Shape-Based Descriptions to Classify Na Dun Cultural Settlement using Object-Based Image Analysis

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Abstract
Rural village forms are classified into 3 main types: Nucleated, Dispersed and Linear villages. The purpose of this paper is to describe rural village shapes using object–based image analysis. This method is demonstrated in the Na Dun district, northeast Thailand. Village form, or village morphology, is a pattern of village components that form an irregular shape via the merging of candidate classes, e.g., roofs, vegetation area, public area, etc. Prior to image object fusion to shapes, village components are classified by rule-based methods with an overall accuracy of 87.33%, and 0.48 of kappa statistics. To do this, an image object fusion algorithm is used to merge the village's candidate classes (based on spatial constraints) into a shape that represents the village's form. The shape of each village type is defined by the essential parameters obtained from the component relationships and spatial factors. These factors are derived from pan sharpened QuickBird images with spatial resolutions of 0.6 meters. The study determines shapes by applying geometry shape features, i.e., elliptic fit, compactness, roundness and shape index, by using statistical analysis and customized relational features. These factors are compared to all neighboring objects across the entire image scene on both the vertical and horizontal image object levels to create class descriptions for village from classification.

1. Introduction

In the study of human settlement, there are two terms of the traditional characterization emerging from this field, pattern and form. Both are used to describe settlement characteristics relevant to a specific landscape unit in a particular area, e.g., distribution and physical morphology, depending on analytical scale (Haining, 1982). In terms of settlement distribution, human settlement can be applied to point features that represent villages spread over a wide area. However, point representations are also used to study the grouping of several villages (settlement pattern) at a regional scale. Nevertheless, it is possible for these characteristics to be used at a local scale. To clearly understand a settlement at a larger scale, certain spatial factors from the study area need to be taken into account. Obviously, rural communities are the settlement type of the vast majority of the populations in developing countries, and most land is used for farming land. Rural landscapes produce commodities, such as food, forage, biomass fuels, fiber and timber (Gulickx et al., 2013 and Pinto-Correia and Kristensen, 2013). The village (clustered houses in a rural area) is one of the most basic human settlements. It can be discriminated by using settlement hierarchy properties, which are used for ranking the importance of settlements based on simple factors, such as size, population density and functionality (Bevan and Wilson, 2013 and Charnwood Borough Council, 2012). Additionally, there are 6 characteristics used for identification of settlements (Lv et al., 2013). Site and situation factors are the most geographically related and are related to a settlement's location. Site factors describe why a settlement was built in a given location with relation to crucial spatial factors, for instance, soil, water supply and relief. Situation factors describe the relation of a settlement to surrounding resources, e.g., other settlements, market places and water resources (Hudson, 1969). These factors are also used to predict whether a settlement will grow from a small village into a town or city. Additionally, Hudson (Hudson, 1969) argued that settlement location theory consists of central place, diffusion, ecological distribution and morphological laws. Village form refers to shape (Nagle, 2000). Some spatial and socioeconomic phenomena, especially a village settled in a high-potential area, lead to different shapes, physical characters and distributions. A high-potential area can be either productive farmland or a place that can be transformed into a larger community because of highly positive factors, which are influenced by population growth, positive infrastructure development and the economy (Haining, 1982). However, physical changes related to human activities can lead to positive or negative results in rural land use/land cover (LULC). Due to development pressure, the loss of rural character in Thailand's northeastern landscape is happening at an alarming rate, compared to the historical development patterns (Welch, 1998). Although the development is required for some areas in order to maintain the basic essentials of life (i.e., housing, food and water), the limitations of the land need to be considered (Parnwell, 1988). Each village shape has developed by physical processes through time. Often, a village came first and scattered farmsteads second. Hudson (Hudson, 1969) and Spencer (Spencer and Thomas, 1973) described 3 main rural village types: nucleated, linear and dispersed (Figure 1). Additionally, Nagle (2000) classified rural village nucleated shapes into several sub-types, such as compact nucleated, green nucleated, cross-shaped nucleated and T-shaped villages (located at the main road intersection). Nucleated settlements are a group of permanent houses that are found in close proximity to each other.

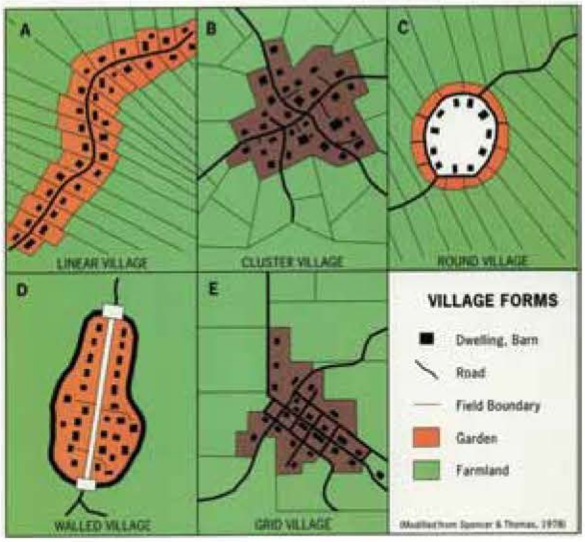


Figure 1: Example of village forms

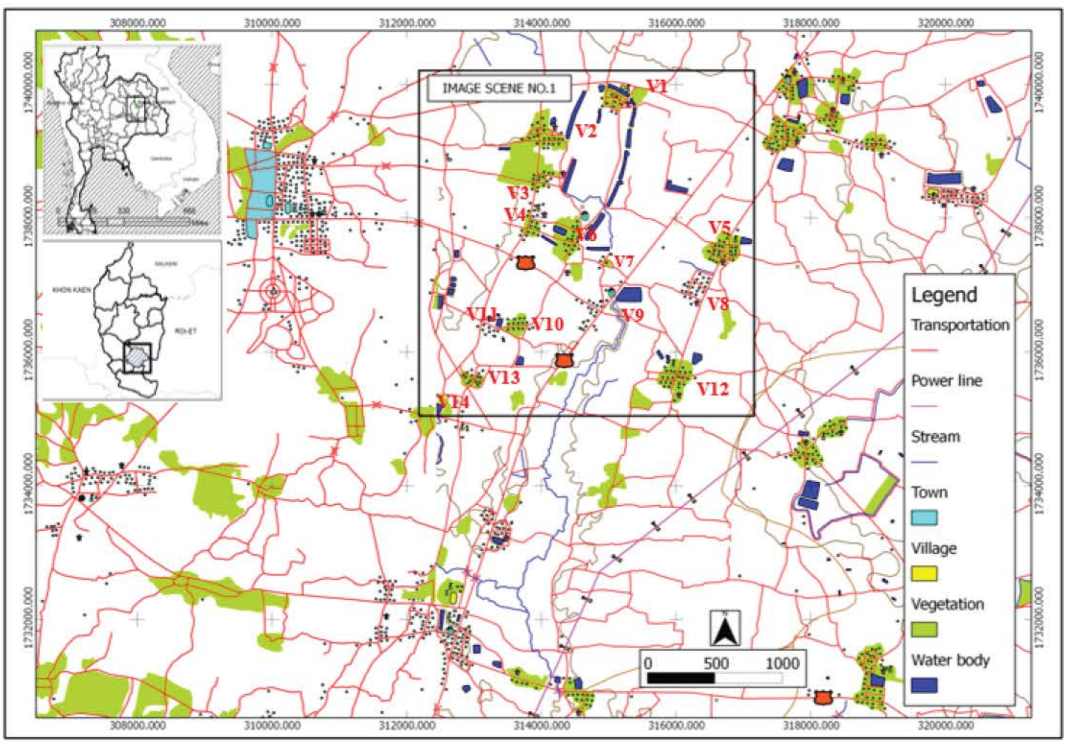


Figure 2:The location of the study area, Na Dun district, Maha Sarakham, Thailand

These houses are often clustered around a crucial point, e.g., post office, temple, local school, or found at the road junction. Linear settlements usually develop along a linear feature, such as along a road, railway or stream. As a result, this type of settlement has a long and narrow shape due to the limitations of the land. Lastly, dispersed villages are houses that are scattered across a large area (Beresford, 1964). A few houses are located in the middle of their farmland, to protect their agricultural products. Settlements are often described by using a scale of analysis and distribution throughout a landscape unit. In reality, truly nucleated or wholly dispersed village are rare, as described by Roberts (Roberts, 1996). Much more crucial factors for investigation are required. Form, or morphology, is used to identify characteristics of an individual settlement, while settlement pattern describes the shape of the distribution of villages throughout a large area. Therefore, the terms nucleated pattern and nucleated form are completely different. To classify rural village forms, many factors need to be taken into account. For example, site and situation factors have been used to describe the reasons why villages developed their unique forms, visible in remotely-sensed data.

Very high-resolution satellite images are important for spatial analysis at a very detailed scale. There are many papers on human settlements using remotely sensed data and image classification techniques (pixel-based and object-based approaches). Few of them, however, are concerned with the comparison between spectral and contextual information (Frauman and Wolff, 2005 and Zhao et al., 2013) or even use computer programs to delineate nucleated villages based on spectral information alone (RGB) (Murtaza et al., 2009). Shape-based change detection applied to remotely sensed data is also an essential method to determine land use/land cover change (Li and Narayanan, 2003), including shape classification theory (Da Costa and Cesar Jr, 2000). The image object fusion algorithm has been incorporated into eCognition (Trimble Geospatial) aimed at grouping and reshaping image objects into a large object, based on neighboring object relationships. It is basically a supervised regionalization technique, taking into account spatial and thematic constraints of the objects.

2. Materials and Methods

2.1 The Study Area

This paper focuses on a group of rural villages in the Na Dun district, Maha Sarakham province, northeastern Thailand (Figure 2). In total, 14 villages, which are physically different in shape and size, are used to extract village forms. The bulk of the population lives in rural areas, where they are employed in the agricultural sector. Sticky rice is the main agricultural crop, which is cultivated for household consumption and as a cash crop. Farmers, however, are being encouraged to diversify into new crops, such as cassava, sugar cane and rubble tree, based on market demands. The rubber tree is likely to be the newest economic plant promoted in this region. The study area in northeast Thailand is located on the Khorat Plateau, across which the Chi River (Main River) flows from the northwest to the southeast. The plateau consists of two plains: the southern Khorat plain is drained by the Mun and Chi Rivers, while the northern Sakon Nakhon Plain is drained by the Loei and Songkhram Rivers. The plains are divided by the Phu Phan Mountains. The differences in elevation are between 140 – 200 meters above mean sea level (Pendleton, 1943). As a result, the physical characters that emerged from remotely sensed data show that the villages are normally clustered on slightly raised land (to avoid flooding) and are surrounded by upland crops and paddy fields. Areas with the low slope at a village scale are normally used as farmland. Villages were often named for geographical features, such as *Ban Don Bom* or *Don Bom* (*Ban* is a Thai word for village; *Don* means an upland). Dispersed villages are rarely found in this region because of cultural settlement and religious belief factors. Sandy loam is the main soil type, with substantial salt deposits, leading to low agricultural productivity caused by flash flooding in the rainy season and rapid drought in the season.

3. Data and Image Classification

Pansharpened images with a spatial resolution of 0.6 meters by using Gram-Schmidt image sharpening technique are used in this paper. The original image pixel size is 2.4 meters. The algorithm has been used to increase the spatial resolution from the original pixel size of 2.4 meters to 0.6 meters to improve roof extraction and increase the visibility of transportation network. Roof objects will represent the residential density versus existing residential area.

Using shape based classification features is not a new method among remote sensing techniques (Ling and Jacobs, 2007), it is one of the core advantages of object-based image analysis (Blaschke, 2010). However, most published papers used applied object-based classification based on spectral statistics without considering shape information explicitly in their classification procedures (Chaudhuri, 2008, Iivarinen et al., 1997 and van der Werff and van der Meer, 2008).

Segmenting an image into (in the best case) meaningful objects makes it possible to create more informative attributes, such as shape, texture and contextual information (Tian and Chen, 2007). Jiang (Li and Narayanan, 2003) proposed satellite image classification via integration of shape information and spectral information to extract water bodies, whose homogeneous pixel values form unique shapes. This technique also incorporated change detection features based on shape properties derived from temporal resolution data. In this paper, however, several techniques used to classify rural settlements are based on the spectral and geographical information. The image was segmented into image objects based on homogeneity criteria using a multi-resolution image segmentation algorithm (Baatz and Schäpe, 2000). Thematic layers (roads) were integrated into the segmentation. The transportation network was used for village borders in the case of villages that are enclosed by surrounding roads (forming a polygon) (Rezayan et al., 2010). However, some villages are more likely to have developed into a linear village along a road. Therefore, the thematic layer (transportation network) could not be used in this type of village. It was discarded from the evaluation of the difference method but still appears in the image scene. By visual interpretation, linear villages in this area appear more likely to cluster along roads than rivers or streams compared with other parts of this region. Therefore, some villages are recognized as linear villages (the condition is that a village should be located on or intersect with a main road). Determination of linear villages is usually based on the elongation of roof areas and adjacent objects, which create such a unique narrow shape (Sarkar, 2010).

3.1 Image Classification

The village component classification (land cover) procedures are based on previous work proposed by Khamphilung et al., (2013) Overall accuracy of the classification was 70%. The main objective of the paper was the development of an OBIA expert rule-set to develop a rural village from classification. In this paper, however, 14 villages were taken into the classification processes with more spatially related and improved relational features (Figure 3). Some thresholds such as the distance to road, house density and object shape property were developed to increase the quality of the classification. The transportation network is classified based on the integrated thematic layer. It was classified into 3 classes: main road (T1), border road (T2) and inner road (T3). The transportation network plays important roles, such as a linkage from villages to market places (main road). Moreover, the transportation network can be used for settlement area delineation in certain instances. To create the mask regions, the AOI polygons were created from distance criteria of less than 500 pixels (300 meters) from the transportation type 2 (border of settlement area). This means that the AOI regions are extended over the exact region of the villages' borders. These areas are the mask regions used for segmenting all image objects related to its super image object level. The image segmentation performed under this AOI level segregates all village components adjacent to the border into an irregular shape, including the farmland surrounding each settlement. The irregular shape will represent the village shape. It can be a free-form shape, as shown in Macleod (MacLeod, 2002), depending on its surrounding factors, which may be influenced by regional stresses, e.g., availability of upland areas for new house allocation.

Land cover classification is composed of 7 classes (i.e., roofs, bare land, vegetation, grassland, transportation, agricultural areas and water bodies). All land cover classes within a certain distance from the transportation network were merged into a shape using an image object fusion algorithm to create a new object class. This technique was applied to human settlements (Figure 4) (Imaging, 2004).

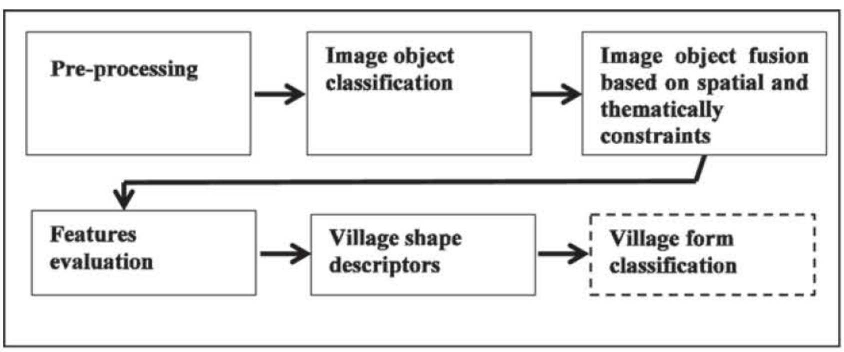


Figure 3: The analytical processes of village shape delineation

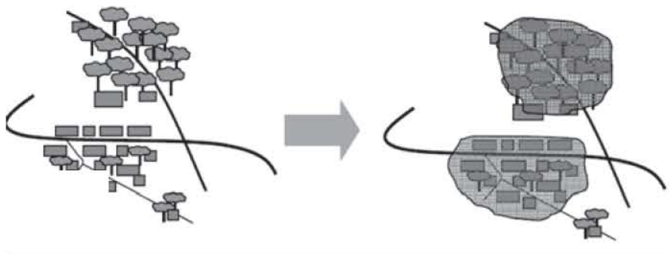


Figure 4: Village shape boundaries created by image fusion algorithm from village component objects

Most fused image objects were used as village shape representations on the super object level. The geometric features were then applied to all objects, including the correlation to sub-object level customized features. The roof density per area, percentage of green area and spaces were calculated, and then statistics were applied to compare minimum, maximum and mean values (Imaging, 2004).

3.2 Shape Features Selection

In principle a plethora of geometry features are available in an object-based environment (similar to GIS based shape descriptors) Circular or elliptic fit of an image object is important in target detection, shape analysis and biochemical image analysis (Chaudhuri, 2008). There are five main geometry features used in this paper, namely, compactness, rectangular fit, elliptic fit, roundness and shape index (1) – (5). The compactness features describe how compact an image object is (1). The compactness value has a value of 1 for most compact objects and higher values for elongated ones. Compactness is the product of the length and the width, divided by the number of pixels of the object (Definiens AG, 2009):

$$\textit{Compactness} = \frac{2\lambda_1 \times 2\lambda_2 \times 2\lambda_3}{V_v}$$

Equation 1

where lv is the length of an image object v, Wv is the width of an image object v, and #Pv is the total number of pixels contained in Pv. Roundness is also a meaningful feature used to compare certain contrasting features, such as roundness versus elliptic fit (eCognition Developer, 2009). Roundness of an image object is calculated by subtracting of the radius of the smallest enclosed ellipse (ε_v^{min}) from the radius of the largest enclosing ellipse (ε_v^{max}).

$$\textit{Roundness} = (\varepsilon_v^{max}) - (\varepsilon_v^{min})$$

Equation 2

Rectangular fit is selected because some villages tend to form rectangular shapes. This shape property is used to determine if an object is similar to a rectangle. Human settlements often tend to form this shape, especially well-planned areas or even a village itself that forms a block. A block of this shape, for example, is used to quantify land cover where objects of interest are completely within a rectangle (3) (eCognition Developer, 2009). Rectangular fit is calculated based on the comparison between the proportions of the rectangle and the proportion of the length to width of the image object, where ρv (x,y) is the elliptic distance at a pixel (x,y), Pv is the set of pixels of an image object.

$$\textit{Rectangular fit} = \frac{\{(x,y)\varepsilon Pv : \rho v(x,y) \leq 1\}d}{Pv}$$

Equation 3

Elliptic fit is used to describe how similar an object is to an ellipsoid. This feature is used to separate linear villages from nucleated villages. A linear village has an elliptic fit threshold lower than others. The value ranges are between 0 and 1; 0 means there is no fit with a threshold lower than 50%, and the ideal perfect fit is 1 (eCognition Developer, 2009) (Equation 4):

$$\textit{Elliptic fit} = 2.\frac{\{(xyz)\varepsilon Pv : \varepsilon v(xyz) \leq 1\}}{Pv} - 1$$

Equation 4

where εv(x,y) is the elliptic distance at a pixel (x,y), Pv is the set of pixels of an image object v, and #Pv is the total number of pixels contained in Pv.

The shape index is used to evaluate the smoothness of image object borders (5). The higher the shape index, the lower the border smoothness (eCognition Developer, 2009). Some villages have rough borders resulting from a village border adjacent to the LULC, such as a vegetation area, which belongs to the village. The lower shape index villages are found to have borders connected to agricultural areas (not a candidate object to merge into an object). The shape index can be calculated by the border length (bv) divided by the fourth root of its area ($\sqrt[4]{Pv}$) – it is basically comparing the perimeter of the object with the perimeter of a perfect compact object (square) of the same area.

$$Shape\ index = \frac{bv}{\sqrt[4]{Pv}}$$

Equation 5

It is not possible to classify villages into particular types using shape properties alone. Village characteristics, such as roof density, space area and percentage of green space, are also analyzed. In reality, however, perfect human settlement shapes do not exist and are rarely found in this region, which features unplanned settlements in a rural area. Settlements are often irregular shapes with significant differences in the degree of variation (Figure 5), as proposed by Iivarinen et al., (1997). The examples in Figure 5 are based on computational shape features. Therefore, the possible geometric features are chosen. Shape features, which are fused into a shape from the candidate classes obtained from the early stage, such as circular (roundness), completely rectangular (rectangular fit), compactness and elliptic fit, can be used as object representations (Figure 4). Each shape variation is measured and compared with all neighboring image objects. Moreover, the selected shape thresholds of fused shapes are also correlated to the sub-object level (LULC). A rectangle can be transformed into a round object, and a round object is possibly changed into an ellipse and so on.

3.2.1 Linear correlation of shape features

All 14 fused image objects (intended to be village form representations) were derived using the classification techniques described above. All of the objects were analyzed using the Pearson coefficient to evaluate the correlation between possible features. The advanced object-reshaping algorithm is used to increase the object border smoothness.

The chosen shape geometric features are calculated and put into a geometric matrix to determine how each pair of selected geometries is correlated. The terms of the correlation are used to define village shape: strong positive correlation, strong negative correlation or no correlation (Figure 6). The idea is that the degree of shape variation of each shape threshold should be used to conduct a rule-based comparison before comparing the land use/land cover level. Obviously, rectangular fit and roundness (circular objects) values are shown to have a contrasting correlation; an object that has a high roundness value has a low rectangular value (moderate negative correlation, r = 0.5882). This condition, for instance, was used to classify compact nucleated forms (Nagle, 2000). A long and narrow shape is obtained from their components merging. However, a long and narrow shape can be interpreted as a linear village. The questions become how far is the village from the main road and what kind of the transportation type is the village using. For example, a village located on the river and another located along a railway must be dramatically different in character, with regards to further development in size, shape and land usage in the future. The relationship between roundness and compactness, for example, shows a strong positive correlation (r = 0.8026). This means that if a village is circular, the area tends to be a larger. Elliptic fit was chosen in order to distinguish linear and nucleated settlements on the first order in the shape image object level (upper object level). Linear village forms obviously feature long, narrow shapes. This can be accomplished by using shape features, such as length, width and length/width. The shape matrixes have shown a strong positive correlation with the rectangular fit, while they show a negative relation to roundness and compactness. Nevertheless, the classification accuracy is ensured by using many features to define a village type. For instance, the shape level is also correlated to sub-objects using a relational customized algorithm involving image object relationships.

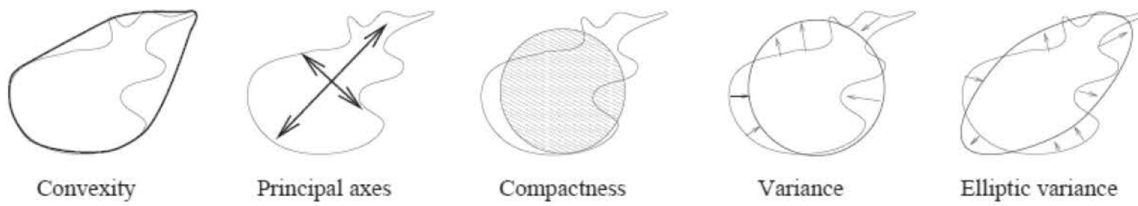


Figure 5: Shape information

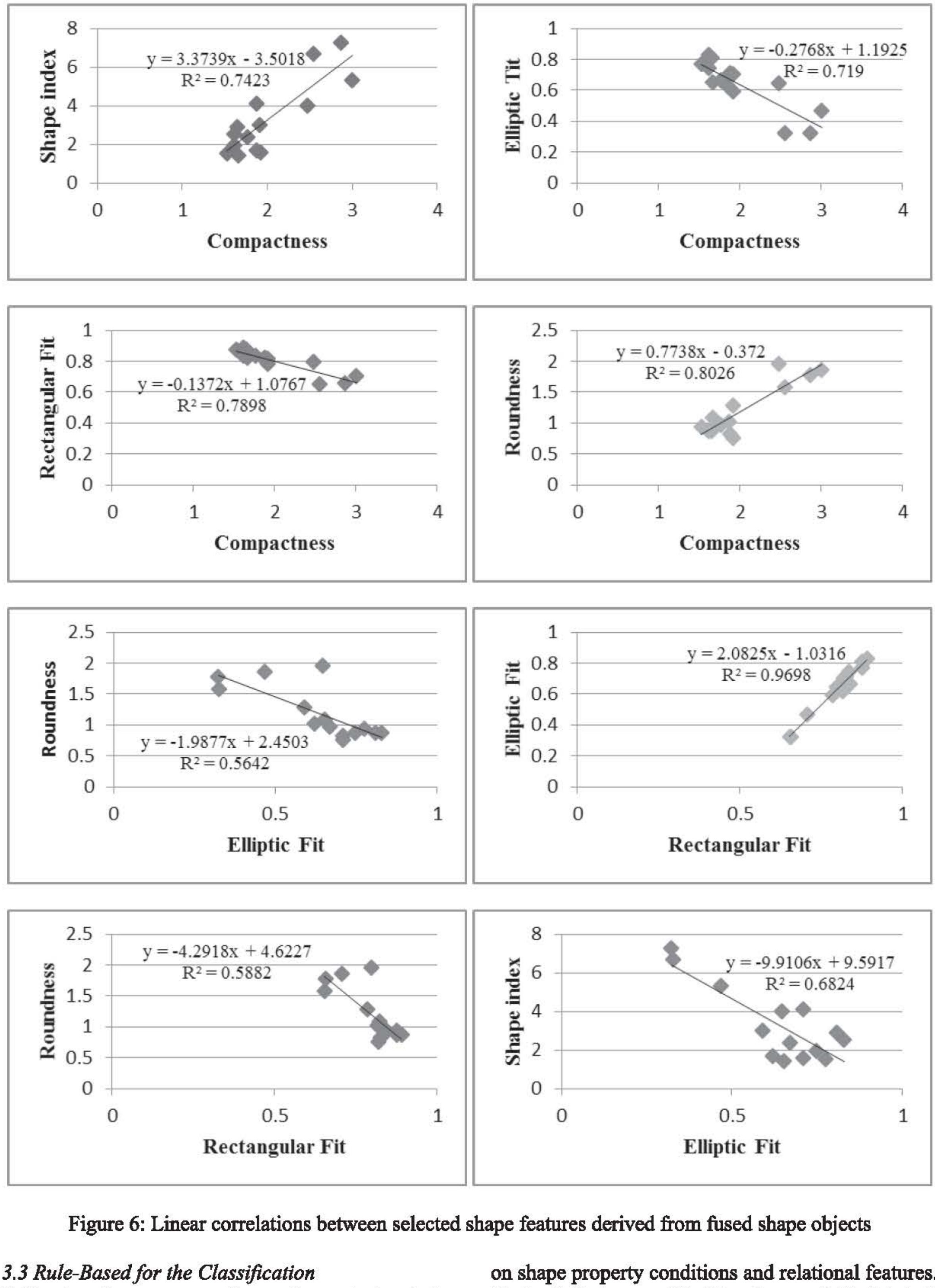


Figure 6: Linear correlations between selected shape features derived from fused shape objects

3.3 Rule-Based for the Classification

Following the processes above, the next step is to create the rule-set for classifying village forms. Class descriptions are used for this part to distinguish the 3 main settlement types depending on shape property conditions and relational features. First of all, image object levels are divided into 2 parts: the shape level (top level) and the land use/land cover level (sub level). On the super object level, 14 shapes represent each village form.

The shape factors shown in Table 1 were calculated. This calculation is the first step to defining forms based on geometric features. The main purpose of this step is to classify all of the shapes into the 3 main settlement types (i.e., nucleated, linear and dispersed) before correlation to the sub-object level. The next step is to classify the village sub-types. Village sub-type classifications were accomplished by comparing the super objects level to its sub objects level using relational features, arithmetic features, constant values and statistical calculations. For example, nucleated villages (focused on the super objects level) are derived from a larger number of roofs, larger area and greater roundness compared to others. A village shape is acquired from clustered roofs; therefore, a larger area contains a larger number of roof objects. The nucleated village form consists of 3 sub-types: cross-shape nucleated, green nucleated and T-shape nucleated (Jain et al., 2013). The number of roofs of a nucleated village should be larger than any other village type. The average number of roofs is still the main factor used for the discrimination of each sub-class. A nucleated green village means a village with a total roof area that is greater than any other village, but it also includes a green area, such as grassland or stand of trees. The class related to sub-objects is used for classifying this village type. The roof area density of a green nucleated village is usually lower than other nucleated forms. Therefore, green nucleated village are classified from the percentage of green area related to the sub-object. Second, if the elliptic fit value is less than the mean value, the distance to T1 is smaller than the minimum and the length/width is greater than the mean. As a result, this village should be classified as linear village. Linear compact is derived from a smaller value of compactness. A linear nucleated classification indicates that there is a large roof area (sub-object), but it is smaller in width and larger in length. Lastly, if the given criterions are not met, these shapes should be defined as dispersed villages (e.g., an isolated house, an individual dwelling, or an undefined purpose building). Because dispersed villages are rarely found in this region due to religious and cultural conditions, the first step was the classification of villages as linear or nucleated. However, some roofs located outside polygon areas were classified as isolated roofs, which may or may not be used as dwellings. The shape information and spectral information used for classification are shown in Table 1. The steps in Figure 7 show the rule-based classification for each village:

4. Results

All 14 selected villages are classified using rule-based classification at the village component level. This level refers to the land use/land cover level, in which every class is fused into shapes that represent village forms. The most essential image object classes included the following 7 classes: roof objects, vegetation, bare land, grassland, water bodies, transportation networks and agricultural areas.

Table 1: Shape-based features and spectral information used to classify rural village forms

-Geometry (Super object level)	**-Village components (Sub object level)**
• Shape Index (pixel) • Rectangular fit (pixel) • Roundness (pixel) • Compactness (pixel) • Elliptic fit (pixel) • Area (m^2) • Length (meter) • Width (meter)	• Number of roofs • Roofs density/Village • Proportion of green areas • Proportion of green spaces • Existence of sub objects (roofs) • Mean distance of roofs of a village • Max distance from roof to roof (mater) • Min distance from roof to roof (meter)
-Spatial relations (Position: Coordinate)	**-Based on Polygons (Super object level)**
• Min. distant to Main road (T1) (m) • Existence of T1, T2, T3 (to sub objects) • Rel. area. of T1, T2, T3 (to sub objects)	• Area (including inner polygons) (m^2) • Compactness (polygons) • Perimeter (polygon) (meter)
-Spectral information	
• Mean Channel 1,2,3,4 • Brightness, NDWI • NDVI	

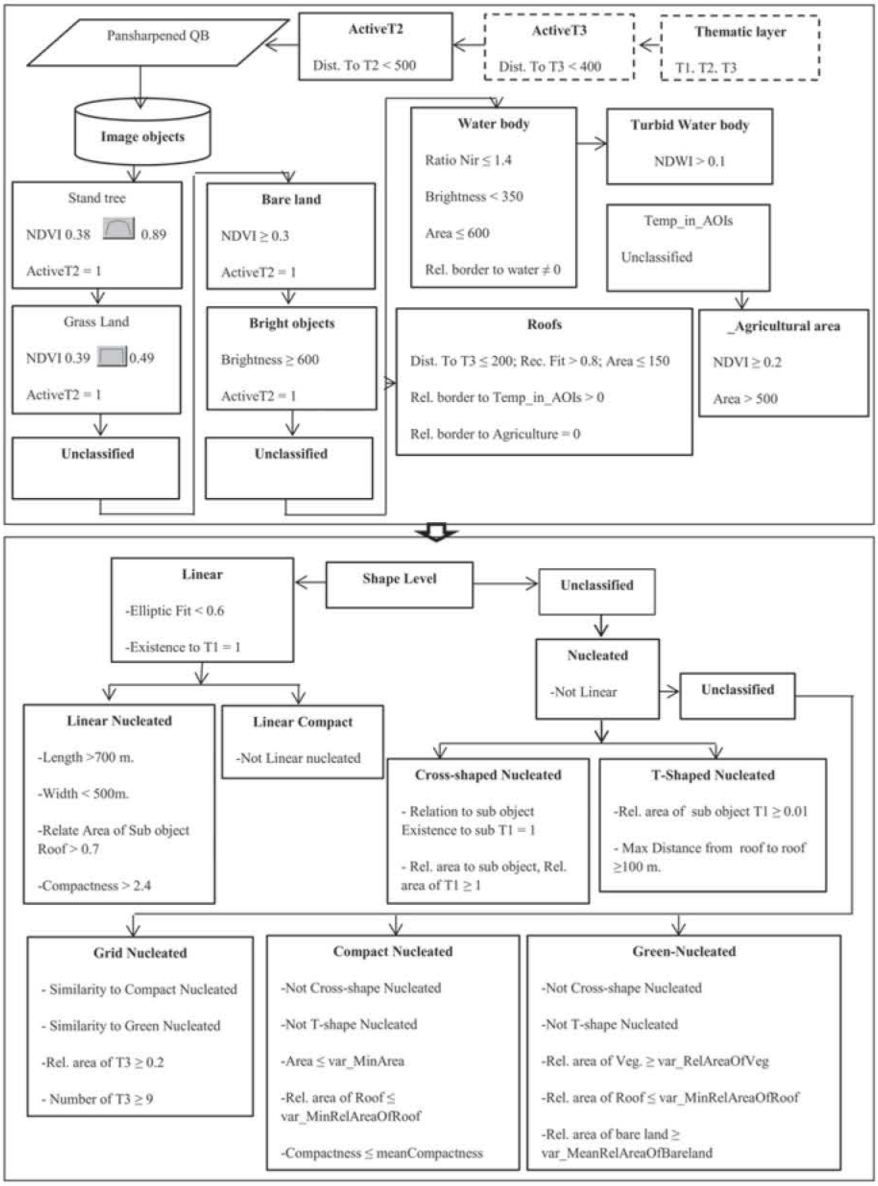


Figure 7: Work flow diagram of village form classification

To create a form, an image object fusion algorithm was used to merge the candidate classes in an area by dividing the layer into 2 parts, shapes acquired from the constant distance (less than 300 pixels) from road type 3 and the minimum distances (less than 400 pixels) from road types 1 and 2 from any position. If the first criteria are met, the shapes are usually intersected by an inner road and surrounded by a border (an outer road), which appears polygonal (e.g., village number 1). However, there are 2 villages that have developed along a line, i.e., village number 3 and number 4. In the post classification process, examination of the village form revealed that there was some artifacts resulting in hallow polygons within expected areas. Therefore, after the image object fusion had been applied, the image object advanced reshaping was used to adjust and smooth polygon edges. Some isolated polygons were assigned to the unclassified class. The results showed that there were 12 nucleated villages (5 grid nucleated, 1 compact nucleated, 1 T-shape nucleated, 2 green nucleated and 3 clusters). Additionally, there are 2 villages classified as linear villages (1 linear compact and 1 linear nucleated) (Figures 8 and 9). The nucleated form is the main village type of this region, but this form possesses differences in size, shape and spatial arrangement.

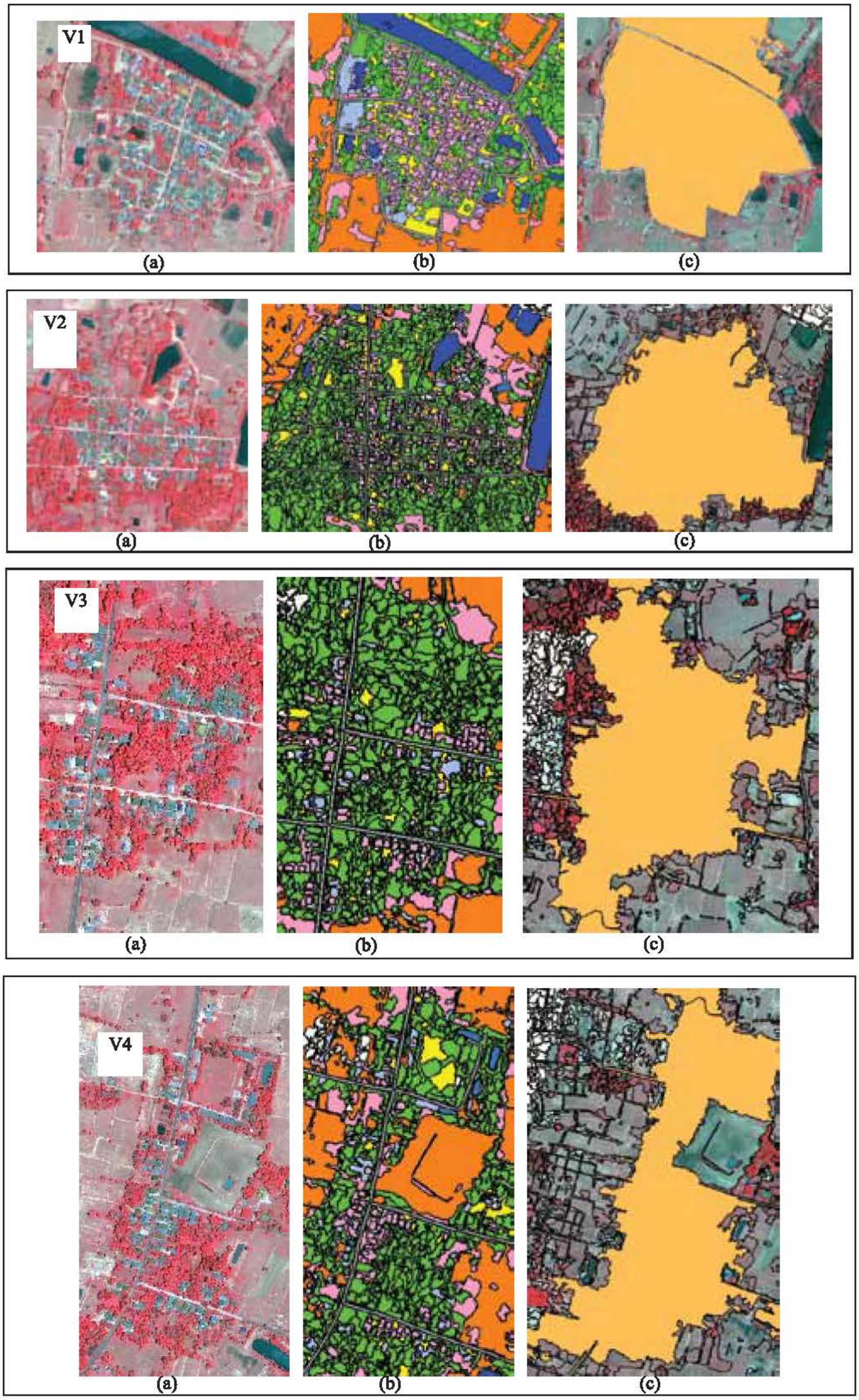
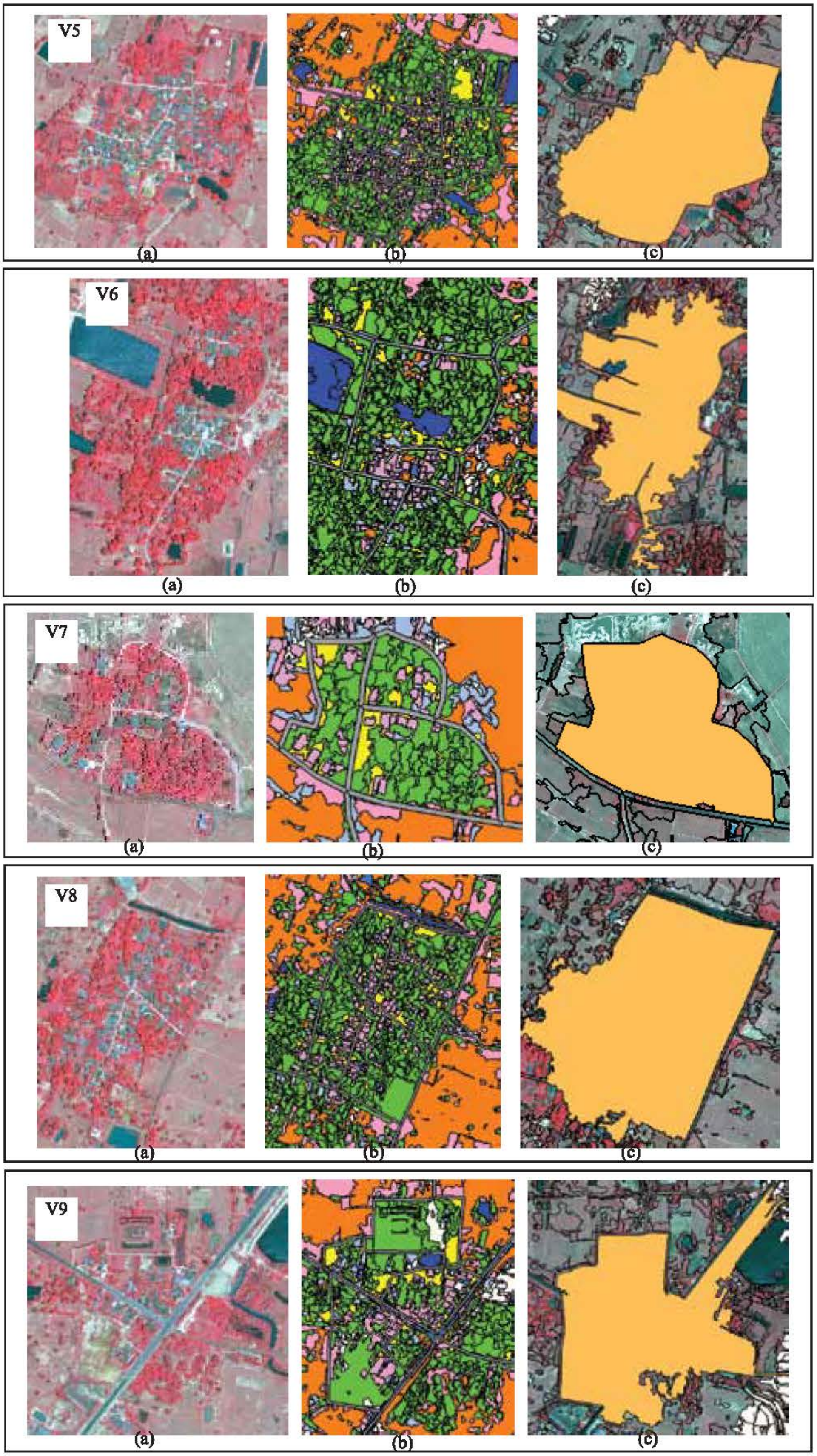


Figure 8: Continue next page



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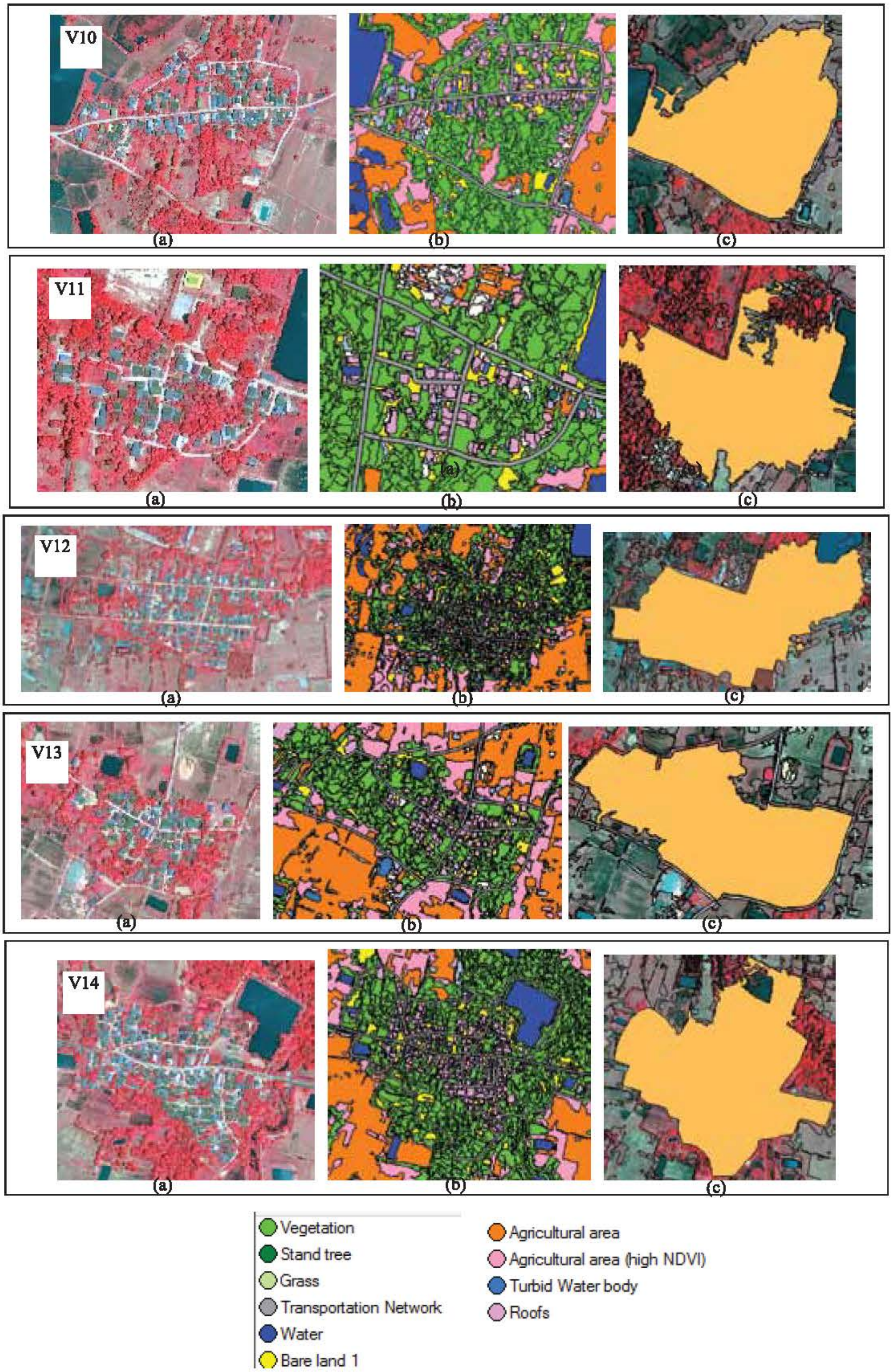

Figure 8: The results of image classification of selected villages using Pansharpened Quick bird images: (a) physical characters (b) LULC classified by rule-based and (c) fusion candidate classes into a shape

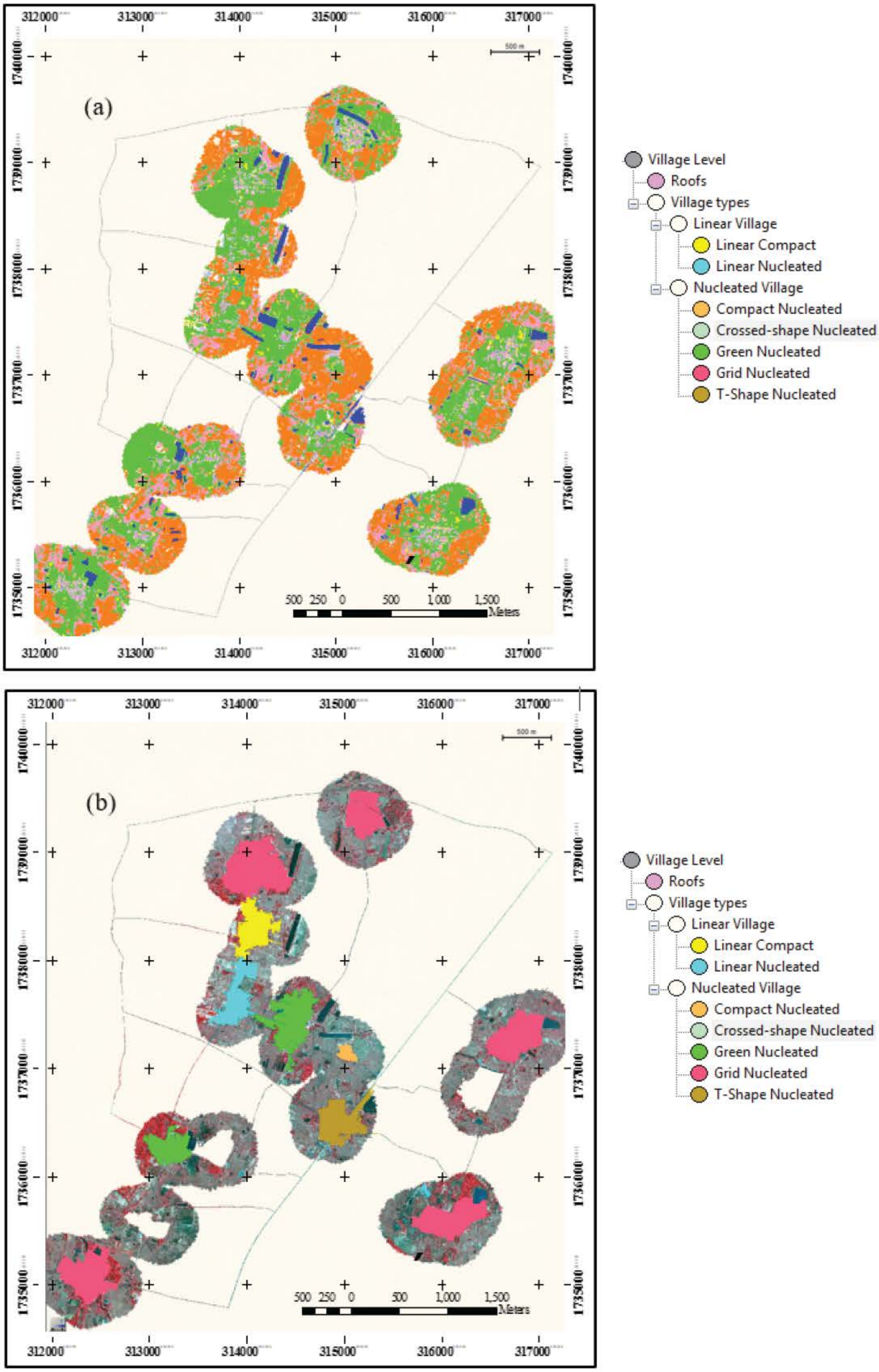

Figure 9: The results of village types (forms) classification, Na Dun district, northeastern, Thailand: (a) village component levels derived from the rule-based classification and (b) village forms classified by shape-based and spatial relationships

Dispersed villages are not found in this area due to cultural and religious belief factors. Site properties show that the area is arable and the villages are clustered around ancient pagodas. The object-based image analysis is the important tool in the classification of human settlement because it employs spatial relations in its procedures.

5. Discussion and Conclusions

This paper presents the methodology to create village shape objects to use as village representation forms. All object classes were merged by applying an image object classification algorithm based on their relationships with other features. This algorithm is incorporated into the eCognition software. All village candidate classes (land use/land cover) are classified using rule-based classifications. Land use comprised 7 classes: roofs, vegetation, bare land, grassland, water bodies, transportation networks and agricultural areas. Based on their spatial relations by relational selected features among neighboring objects, the land use classes are used as the candidate classes to create fused shapes that represent village forms in the Na Dun district. The rules of the classification are extracted, developed and applied to all 14 villages. Each village has factors that reveal certain characteristics. The rules are derived from human settlement descriptions, spatial characteristics of the study area, spectral information directly derived from satellite images and shape feature properties obtained from the image fusion process. The results from the classification procedures indicate that there are 3 main types of the rural settlements in Na Dun district (nucleated, dispersed and linear villages). Each village consists of sub-types. The village forms can be used as AOI data to evaluate the rural village shape changes in this region. The area tends to change significantly. Therefore, these results (forms) can be used as the reference object (mask area of settlement) to analyze rural characteristic changes based on remotely sensed data and ancillary information collected from local governments over time. Due to the fact that the village types in this area do not exist for comparing with the classified map (the ground truth data). Therefore, in the future works should be evaluated village types based on the existing evidence from secondary data, such as prehistoric maps or existing object references derived from object-oriented approach (Forghani et al., 2007).

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