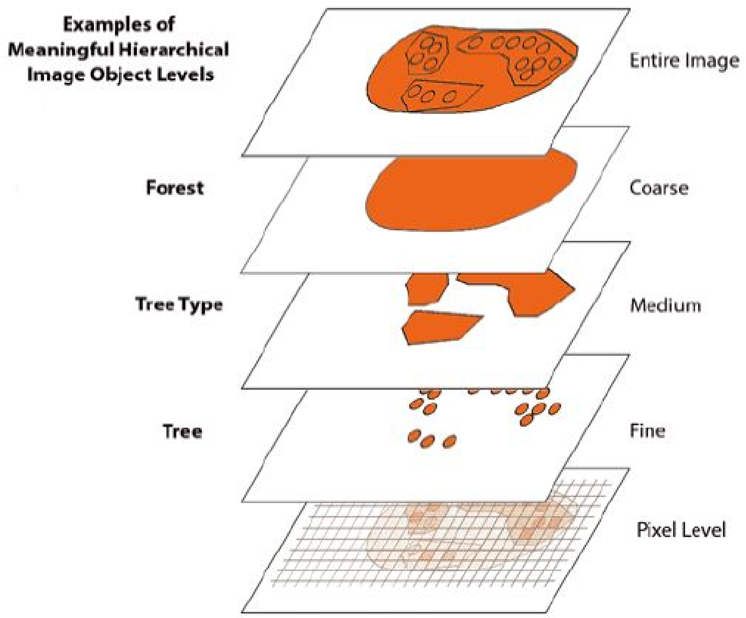
The full power of the eCognition object-oriented image analysis unfolds when using multiple image object levels(Definiens, 2008). Multi-resolution segmentation matches perfectly with the concept of image object levels and hierarchy in eCognition (Figure 8). On each of these levels, objects are defined by their sub-objects on the level below them. Similarly, pixels define the lowest level image objects. Differing size of segments on different image object level give rise to a reasonable object hierarchy which is the key to a meaningful segmentation and knowledge-based classification(Flanders et al., 2003). In most cases, with any given average size of image objects, multiresolution segmentation yields satisfying extraction and shaping in any application area(M Baatz & Schäpe, 2000; Benz et al., 2004; Darwish, Leukert, & Reinhardt, 2003; Ezhili & Akshaya, 2013; Giada et al., 2003; Gupta & Bhadauria, 2014). However, it is more demanding on the processor and memory, and thereby significantly slower than some other segmentation techniques.

Classification

The step classification refers to assigning objects to a certain class according to the class's description. In object-oriented classification approach, the classification description is knowledge-based rules that include not only spectral information but also shape, size characteristics, context, and texture properties. Knowledge base for the analysis and classification of image objects is represented as class hierarchy in the frame of eCognition. Within this class hierarchy it is possible to inherit image object properties from a super-class to a sub-class and also to group classes semantically. The objects then get assigned according to whether they have or have not met these classification rules.

eCognition software provides its users with two different classifiers: a nearest neighbour (NN) classifier and fuzzy membership functions. During the classification process using fuzzy membership functions, the image segments are classified by building up class hierarchy, which is based on fuzzy logic. In a classification scheme, each class contains a class description, which consists of a set of fuzzy rules allowing the evaluation of specific features and their logical operation(Tadesse et al., 2003). A fuzzy expression can be comprised of one single condition or a combination of several conditions. These conditions have to be met for an object to be assigned to a certain class. The fuzzy sets were defined by membership functions that identify those values of a feature according to a high, low, or zero membership to this class respectively. The advantage of fuzzy logic features in a transparent and adaptable set of classification rules.

In the method nearest neighbour (NN) classifier, each feature offered by eCognition can be used to determine the feature space based on minimum distance measurements in feature space. Similar to fuzzy membership functions, nearest neighbour classifier also needs to define its fuzzy rules. User interacts with the procedure and based on statistics, texture, form and mutual relations among objects defines training areas.The strength of NN method lies in the fact that it is a powerful supervised classification technique, combing intelligent image objects in multi-resolution segmentation with supervised classification.



(Trimble Documentation, 2013)
Figure 8: Meaningful image object levels within an image object hierarchy

3 Study Area

From the earlier stage of the study, we actually observed some of the changes between years across the country, as is shown in Google clips in Figure 10. Based on this, our detailed study wants to take a look at effect of different landscape and land cover on field size change. Therefore our final study area zooms in to three 5km×5km area in Anhui Province (Figure 9).

Figure 9：Anhui Province and sampling study area

Geography

Anhui Province is situated in eastern China, extending across Yangtze River and Huai River valleys. The total area of the Province is over 139,000 square kilometres with a population of about 60 million. Anhui is topographically diverse. The north of the province is part of the North China Plain, these regions are quite flat and densely populated. The land becomes hillier further south, with the Dabie Mountains occupying much of south-western Anhui and a series of hills and ranges cutting through south-eastern Anhui. Lake Chaohu, in the centre of the province, is the largest lake with an area of about 800 km^2(“Anhui,” 2016). The study areas in this study are situated at the foot of Dabie Mountain and near the Lake Chaohu.

Agriculture

It is one of China’s major agricultural production bases, with its agricultural economy ranking the ninth in China (”China Through A Lens”, 2003). Agriculture in Anhui varies in accordance with the climate zones that the province crosses. North of the Huai River wheat and sweet potatoes are grown, while south of the

Figure 10: Observation of changes in fields between years from Goole Earth clips

Huai River it is rice and wheat instead. Most of the land produces two crops a year. Anhui is also one of China’s most important soybean producers; the beans are grown mainly in the north in rotation with wheat or barley (Tregear, n.d.). According to the statistic report from Chinese Development Information centre, Anhui, with a rural land circulation of rate 41% by 2014, is among top ten provinces in implementation of rural land circulation.

Climate

As with topography, the province differs in climate from north to south. The north has more clear-cut seasons. There are great yearly variations of rainfall in the northern part of the Province, consequently the frequent occurrences of drought in springs and floods in summer season. January temperatures average at around -1 to 2 °C north of the Huai River, and 0 to 3 °C south of the Huai River; in July temperatures average 27 °C or above(“Anhui,” 2016).

Economy

Anhui was regarded as the most economically undeveloped province of eastern China. Most of its population was rural, and the efficiency of agriculture was very low because water resources were poorly utilized. Since the 1950s great advances have been carried out in agriculture and industry. Improvements in irrigation now allow more farmland in the south to be double-cropped in rice, and other water conservancy and land improvement countermeasures along have improved yields and increased per capita net farm income. The Shanghai special economic zone, established to promote industrial growth, included Anhui province("China Through A Lens", 2003).

4 Method

This chapter describes the data and methods used in this study which investigate field size changes in study area as well as how to extract field information from Google Earth high resolution images using object-oriented classifications in eCognition. The flow chart in Figure 11 presents an overview of the methodology for this research.

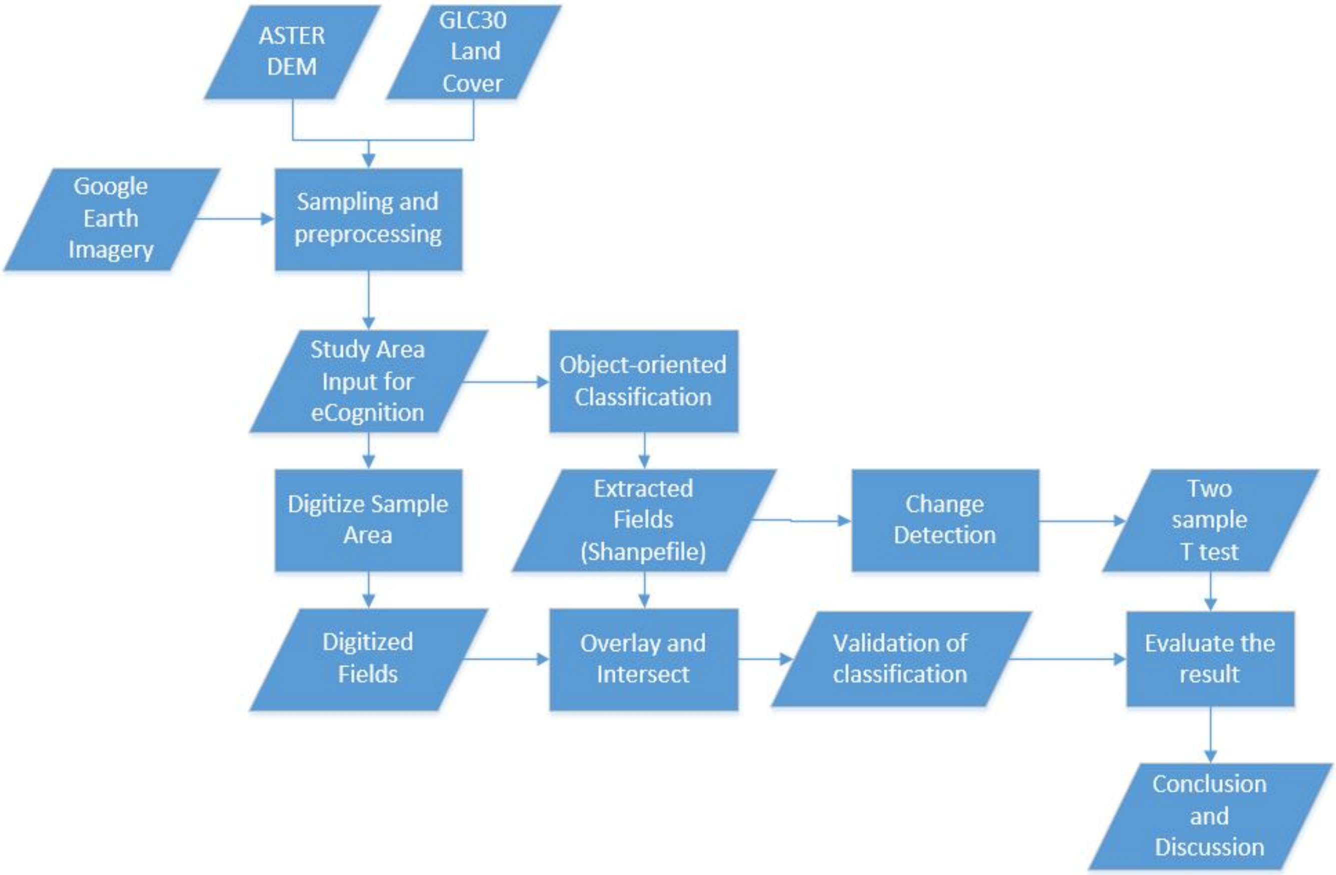


Figure 11: Flow Chart of Methodology

4.1 Data Source

It has been found that one of the main limitations in efficiently applying image segmentation is the spatial resolution of the input imagery (Acton, 1996; Gorte, 1998; Wrbka et al., 1999). Indeed, in our study, segmentation was first conducted on Landsat 30m resolution imagery. However, the general field size is too small to make meaningful segments based on this resolution. Fields on the terrain are frequently covered by only one or a few image pixels, sometimes even one pixel would cover more than one field. As a result, the segmentation makes no significant contribution to the information extraction unless finer resolution data is employed.

Figure 12: Segmentation on Landsat 30m resolution (left) and GE imagery overlay on Landsat (right)

Google earth pro is now a free application of Google Inc. that enables you to search and view any place on earth, making use of the latest available high resolution satellite or airborne imagery. Compared to normal Google earth, Pro version allows you to save high resolution images on screen with resolution up to 4800×4800, which largely widen the availability and promote the application of high resolution earth observation data.

As discussed in the last chapter, the watershed of rural land circulation occurred in the year 2008. In order to better compare the spatio-temporal changes, the images of study area were acquired from the year 2006 and 2015, before and after the watershed. Images obtained from different years were made sure that they are in the same month or with the time difference within a month, in order to rule out the possible disturbance of phenology. The resolution of obtained imagery is 1.04m, which provided a relatively ideal basis for segmentation. However, the spectral information was limited with only three visible bands, namely red, green and blue, which may propose some challenging tasks in the later process of object-oriented image analysis.

In addition, Aster DEM data *ASTGTM2_N31E117* and GLC 30 data *N50_30_2010LC030* were collected to serve as ancillary data for sampling and analysis. All the images have been geo-referenced and projected to WGS_1984_UTM _Zone _50N referenced coordinate system in ArcGIS before being processed in eCognition.

4.2 Sampling Method

The selection of study area is based on different land cover, elevation and slope as well as previous study in Shusheng County in this region. Firstly, put 100km×100km grid over the whole province (see Figure 9). Only the intact square of area would be taken into further selection to exclude the marginal area in Anhui. Then these grids would overlay with land cover map and elevation map. By comparison, the grid located in the centre of Anhui Province, ranging from 32.102814°N, 117.021268°E to 31.214950°N, 118.063662°E, shows a great variety of landscape and land cover. In the meanwhile it covers part of Shusheng county, area of interest in previous study. Thus, this grid was chosen to conduct further sampling. Within this grid, three 5km×5km study area were decided according to their differing characteristics in landscape and land cover. Study area 1 is located in agricultural area; Study area 2 is partially forest; Study area 3 is mainly residential and closed to urban area because the main land cover is artificial surface.

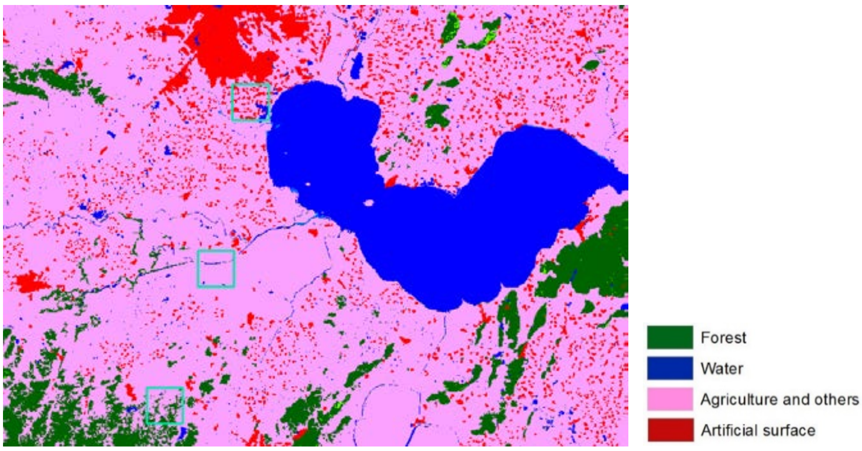


Figure 13: Land cover map

Regarding landscape, elevation and slope have been taken into consideration. The elevation map and slope angle map were generated from Aster DEM data in ArcMap. As is shown in Figure 14 and 15, Study area 1 is part of the lake plains with relatively flat landscape; Study area 2 is located in mountain area with much more steep landscape; The elevation of Study area 3 is between 1 and 2, and Study area 3 has relatively hilly land.

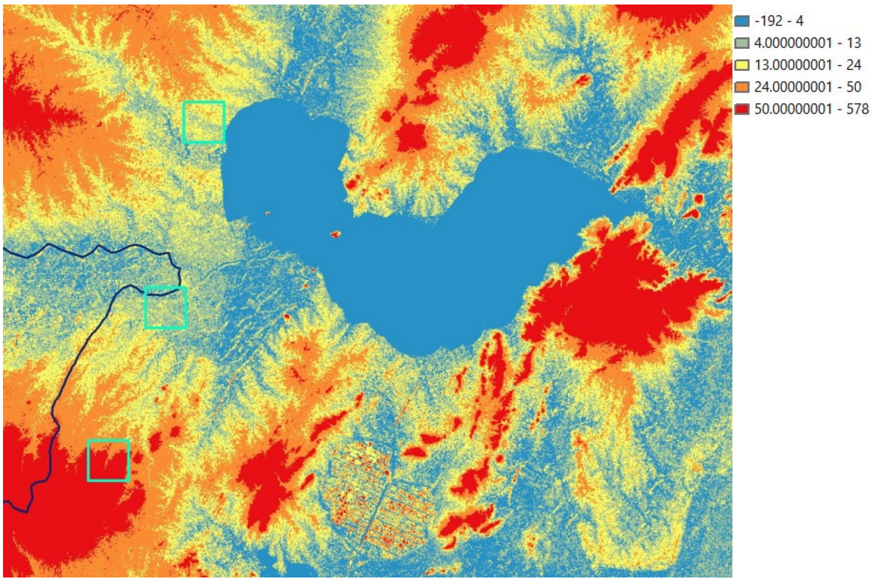
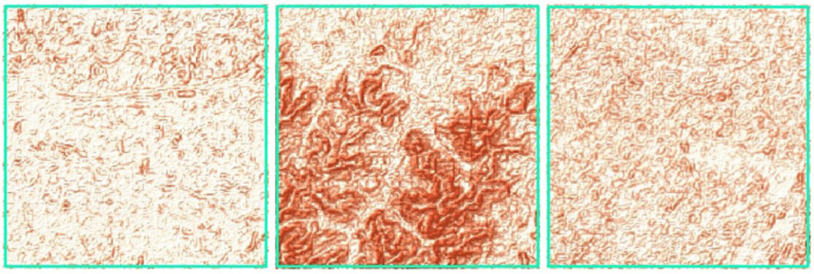


Figure 14：Elevation map



1　　2　　3

Figure 15：Slope Angle (Study area 1,2,3)

4.3 Object based Information Extraction by eCognition

The first general object-oriented image analysis software on the market was eCognition, produced by Definiens, Germany. It is a state-of-the-art package for object-oriented classification, adopting the region-growing Fractal Net Evolution method in object extraction (Baatz & Schäpe, 1999). Studies(Giada et al., 2003; Griffith, 2005; Gupta & Bhadauria, 2014; Hansen et al., 2006; Tadesse et al., 2003) have proved that eCognition has been an effective and efficient tool for object-oriented classification. The general workflow of object-oriented classification in eCognition is presented in Figure 16. It can be broken down to following steps: 1) Input images; 2) Multiresolution segmentation based on user defined; 3) Image object hierarchy; 4) Creation of class hierarchy, the knowledge base; 5) Classification using Training samples or fuzzy expressions, 6) Classification based segmentation, 7) Repeated steps for best result, and 8) Final merge classification (Laliberte et al., 2004).

4.3.1 Multi-resolution Segmentation

Accurate segmentation is a prerequisite for an effective object-oriented classification. During the multi-segmentation process meaningful image objects are created by adjusting homogeneity criteria. Starting from single pixels, small objects gradually merge into larger objects based on the spectral and shape heterogeneity. The pair of image objects with the smallest increase in the defined criteria is merged. The process terminates when the smallest increase of homogeneity exceeds a user-defined threshold. Therefore a higher threshold will allow more merging and consequently larger objects, and vice versa.

Consequently, meaningful objects at different scale are formed and thus constructing a semantic hierarchy. The entirety of image objects is organized into a hierarchical network of image objects. As is shown in Figure 8, the resulting image object hierarchy allows the efficient propagation of various kinds of relational information(Benz et al.,2004).
This study, in the same way, creating different levels of image objects to provide information for classification. For instance, forest in Study area 2 and residential area in Study area 3 are of no interest in this study yet they take up quite large area. By first creating image object level with large scale parameter, these objects could be better

extracted and excluded although fields may be faced with under-segmentation. Then finer level of segmentation would be specifically focused on our area of interest – Fields.

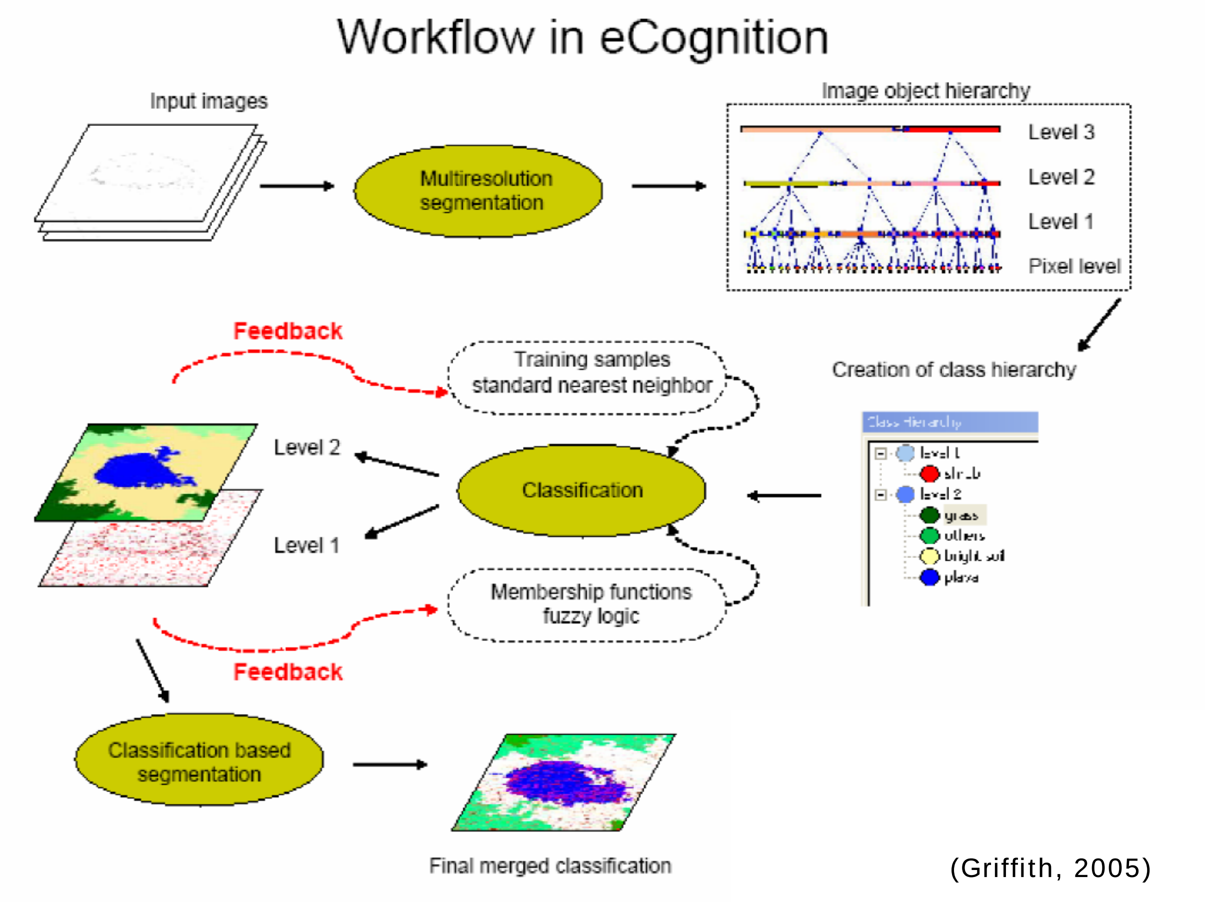


Figure 16：General Workflow in eCognition

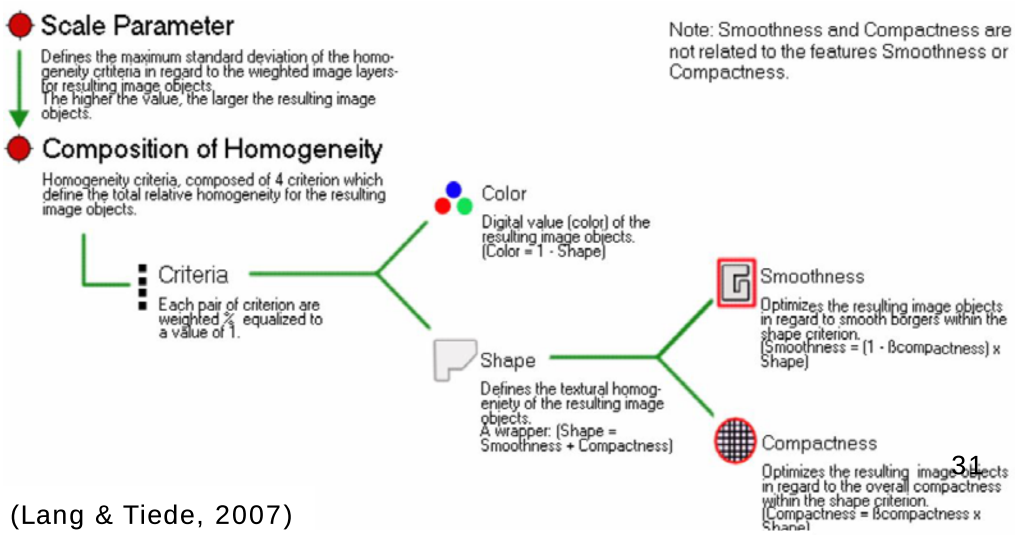
On the other hand, it is also crucial to weigh following parameters properly due to their different influences on classification accuracy:

Scale parameter: The value of the scale parameter decides the average object size. This parameter influences threshold heterogeneity of the objects. The larger the scale parameter the larger the objects become. According to the user guide of eCognition, scale parameter should be as large as possible, but at the same time small enough to ensure the separation between different land cover classes.

Color/Shape: Color homogeneity is based on the relative importance of the standard deviation of the spectral colors while the shape homogeneity is based on the deviation of a compact or smooth shape.
The shape criterion can be given a value of up to 0.9. This ratio determines to what degree shape influences the segmentation, as compared to color. The ratio of shape and color altogether equals 1, which means the higher the shape criterion the less spectral homogeneity influences the object generation. According to the user guide, this parameter should be weighted as high as possible, while the shape parameter should be weighted only as high as necessary.

Smoothness/Compactness: when the shape criterion is larger than 0 the user can determine whether the objects shall become more compact (fringed) or more smooth. Similarly, the value assigned for compactness of objects gives it a relative weighting against smoothness of the object border. The ratio of compactness and smoothness altogether equals 1, which means the higher the compactness the less smoothness influences the creation of object.
The importance given to compactness has to depend on the properties of objects of interest.

In short, Baatz et al. (2004) suggest emphasizing the spectral information as much as possible, and keeping the shape information as much as necessary. These kinds of guidance are useful yet general. In this study, in order to achieve satisfying segmentation result, parameter tests were conducted on six images in all three study areas and then the results are evaluated. The test, based on the image of study area 1 in 2006, for different choice of parameters is presented as followed.



(Lang & Tiede, 2007)

Figure 17: The composition of homogeneity criteria

For segmentation scale, three different values were tested: i) 20, ii) 50 and iii) 100. The weight of shape and compactness were controlled at 0.3 and 0.5 respectively. Then, segmented objects at different scales, different levels of extraction can be observed (Figure 18).

For color and shape, as well as compactness and smoothness parameters, special value combinations (for high: 0.9, average: 0.5 and low: 0.1) were tested while scale parameter was set as 50. In Table 3, the parameter values are given for each different combination named as a, b, c, d, e, f, g, h and i. The segmented images of each condition are given in Figure 19.

Table 3: The combination of parameter value

	a	b	c	d	e	f	g	h	i
Shape	0.1	0.1	0.1	0.5	0.5	0.5	0.9	0.9	0.9
Color	0.9	0.9	0.9	0.5	0.5	0.5	0.1	0.1	0.1
Compactness	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Smooth	0.9	0.5	0.1	0.9	0.5	0.1	0.9	0.5	0.1

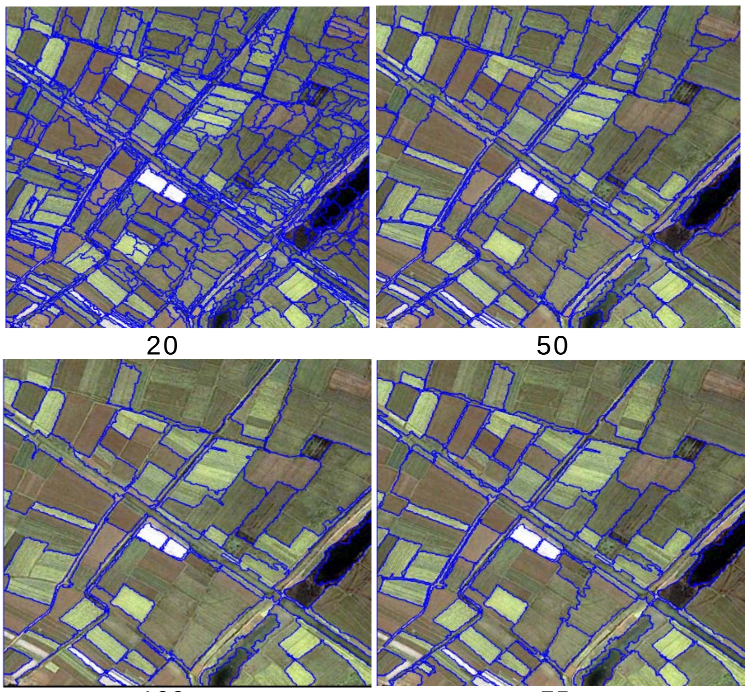


Figure 18: Segmentation result of different scale parameter

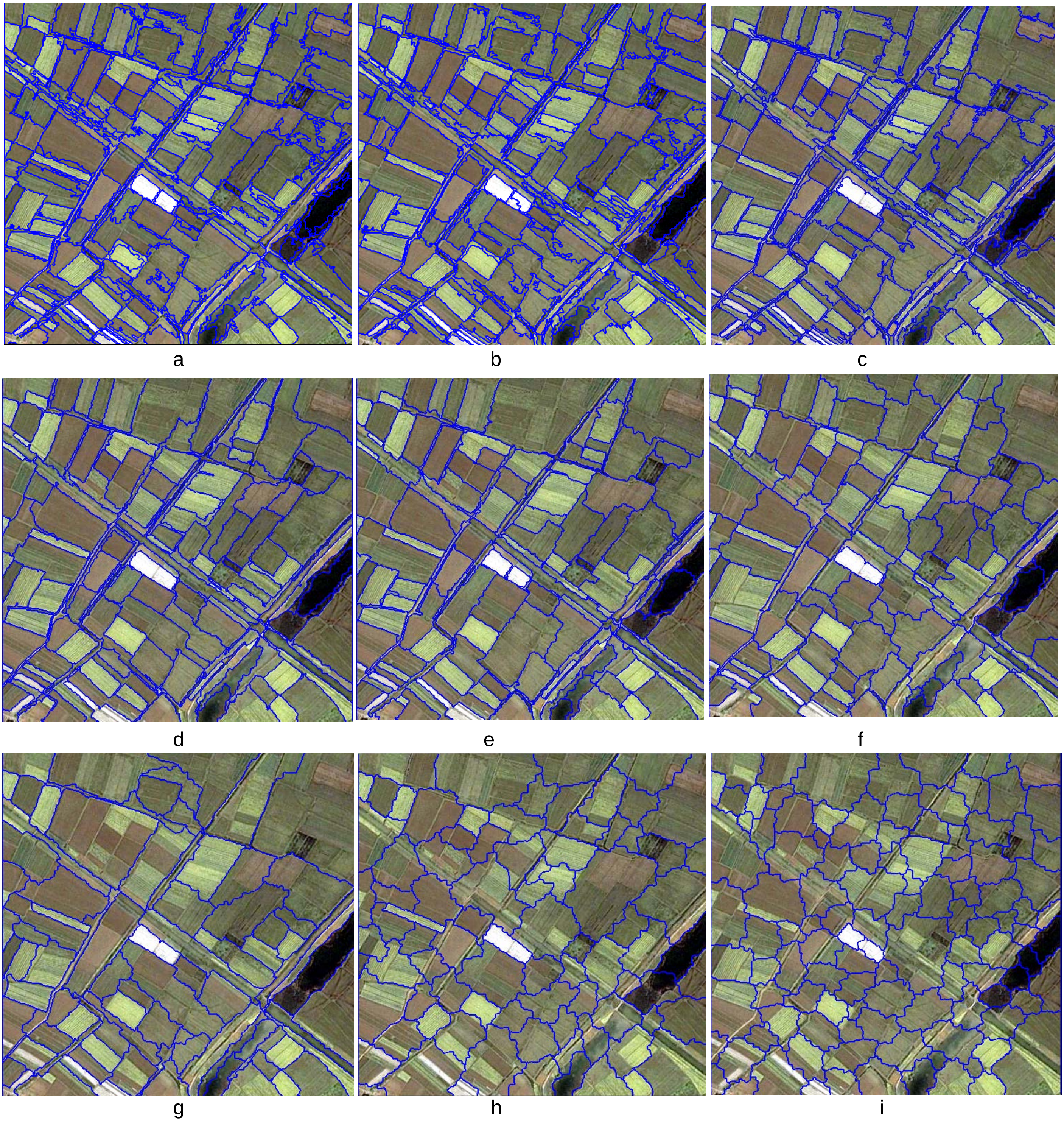


Figure 19：Segmentation result of different shape and compactness weight

It is suggested by Definiens User Guide that "a strong and experienced source for the evaluation of segmentation techniques is the human eye", claiming that even a result is sufficient by a quantitative assessment, it still has to seem visually correct for the human eye to be evaluated as a satisfying segmentation (Lang & Tiede, 2007). In this study, visual evaluation is applied. By visual analysis it is clear that the objects produced in each case differs from each other. Observing the total 12 different segmentation result for the same area in images and comparing the parameter values, empirical discipline of choosing parameter values were concluded. Along with this, the final choice of most proper parameter value combination were made after several more trial and error attempts based on the conclusion drawn from tests.

The tests for other images are in the same manner. Due to different spectral properties and variance in geographic objects, each image requires a trial and error process all over again to figure out the best combination of parameter values.

4.2.2 Knowledge-based Classification

After multi-resolution segmentation, all image objects were within the topological network, namely the image object hierarchy (See Figure 17) in which each image object contains the information of its neighbours, thereby contributing important context information to the knowledge-based classification step. The classes defined by users can then be grouped into a hierarchical manner enabling the passing down of class descriptions to child classes on the one hand, and meaningful semantic grouping of classes on the other(Wong et al., 2003). This kind of hierarchical class offers a wide range for the formulation of image semantics and for different analysis strategies.

In this study, fields are the only objects of interest. Thereby, class hierarchy were simplified into Fields and Not Fields using fuzzy membership functions. For some images with plenty of water, a child-class of Not Field as Water was generated to better represent the classification. The class hierarchy is presented in Figure 20.

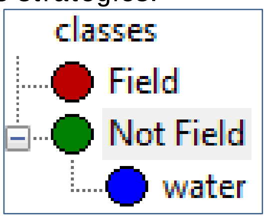


Figure 20: Class Hierarchy

In eCognition, two classification methods, namely membership function classification and Nearest Neighbour classification, are offered. Classification with membership functions is based on fuzzy logic and allows its user to define the degree of membership by using thresholds whereas Nearest Neighbor classification needs training

area and a set of samples of different classes to assign membership values, which makes it a supervised classification.
In this study, both of these two methods have been conducted on Study area 1 in order to compare the segmentation result.

Membership function classification

Firstly feature tools were used to observe the feature characteristics between objects. Then these feature could be used to create fuzzy expressions to define each class. By launching the class description dialog box and inserting fuzzy expressions, class description was completed. Due to the fact that most of the fields are vegetation covered, it is difficult to discriminate them from grassland or short shrub. In the meanwhile, some other fields were just harvested or fallow, resembling bare ground or unpaved road. In this case, it would be quite challenging to use limited fuzzy expressions to assign fields accurately. On the other hand, road, residential area, forest has much clearer feature characteristics and thereby easier to extract using thresholds. For example, road can be extracted by setting thresholds in feature ”Border index”, ”Density” and etc.

After successfully extracting all the other objects, a very useful method that could help with this is the application of feature “ClassifiedAs”, in which we could define anything that is not NotField would be classified as Field.

Nearest Neighbor classification

The procedure of Nearest Neighbor classification consists of two major steps: 1) Training the system by giving it certain image objects as samples, and 2) Classifying image objects in the image object domain based on their nearest sample neighbors(Trimble Documentation, 2013). It classifies image objects in a defined feature space and with given samples, typical representatives for each class. First the software needs samples. After a representative set of sample objects has been declared the algorithm searches for the nearest sample object in the given feature space for each image object. And the object will be assigned to the class to which its closest sample belong. The features to be considered in the feature space can be decided by user. Meanwhile, Feature Space Optimization function could help with choosing the best group of features.

4.2.3 Classification-based Segmentation

An iterative application of segmentation and classification would be helpful regarding successful information extraction(Benz et al., 2004). After initial segmentation, image object primitives are given some certain spectral properties, shape and context. These object features enable a preliminary classification. This is typically followed by another segmentation step, with the preliminary classification result being used as input, to obtain more functional objects and this cycle is conducted iteratively until reasonable segmentation is reached. Thereby, the shape, classification and contextual relations of image objects can be continuously changing when processing.

In this study, since trees, houses, roads and water area are all irrelevant information in this study, they will be all grouped into Not Field. However, these features are at different scales. For example, trees and houses can be rather small while water area like rivers and lakes are rather large objects. To extract trees and houses may result in over-segmentation of fields and rivers, as is shown in Figure. In this case, after the initial segmentation at low level and classification, only part of the objects are extracted appropriately, then the remaining objects can be categorized as Unclassifed and put into segmentation above or below the current object level to create objects at appropriate scale. Each segmentation other than the first one, will be operated using the parent segmentation boundaries as the basis. Therefore, repeatedly taking output of classification as the basis for image segmentation will help to obtain meaningful objects at different scale (Yogeswara et al., 2012).

4.4 Validation

For the result from membership function classification, data for validation is acquired by digitizing fields in a random sampling area within study areas. The total area of digitized fields is 112.1Ha with 150 fields. The index Goodness of Fit was referenced to evaluate how well do the automatically segmented fields match with the same fields that are manually digitized.

Goodness of Fit:

D value: $D = \sqrt{\frac{Area\ of\ commission^2 + Area\ of\ omission^2}{2}}$ (Van Leeuwen, 2015)

Area of commission refers to the area within output fields however falls outside the digitized fields, which is caused by under-segmentation; Area of omission refers to area within digitized fields that output fields failed to cover, which is caused by over-segmentation. By intersect and erase operation in ArcGIS, the area of commission and omission can be generated separately and then calculated.

On the other hand, for the result form Nearest Neighbor classification, eCognition provides error matrix based on Training and Test Area (TTA) mask. The TTA mask can be loaded by the samples used for supervised classification.

5 Result

5.1 Accuracy Assessment

For the validation by digitized test area, in the same area, the total area of fields from classification output is 103.7Ha with 151 fields, whereas the total area of digitized fields is 112.1Ha with 150 fields. The area of commission was calculated as 1.99ha while the area of omission is 10.4ha. Thus fields extracted from eCognition are generally smaller than actual size. Figure 21 demonstrates these areas in part of the test area. Finally, by calculation, D value is 7.4 with an accuracy of 89%.

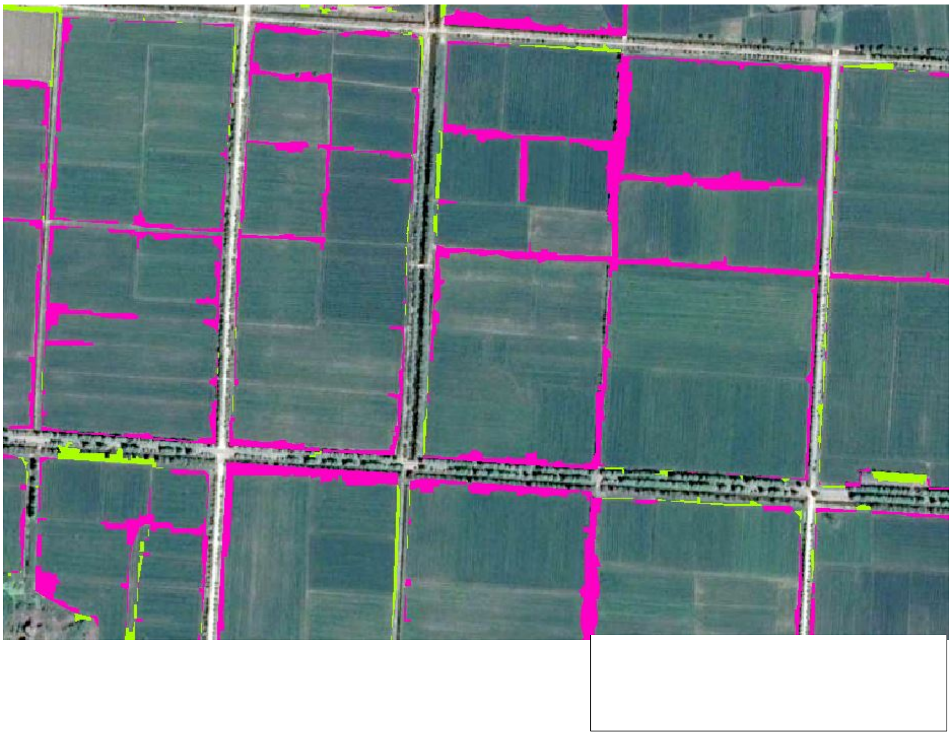


Figure 21: error in segmentation

For the accuracy assessment of Nearest Neighbor classification, after loading the existing samples into the Training and Test Area (TTA) mask, the error matrix based on TTA matrix was generated and the statistic was presented in Table 4. It achieved an overall accuracy of 84.67%, however, this was largely counted on the high accuracy of water and Not Field class. With kappa coeffcient at 0.42, the accuracy of class Field is barely satisfying. As the matrix shows, many fields were misclassified as Not Field.

Table 4: Error Matrix based on TTA mask

User \ Referenc...	Not Field	Field	water	Sum
Confusion Matrix				
Not Field	1447151	381934	0	1829085
Field	0	420243	0	420243
water	0	7031	297042	304073
unclassified	0	2892	0	2892
Sum	1447151	812100	297042	
Accuracy				
Producer	1	0.5174769	1	
User	0.7911885	1	0.9768773	
Hellden	0.8834229	0.682	0.9883034	
Short	0.7911885	0.5174769	0.9768773	
KIA Per Class	1	0.4225461	1	
Totals				
Overall Accuracy	0.8467089			
KIA	0.7101617			

In this study, membership function classification seems to have better performance when it comes to field extraction. Therefore, membership function classification was chosen to serve as the main classification approach and was applied on all the other images.

5.2 Segmentation

5.2.1 Parameters Setting

By repeatedly trial and error process, most proper combinations of parameters were decided for each image. Each image has at least two image object levels and different scale parameters, sometimes different color and shape parameters have also been adjusted to yield appropriate image objects with various scale on each level. Three visible spectral bands of image have all been put into use with the same weight. Table 5 reports the utilized scale parameters and criterion combinations by six images in three study area.

As can be observed from the previous parameter test (Figure 18, 19), the optimum fitting object size for the agricultural fields in the image was obtained at scale 50. 100 was too large that many fields were merged and the boundaries were ignored, so the segmentation was too coarse while in scale 20 lead to an over segmentation. It can be realized that smaller scale decreases the dimensionality and partitioning the object into the sub-objects, while the larger scale merges the multiple segments into one, and thereby creating hierarchical net of image objects.

Table 5: Segmentation parameters

Image	Image Object Level	Bands	Scale Parameter	Shape		Color	Segmentation Mode
				Compactness	Smooth		
Studyarea1_2006	Level1	1,2,3	30	0.7	0.3	0.8	Multi-resolution
	Level2	1,2,3	40	0.7	0.3	0.8	Multi-resolution
	Level3	1,2,3	50	0.7	0.3	0.8	Multi-resolution
Studyarea1_2015	Level1	1,2,3	50	0.7	0.3	0.8	Multi-resolution
	Level2	1,2,3	75	0.6	0.4	0.7	Multi-resolution
Studyarea2_2006	Level1	1,2,3	30	0.6	0.4	0.7	Multi-resolution
	Level2	1,2,3	40	0.6	0.4	0.7	Multi-resolution
	Level3	1,2,3	200	0.6	0.4	0.7	Multi-resolution
Studyarea2_2015	Level1	1,2,3	40	0.7	0.3	0.8	Multi-resolution
	Level2	1,2,3	200	0.7	0.3	0.8	Multi-resolution
Studyarea3_2006	Level1	1,2,3	50	0.5	0.5	0.7	Multi-resolution
	Level2	1,2,3	200	0.7	0.3	0.8	Multi-resolution
Studyarea3_2015	Level1	1,2,3	50	0.5	0.5	0.7	Multi-resolution
	Level2	1,2,3	150	0.6	0.4	0.7	Multi-resolution
	Level3	1,2,3	300	0.6	0.4	0.6	Multi-resolution

For the homogeneity criteria combinations, image d has best performance, which has color and shape both weighted 0.5 with compactness and smoothness in the ratio of 1 to 9. The results from c, e were acceptable whereas other segmentations were all unsatisfying. When increasing the value of shape parameter, fields with different characteristics can easily be distinguished well. For example, if neighbouring fields have different crop types, or vegetation covered fields and harvested bare fields, these fields can be extracted and discriminated properly. However, when the neighbouring fields are more or less similar, with the same crop type and belonging to the same planting term, fields are not extracted successfully despite there is road lying between them, because the aim of this algorithm is to search for a line that is able to split the area into parts having sufficient difference. However, if the two sides have similar spectral values and the field boundary or track line of a road is not so obvious, then these two sides can be considered as one filed and thereby these lines can be eliminated.

On the contrary, increasing the value of color improves the performance of discriminating the fields having same or similar kind of crops even with little disparities, depending on efficient recognition of the roads between the fields. However, the extracted boundaries become crooked and twisted due to the high response to the spectral difference, thus affecting the cleanness and elegance of the output. Moreover, when there are even little variations within one field, high color ratio could also give rise to over-segmentation, creating small fields inside one field. For example, the variations in vegetation color within one field can arise from the influence of different topographies, sunshine angle, or irrigation, bur high color value will recognize these variations as different fields.

Increase in compactness value offers a well discrimination of sharp boundaries or clear artificial structures. However, it tends to follow round closed polygons since the algorithm automatically searches for compact regions. As a consequence, sometimes regular-shaped fields were extracted as irregular shape with too much roundness. In addition, it can also merge regions having very different characteristics since it ignores reflectance. Therefore the performance is mostly disappointing when dealing with for legged shapes, such as passing over roads, railways, rivers. However, with the right weight, it does have advantages over extracting regular-shaped fields. According to Damla (2014) The weight assigned to compactness has to be kept in minimum weight as necessary.

In this study, the value of smoothness parameter does not have as much influence on the segmentation results as the other parameters. However, from visual analysis it could be found that segments consisting of mixed features came into being, such as crop fields including man-made structures, when the value is higher than necessary.

5.2.2 Segmentation Result

The hierarchical network of an image object hierarchy is topologically definite. In other words, the border of a super-object is consistent with the borders of its sub-objects. The area represented by a specific image object is defined by the sum of its sub-objects. Reversely, if a level is created below another, then the border of sub-objects are confined by their super-object and all the sub-objects will be created within the area of their super-object. Region-merging algorithms enable eCognition technology to accomplish the hierarchical network of objects this quite easily. Therefore, this study take full use of this edge and yield segmentation results with structured and stratified information. Figure 22 is an example from part of Study area 1. Due to the large size of imagery, only partial presentation of each image's final segmentation result are displayed in Figure 23.

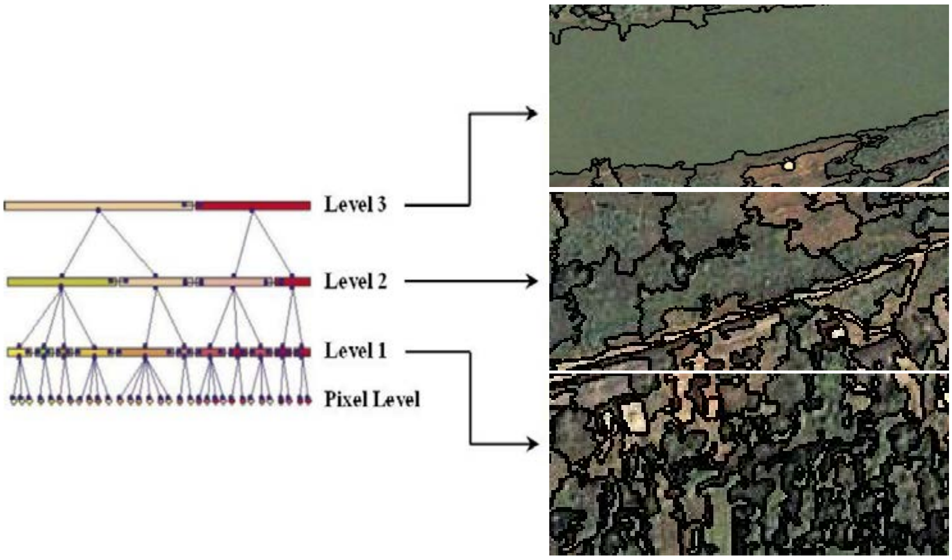
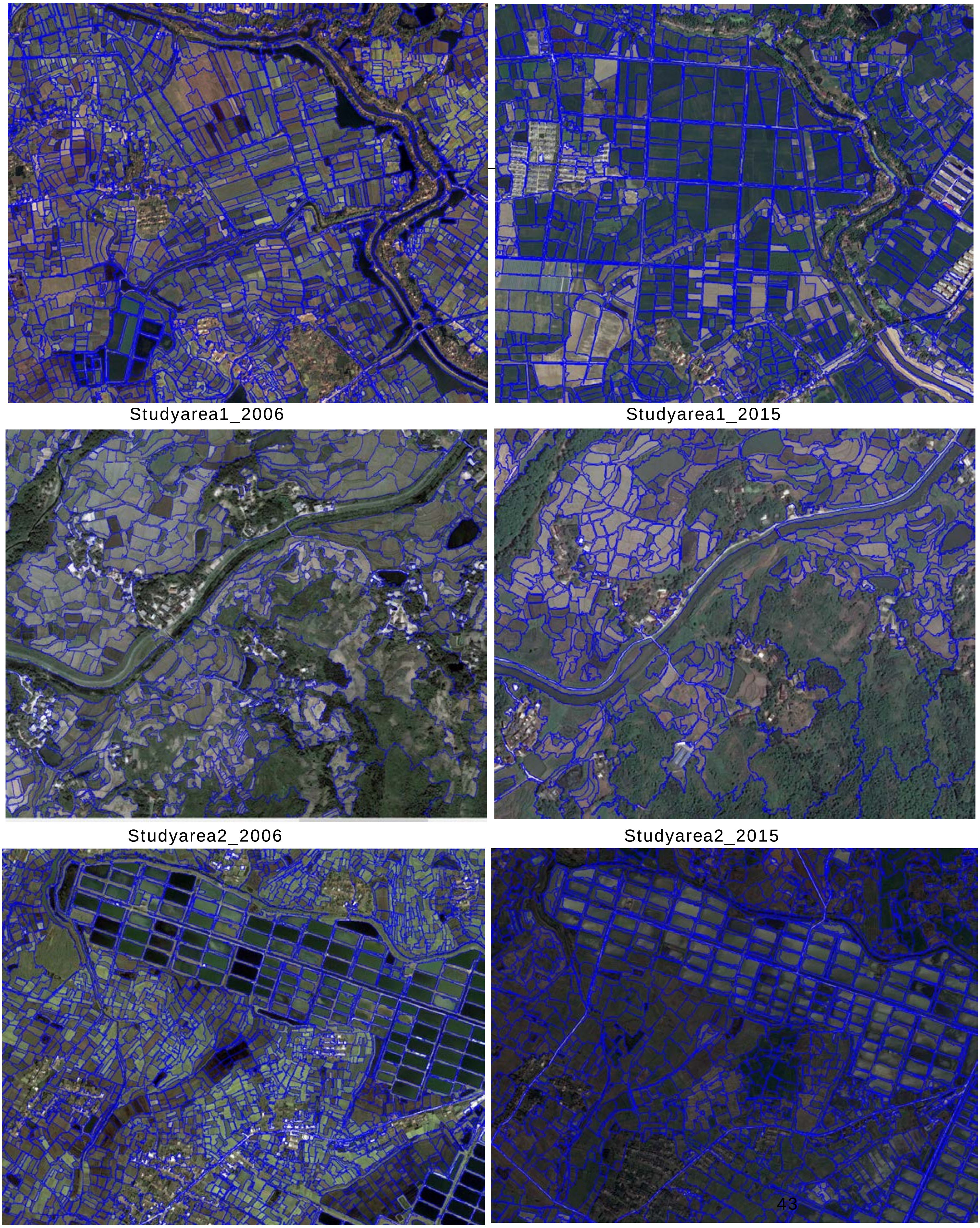


Figure 22: Image object hierarchy

As observed from these images, most objects from segmentation properly represents the shape and scale of objects in the real world. The segmentation demonstrates patent multi-scale hierarchy of image objects, which lay a solid knowledge base for classification in the next step. On one hand, according to the thumb rule of visual evaluation, these segments mostly could make sense to human eyes, and errors or omissions are still acceptable; On the other hand, the validation of classification gives back 89% accuracy, which is much improved compared to traditional pixel-based classification. Therefore, it would be safe to say that the segmentation result has achieved expectation and would be a good foundation for further analysis.



Studyarea1_2006 Studyarea1_2015

Studyarea2_2006 Studyarea2_2015

Studyarea3_2006 Studyarea3_2015

Figure 23: Segmentation results of study area (partial)

5.3 Classification

As mentioned earlier, fuzzy membership function resulted in higher accuracy in Field class. Under this circumstances, six images in three study area have all been classified by using thresholds or fuzzy membership. The classification of each image is based on its different object level and various feature tools were applied to assign objects to different classes. Ruleset is essentially the registration of all the operations that controls over the whole process of information extraction. An example of relevant ruleset and classification output of each image are displayed as followed.

In addition, from trial and error, it was found that
1) Feature “border index”, “Density”, “Length/Width” , “Compactness” could be applied to extract road
2) Feature “Standard Deviation of Layer 1(Red)” proved to have good effect on extracting residential area.
3) Feature “Brightness” could be used for extraction of water.
4) Index ”Greenness”, to put it another way, the ratio of layer green value, could serve as substitute for NDVI to extract vegetation. Although the performance is not as good as NDVI, while working with other texture and geometry feature, the result is acceptable

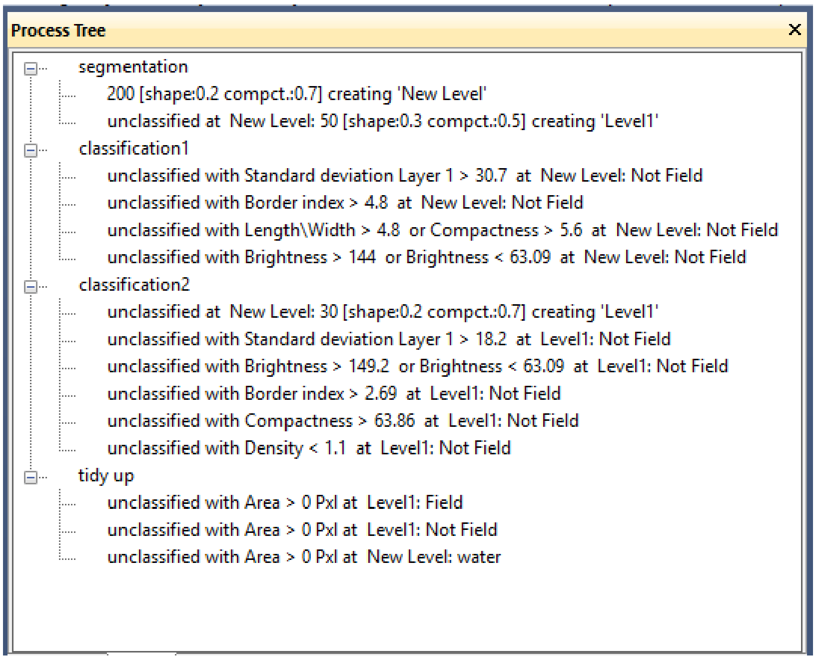
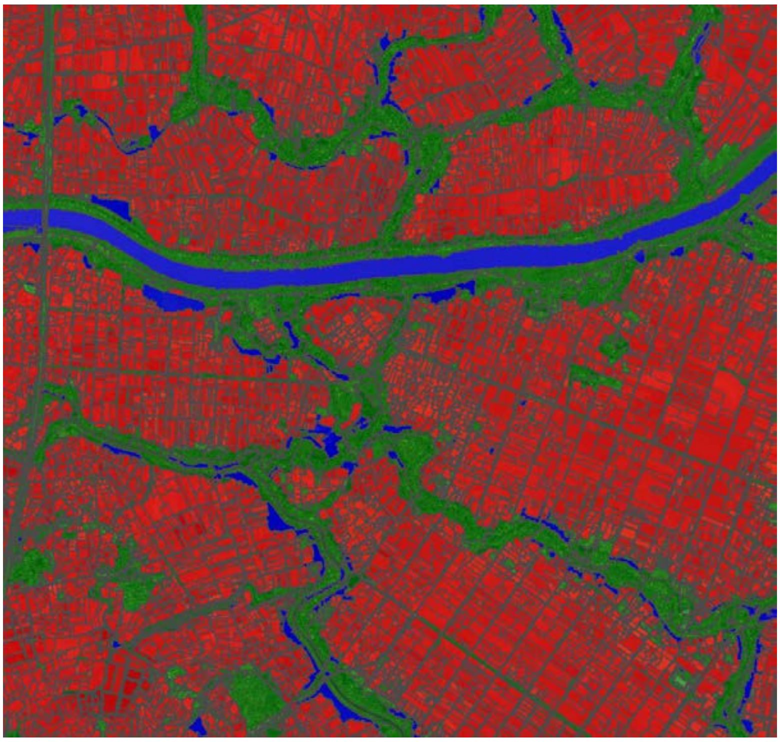
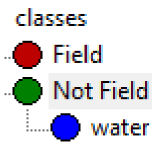


Figure 24: An example of ruleset (Study area 3_2006)



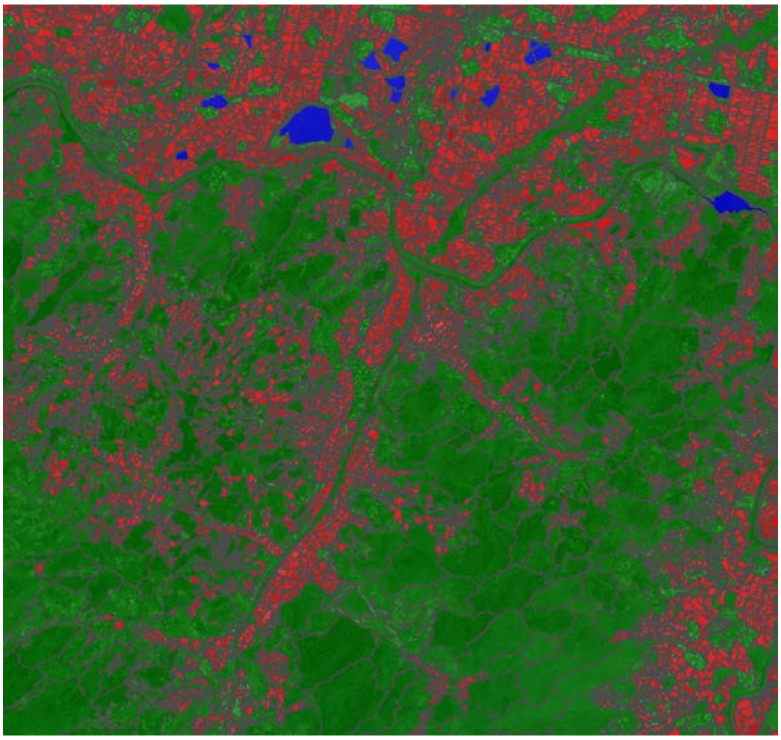
2006

Study area 1

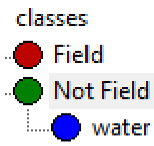


2015

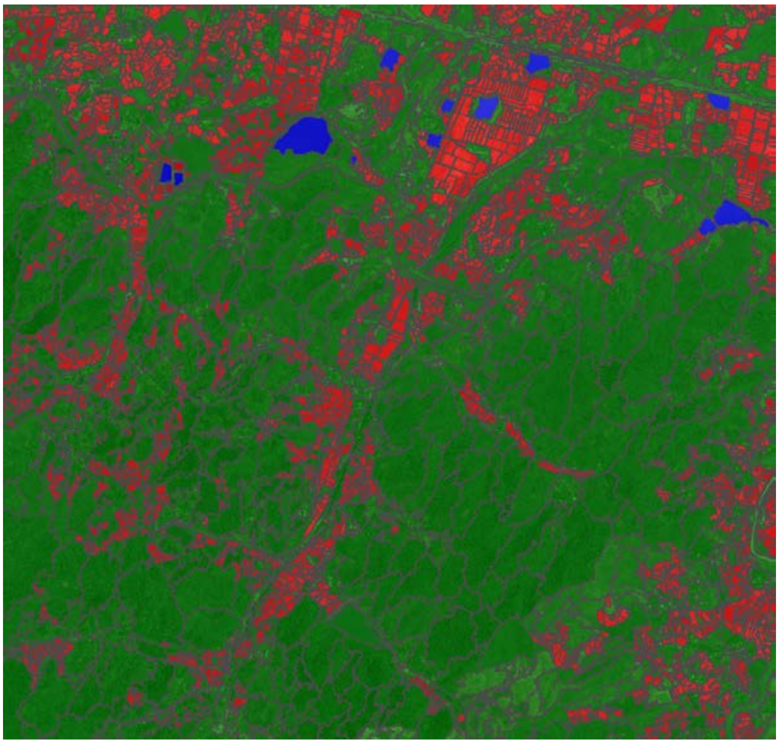
2006



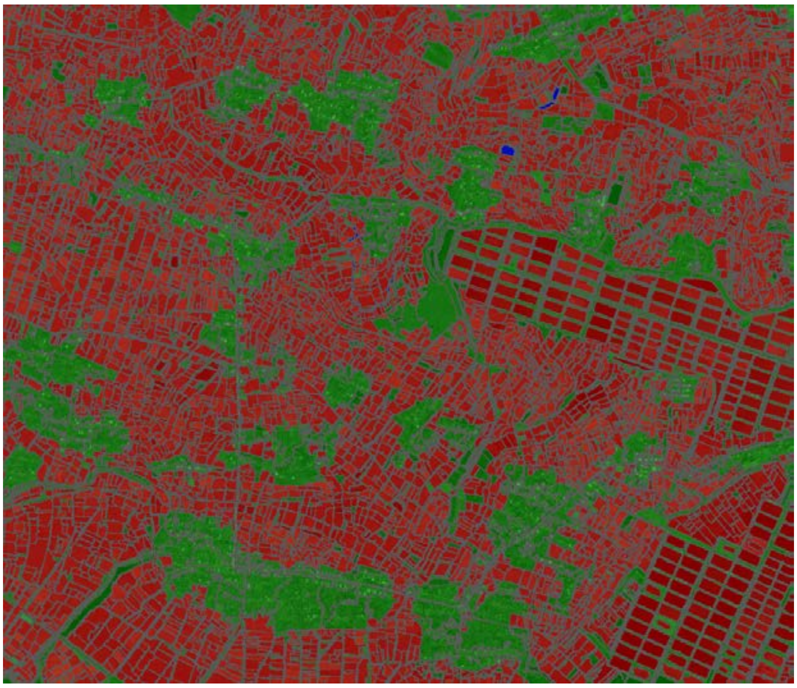
Study area 2

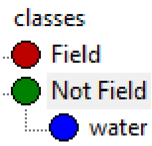


2015



2015





Study area 3

2006

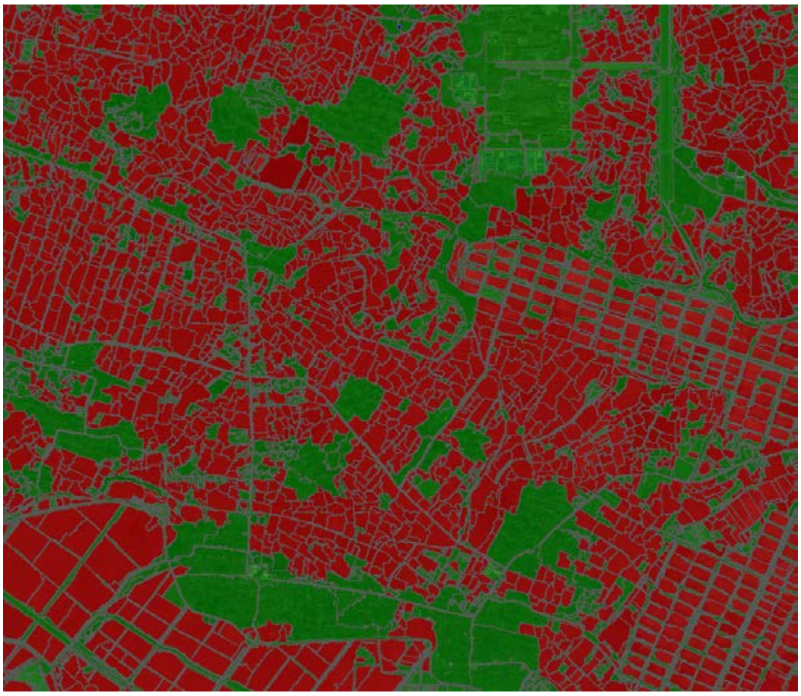
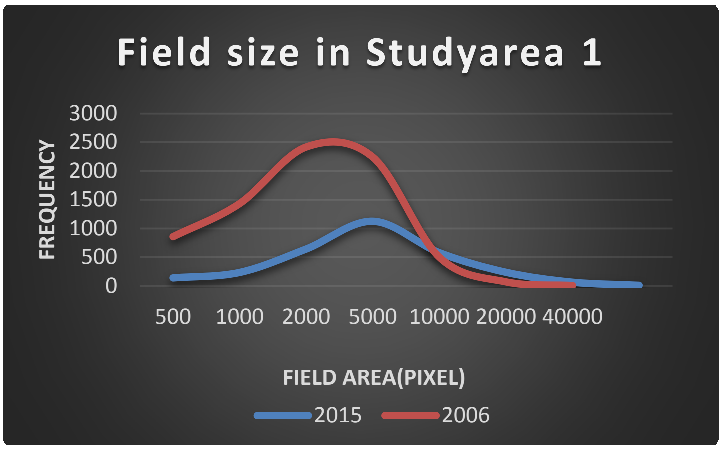


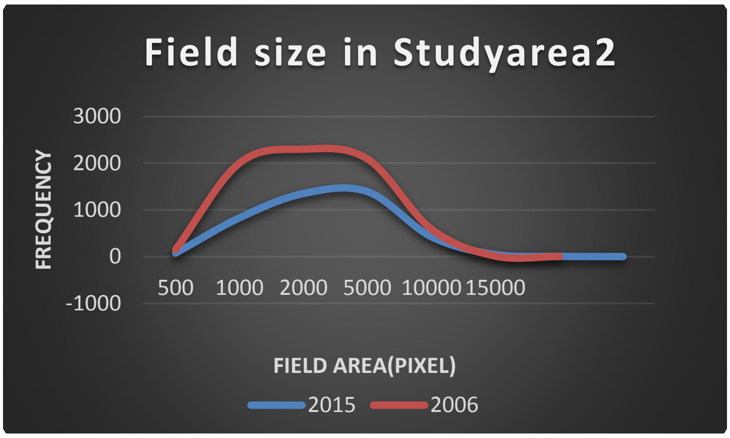
Figure 25: Classification of three study area in 2006 and 2015

5.4 Changes in Field Size

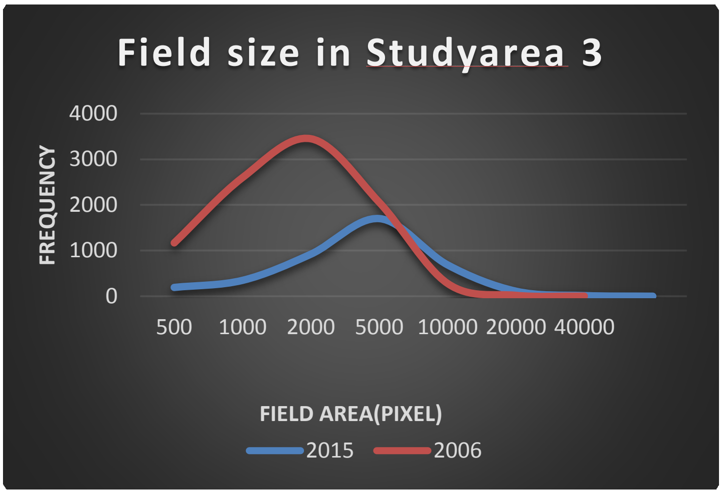
After classification, eCognition allows its users to export the result as raster or vector (Shapefile) file. In this study, class Field has been exported to ArcMap with geometry features including area (pixel) as its attributes. Since eCognition enables geocoding when conducting analysis, the exported shapefile has consistent projection with the original input data in eCognition. In ArcMap, by calculating geometry in attribute table, the size of each field was obtained and then later exported to Excel to study the statistics.



(a)



(b)



(c)

Figure 26: Field size change in study area (a,b,c)

The result reveals that all three study area has experienced an increase in mean field size whereas the number of fields and the total area of farmland has dropped down. This means all three study area shares the same trend in farmland changes. From the graph in Figure 26, a shift in mean field size is rather clear and obvious. The statistics disclosed that the main changes of size happens on fields with the size of around 2000 pixels , transferring to 5000 pixels range, that is, approximately from 0.22 hectares to 0.54 hectares. However it is still below the national average field size, which is 0.6 hectares.

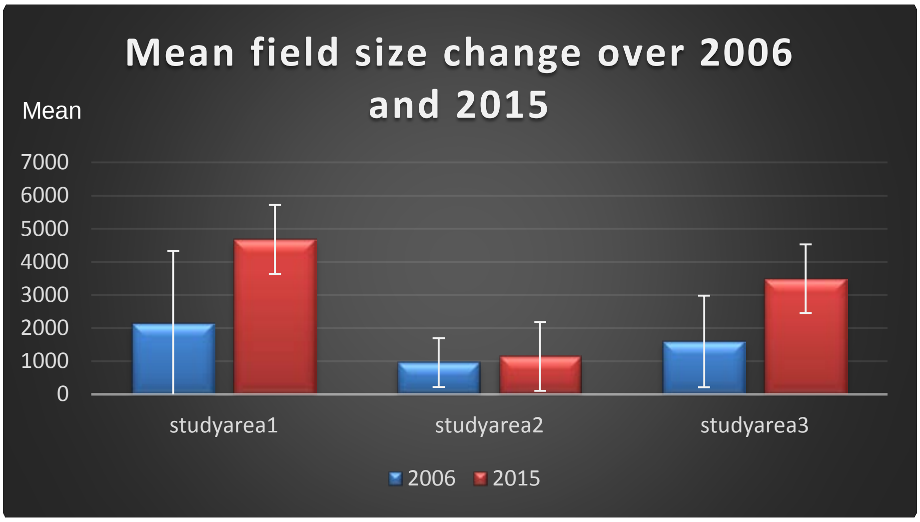


Figure 27: Mean field size change over 2006 and 2015

The changes in mean field size shows variety on quantity. When looking into detailed statistics, size is even smaller than estimated from the graph. The average field size in study area 1 has grown substantially, from 0.216 hectare to 0.51 hectare and resulting in more than doubling in size. However this number is still below national average level, despite the already rather small average field size in China. Study area 2, with smallest fields among three study area, also seems to be most stagnant with an only 0.02 hectare in average size. The scale of fields in study area 3 is between the former two area, rising from 0.17 hectare to 0.377 hectare, also achieve a doubling in mean size.

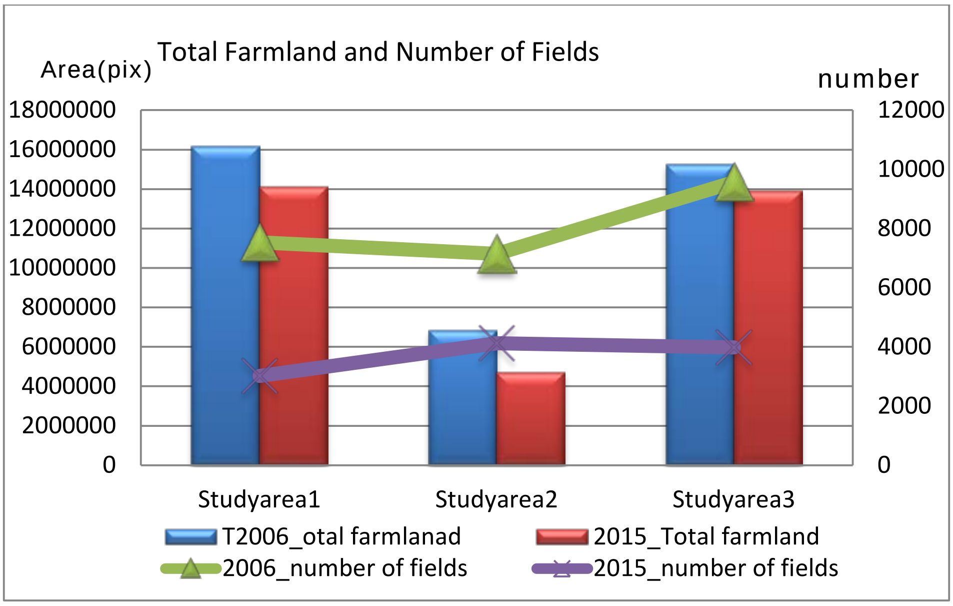


Figure 28: Total farmland and number of fields

Figure 28 has attended to the issue of total farmland area and number of fields. As is indicated from the graph, all three study area has been faced with farmland loss while the farmland in study area 2 decreased the most, with a loss of 229.5 hectare out of 739.4 hectare farmland in 2006. Although the error of classification could affect the statistics analysis, the other factors may cause this situation also worth discovering. For instance, there have been news about landslide in Dabie Mountain region years ago, thereby natural disaster like landslide could be the possible explanation. As generalized from all the study area, fewer fields with larger size yet farmland decreasing are the general trend.

5.5 Two Sample T-test

The two-sample *t*-test (Snedecor & Cochran, 1989) is used to determine if two population means are equal. Our study areas in different years are samples from the whole agricultural land in Anhui province. Therefore, this two sample t-test could shed light on if there is change in mean field size of the whole province between years. The first step to examine this question is to establish a null hypothesis and an alternative hypothesis to be evaluated with data.

Null Hypothesis

H_0 : mean field size didn't change over 2006 and 2015

Alternative Hypothesis

Ha : mean field size did change over 2006 and 2015

Significance level α = 0.05

Calculate Test Statistic

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\left(\frac{SD_1{}^2}{\eta_1} + \frac{SD_2{}^2}{\eta_2}\right)}}$$

The average of both sample (observed averages) Statistically represented as $\overline{X_1}$ and $\overline{X_2}$. The standard deviation represented as SD_1 and SD_2. η_1 and η_2 are the number of observations in both populations.

Critical Region: Reject the null hypothesis when

|T| > t-critical

In each study area, the field size in 2006 and 2015 are two samples. The result are presented in Table 6. It is clear that t stat is smaller than t Critical two-tail(1.96), and P value is way smaller than 0.05.

Decision: Reject H_0 at α = 0.05

Conclusion: There is evidence of significant difference between mean filed size in 2006 and 2015

Table 6: Two sample t-test statistics result

	Study area 1		Study area 2		Study area 3	
	2006	*2015*	*2006*	*2015*	*2006*	*2015*
Mean	2147.209	4679.936	958.9496	1145.218	1595.879	3492.11
Variance	4733002	30827924	538089.8	1063089	1915656	11587069
Observations	7528	3021	7139	4122	9564	3983
Hypothesized Mean Difference	0		0		0	
df	3398		6558		4540	
t Stat	-24.3337		-10.2031		-34.0056	
P(T<=t) one-tail	5.3E-121		1.46E-24		2.7E-226	
t Critical one-tail	1.645302		1.645086		1.645189	
P(T<=t) two-tail	1.1E-120		2.91E-24		5.3E-226	
t Critical two-tail	1.960662		1.960326		1.960487	

6 Discussion

The topic of assessing the actual implementation of rural land circulation policy in China was addressed in this study. Due to the fact that land circulation really took off after 2008, there is no available agriculture census for a comprehensive up-to date understanding. Unlike normal approach would turn to cadastral survey, this study tries to observe the changes in fields to see if it can support the reported current development of rural land circulation, more importantly, to have a better understanding of its impact on field size and vice versa.

6.1 Land circulation and Field size

In this study, field size could be regarded as an index of land circulation. If the “index” changes then these changes will reflect on the subject. From conducting image analysis on high resolution earth observe data, fields in the same area whereas would consider its impact on these area. Fields in study area has been successfully extracted and calculated.

All three study area has displayed distinct changes in field size, with average field size increasing but the total farmland area and number of fields has decreased. From the fields area distribution graph, there is a clear shift in major fields size, most changes happens on fields transferring from 2000 pixel to 5000 pixel, that is, approximately from 0.22 hectares to 0.54 hectares. Therefore, there is a possible trend that rural land circulation has worked as impetus to fields size increase, and it is a tendency that this shift will continue and enlarge.

Also, the changes in mean field size vary on quantity in different study area. The mean field size in study area 1 and 3 has achieved more than doubling in size. Meanwhile, mountain area (Studyarea2) has stayed relatively stagnant with an only 0.02 hectare rise. This reveals that landscape could be an important factor for the implementation of rural land circulation. Flat land and suburban area would be more ideal to carry out land circulation, which in the meanwhile suggest government should make more efforts on rural land reform in landscape-challenged area.

However it would be too early to draw a conclusion to define the relationships between land circulation and field size without considering other factors may also have influence over this issue. Determination of the causes of field size changes is not easy because of the complex interrelationships and interactions between natural and socio-economic factors. This study would provide a framework as followed, within which the impact of land circulation will be evaluated and interpreted.

Urbanization

As mentioned in Literature review, there is a positive correlation between the level of urbanization and the proportion of rural land circulation(Liu et al., 2013). This is maybe caused by the large rural labour migration from rural to city, for these migrants they won't be able to attend their farmland anymore, so it only seems fair and reasonable to transfer or leave it to someone else. In this case, the more urbanized, the more land circulation. Our study also implies that suburban area (study area 3) is quite active in land circulation according to the scope of changes observed in remote sensing images, which can support the argument.

Introducing technology into operation

According to the news report from Xinhua News Agency, the mechanization of agriculture in Anhui has developed rapidly, with half of the province realizing full mechanization in agricultural operation. This maybe could explain the fast growth of field size in flat and slightly hilly land, since it would require at least moderate operation to provide opportunities for mechanized agriculture. However in the mountain area, medium- or large-sized tractors won't be applicable. Under this circumstance, these areas may suffer slow progress of introducing technology into agricultural operation and thus lack of driving force to expand their farmland.

Existing rural land system

For the existing rural land system, it mainly refers to the general agricultural system and household registration system. These are the main constraints and fundamental issue lie in the promoting of field size enlargement. Chinese agricultural system only gives farmers the contract management right of their land and assigns each households with fragmented farmland with combination of fertile and relatively barren land for the purpose of fairness. This is one of the main reason why the general field size are so small. For the household registration system, it creates a giant gap between rural area and urban area by restricting rural population to have every right to live in the city. Because of these factors, farm size growth is lagging behind the process of urbanization, despite rural land circulation being active in the country.

As abovementioned, these are several major factors that facilitate or hinder the field size increase. In the meanwhile, urbanization could also be blamed for the farmland loss. In the mountain area, the pace of urbanization would expect to be slower and thus have less farmland loss. However, in this study, the mountain area (study area 2) experienced a relatively high loss of 31% over these years. This phenomenon may be caused by landslides as reported years ago or the land conversion program of converting fertile farmland to forest, in order to conserve the water and land.

After also taking these factors into consideration, it is easy to find that each of them tend to influence the field size through influencing the land circulation process. Therefore, rural land circulation has a most direct and strong connection with farm field size. According to literature, by 2014, the ratio of rural land circulation in Anhui province is 41%. It is matching with the scope of changes in our study area.

6.2 Field Information Extraction

This study adopts object-oriented classification in eCognition to extract field information from online-Google earth high resolution images. For the temporal analysis, Google offers historical images. The quality of these images is not consistent, so the selection and filtering of imagery could be quite troubling. In earlier stage of study, Landsat imagery with 30 m resolution was employed however the result is unsatisfying. Because 30 m resolution is too coarse for fields in Anhui province, where one field is normal to be smaller than one singe pixel in Landsat imagery.

The general work in eCognition is based on error and trial. The construction of a hierarchical image objects network requires iterative selection of segmentation parameters by trial and error, which is time-consuming and needs a large degree of manual interaction (Schiewe et al., 2001). Next in classification, fuzzy membership function needs to play with the feature tool and by error and trial reaching a proper class description; Nearest Neighbor classification, on the other hand, needs manual input training samples. Generally, the more samples chosen, the higher the classification accuracy, which can also be time-consuming if you want to obtain good accuracy.

According to literature(Hofmann, 2001; Yang et al., 2009.; Ziems et al., 2007) ,NIR channel can be quite helpful when extracting a series of objects like vegetation, water and roads. However, google earth imagery only keeps the three visible bands. Consequently, other substitutes were discovered to extract these objects without NIR information. The performance may drop a little, but working with other features and adding manual editing in the end could also lead to a satisfying output.

Despite the process is demanding in time and patience, the classification accuracy has been much improved compared to traditional pixel-based classification. To validate the adopted method for extraction of the agricultural field boundaries, on-screen digitized fields in test area were used as reference. The goodness of fit was adopted to evaluate the result. Finally, the accuracy of classification reaches 89%. Overall, eCognition has proven to be an efficient and effective approach for object-oriented information extraction.

6.3 Limitations

This study illustrates a more approachable way for public to conduct spatiotemporal analysis of relevant issue. Thanks to Google earth, acquiring high resolution remote sensing imagery don't have to be expensive anymore. Now it's easy and quick to collect high resolution earth observation data. However the choice of data is quite limited regarding historical imagery. Only few historical high resolution images from pre-2008 available across Anhui and these data are from various sources, with different quality. Also, google earth images are inconvenient when it involves up-scale study area, even given there is enough data. Because google earth pro only allows its users to save images on screen with up to 4800×4800 resolution. If you want to use high resolution data for a provincial study area, then it would require a huge amount of work to screen-save maybe thousands of small area and stich all the images later. It will be a very time-consuming process and subject to high risks of error.

Due to this limitation in data, up-scale to provincial level in this study was out of plan. Additionally, as mentioned before, Google earth images only keep three visible bands, which add unnecessary difficulties to extraction of objects. Despite all this, the biggest limitation of data lies in the deficiency of ground data. The method will be more robust if could link the classification result to see what is it in the real world that is changing. That could add more depth to this study. Furthermore, the accuracy assessment is not very sound and convincing without ground data as reference.

To use Worldview or SPOT imagery could possibly avoid abovementioned problems about remote sensing data. However, Google earth has easier access and more cost-effective. Therefore this would be a trade-off depending on the purpose of study. As for the ground data, a field trip would be ideal to solve this problem. At least, to get access to an updated crop type map of study area will also be helpful.

On the other hand, use remote sensing to detect changes in fields in terms of land circulation has its deficiency in methods. It could easily cause confusion in several situations and thus lead to in accuracy in analysis. Firstly, land use right is not visible. We only try to observe the activity of land circulation by detecting changes in fields. However, changes in field are not indispensible even if there has been implementation of land circulation. For example, a farmer may rent a field near his own farmland but he keeps the same operation and crop type as before it was rented to him. Then we won’t discover any change in remote sensing images whereas land circulation has already happened. Contrarily, if there is no land transfer but a farmer just change his field to grow different crops or even into a pond. Then we would assume there is land circulation occurring since clear changes in fields has been discovered.

Therefore the changes in fields discovered in this study cannot fully represent the situation of land circulation. It could only give a general ideal of the trend. This study thereby depends on assuming most farmers change their land on account of land circulation. Another factor may cause disturbance is the influence of phenology. Although images were made sure within same month, due to the change of climate or change of crop type, there may still exist unavoidable errors. Similarly, an updated ground truth map of crop type would help alleviate the problem.

Finally, the classification conducted in eCognition software could be further refined if given time and resource. It is a really powerful software with many tools and algorithms that is worth trying. Furthermore, due to its trial and error principle, I am convinced that with better understanding and grasp of this software better output would be generated(Hansen et al., 2006; Trimble Documentation, 2013).

7 Conclusion and Recommendation

The overall aim of this study is to have a better understanding of distribution and changes in field size, to evaluate the role of Rural Land Circulation in these changes, and to find possible trend or correlation between field size and other factors like landscape/slope.

This study first presented the results of applying the object-oriented method as an effective tool for agricultural field information extraction from high resolution Google earth imagery. At earlier stage of this study, it was realized that it is not applicable to extract the field boundaries of the farmland from the Landsat imagery (30m) due to its relatively coarse resolution. Then three sampling area in study area was selected based on variety of landscape and land cover. The object oriented image analysis was conducted in the eCognition Developer software, using multi-resolution segmentation and fuzzy membership function classification methods. It could be concluded that these methods are effective and efficient tools for extract fields, producing results with an accuracy of 89%.

Then fields information in study area with differing landscape and land cover were compared between years, trying to find changes in fields. The result reveals that in all three study area the number of farm fields and total area of farm land has dropped down, however, the mean size of fields has increased remarkably. Changes tend to be more active in flat area and suburb, with both achieving more than doubling in average field size. Meanwhile the agriculture land in this study has managed to observe the real progress of rural land circulation in China, provided a way to understand the possible cause for variation of implementation and its impact on rural land reform. Policy-makers could consider this and put different emphasis when making policy to promote the implementation of rural land circulation in less-developed part of China.

This study as any research has its limitation and naturally, it can be improved by incorporating ground truth data or updated map of croptype. For future study, up-scale study is of great importance. A provincial or even national analysis could better help with our understanding of current development and have much more influence over policy-making. This study could also be followed by connecting the field size changes with crop yield to see if there is any correlation or influence, which would also be intriguing.

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