GENERIC APPROACH FOR EXTRACTION OF BUILDING FEATURES IN VARIABLE TERRAIN CONDITIONS USING HIGH RESOLUTION IMAGERY

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Abstract:

Application of remotely sensed satellite images for the urban mapping is one of the important & challenging tasks. In recent years, drastic growth and dynamic behavior of urbanization, it is very important to have a planning strategy for updating the maps, decision making, etc. Buildings features have high amount of heterogeneous structures & therefore, difficult to interpret the shape & pattern at common landscape area. In this paper, Generic rulesets using knowledge based approach along with object based classification for building feature extraction from high resolution imagery by using spectral, spatial and contextual approach is proposed. An attempt has been made to evaluate the methodology on different urban scenarios (planned and unplanned) depending on slope & nature of the terrain (hilly area and flat regions) using Worldview-2 imagery. The hierarchical approach for feature extraction has been adopted. Initially the image was classified into built-up & nonbuilt-up area; subsequently, categorization using linearity & nonlinearity on built-up area was performed to separate buildings from other built up features; and finally, automatic classification of buildings & attribute labeling was implemented. Classification accuracy and kappa statistic depends on the terrain variability conditions. The extracted building accuracy observed to be 86.30% for hilly area & 89.42% for planned areas & 85.10% for unplanned areas in flat terrain. The generic rulesets are transferable to other datasets with similar spatial and spectral resolution.

Keywords: Automatic Approach, Object based classification, Generic Rulesets, Terrain Conditions

INTRODUCTION

With the advance growth of technological field and drastic expansion of small cities, there is a need of planning strategies to maintain the lifestyles of anthropoid. Therefore, monitoring of expansion of urban area (i.e. buildings, roads, etc) is one of the key parameter in remote sensing and GIS. Buildings are the most dynamic factors in urban environment and used to observe the increasing population, estimation of damages in disaster areas, maintaining infrastructural background, etc. Therefore, identification and extraction of buildings is the most important part in landscape area mapping.

One of critical problem occurs in building extraction is spatial & spectral complexity. Urban area have nearly; similar spectral ranges [ex. roads, buildings have similar spectral characteristics.]and constructed from similar[concrete]materials (from sediments of dry riverbed).Also, the buildings are having irregular geometric boundaries. Therefore, it is very challenging to differentiate buildings from other area. Previously, pixel based classification techniques using spectral properties were used for extraction and classification. But these techniques have limitations in identifying different object having similar spectral characteristics. Therefore, Object based classification approach using additional spatial, texture, etc. properties are used for high resolution datasets(Blaschke, 2010). Many algorithms were proposed for building feature extraction using high resolution remotely sensed imageries. Some of the approach uses surface model classification, Hough transform(Planning, 2010),rule based classification(Uzar, 2014;Jabari & Zhang, 2013),morphological approach & building index approach(Huang & Zhang, 2012). Some of the techniques utilizes semiautomatic(Mayunga, Zhang, & Coleman, 2005;Rottensteiner, 2001) and automatic approach(Jin & Davis, 2005;Uzar & Yastikli, 2013), Semiautomatic (Mayunga, Zhang, & Coleman, 2005),knowledge based system(Tiinjes, Glowe, Biicknel, & Lledtke, 1999),ontology(Belgiu, Tomljenovic, Lampoltshammer, Blaschke, & Höfle, 2014), object correlative index(Zhang, Lv, & Shi, 2013), Parametric and Prismatic Models(Weidner, 1997),EDM(Zeng, 2014),Shadow based extraction(Singh, Jouppi, Zhang, & Zakhor, 2015),using DSM(Emmanuel P., Scott, & Dirk, 2010; Grigillo & Kanjir, 2012; Seo, 2003; Yang, Wei, Li, & Li, 2013),using morphological filter()for building feature extraction.

In this paper, a combination of object based, knowledge based rulesets and a morphological approach is proposed to automatically extract building features.

STUDY AREA & DATASETS USED

Three terrain areas i.e. Hilly, planned and unplanned area having diverse nature of urban structure is used as test sites in this paper. The datasets captured is of worldview-2 imageries having resolution of 0.5 m (Pan sharpen data) and 8 spectral bands. The description of each test site is given below:

	Lat-Long	Altitude	Type of terrain	Complexity in road extracted features
Test Site 1	30.454334°, 78.092351°	**2045.82** m(6712 ft)	Hilly Area	Irregular roads, occlusion due to trees, mountain, etc.
Test Site 2	30.361643°, 78.086168°	**794.9 m** (2543 ft.)	Unplanned Area	Shadow due to buildings, spectral complexity,
Test Site 3	30.344408°, 77.998779°	**321 m** (1053 ft.)	Planned Area	Regular, linear roads

Table 1: Description of different test Sites

a)Test Site 1(Hilly Area) b) Test Site 2(Unplanned Area) c) Test Site 3(Planned Area)

Figure 1: Study Area

METHODOLOGY

In this paper, a hierarchical stage of classification is used for the intra-urban building extraction. The classification scheme is subdivided into 3 levels/stages as illustrated in figure 2

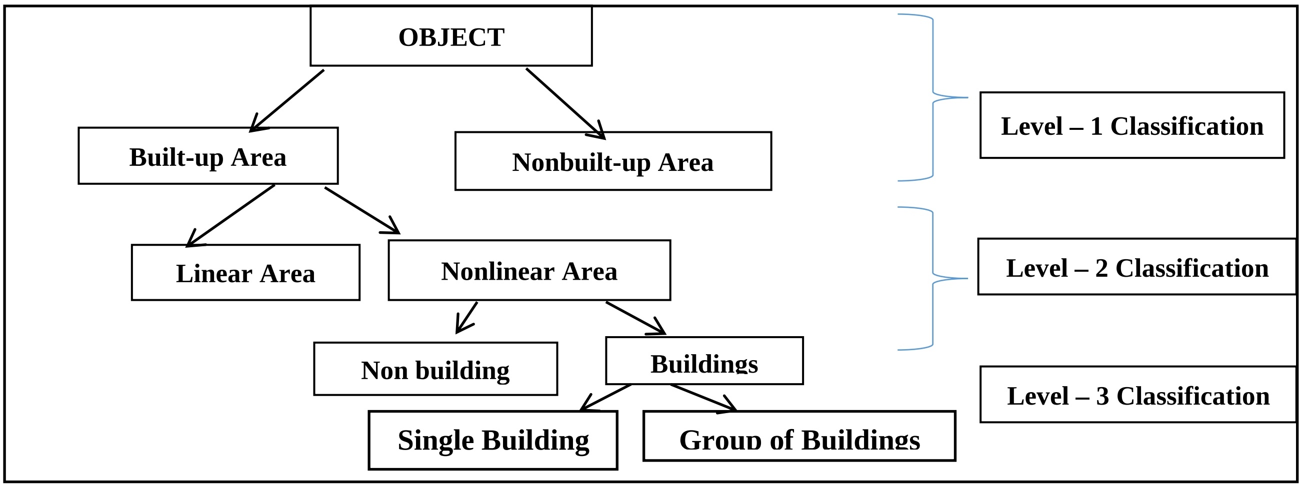
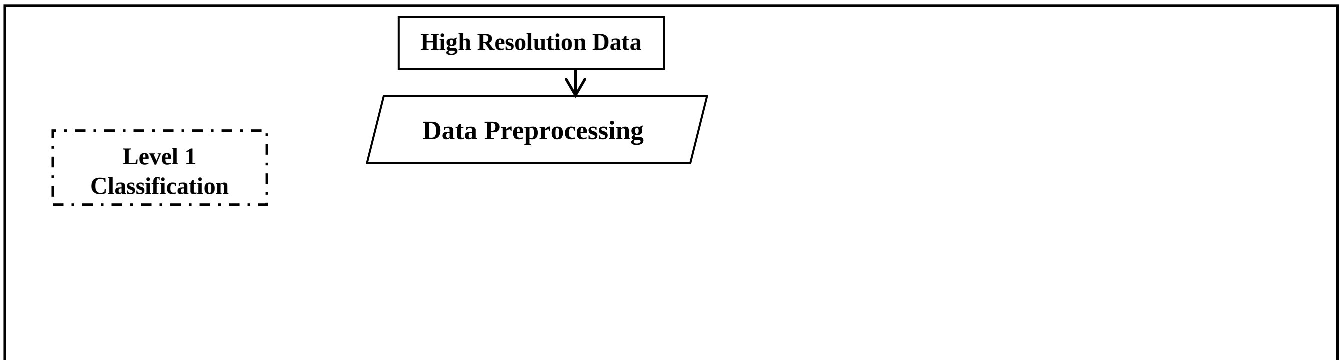


Figure 2: Schema of Building Extraction

The methodology of this paper is illustrated in figure 3.



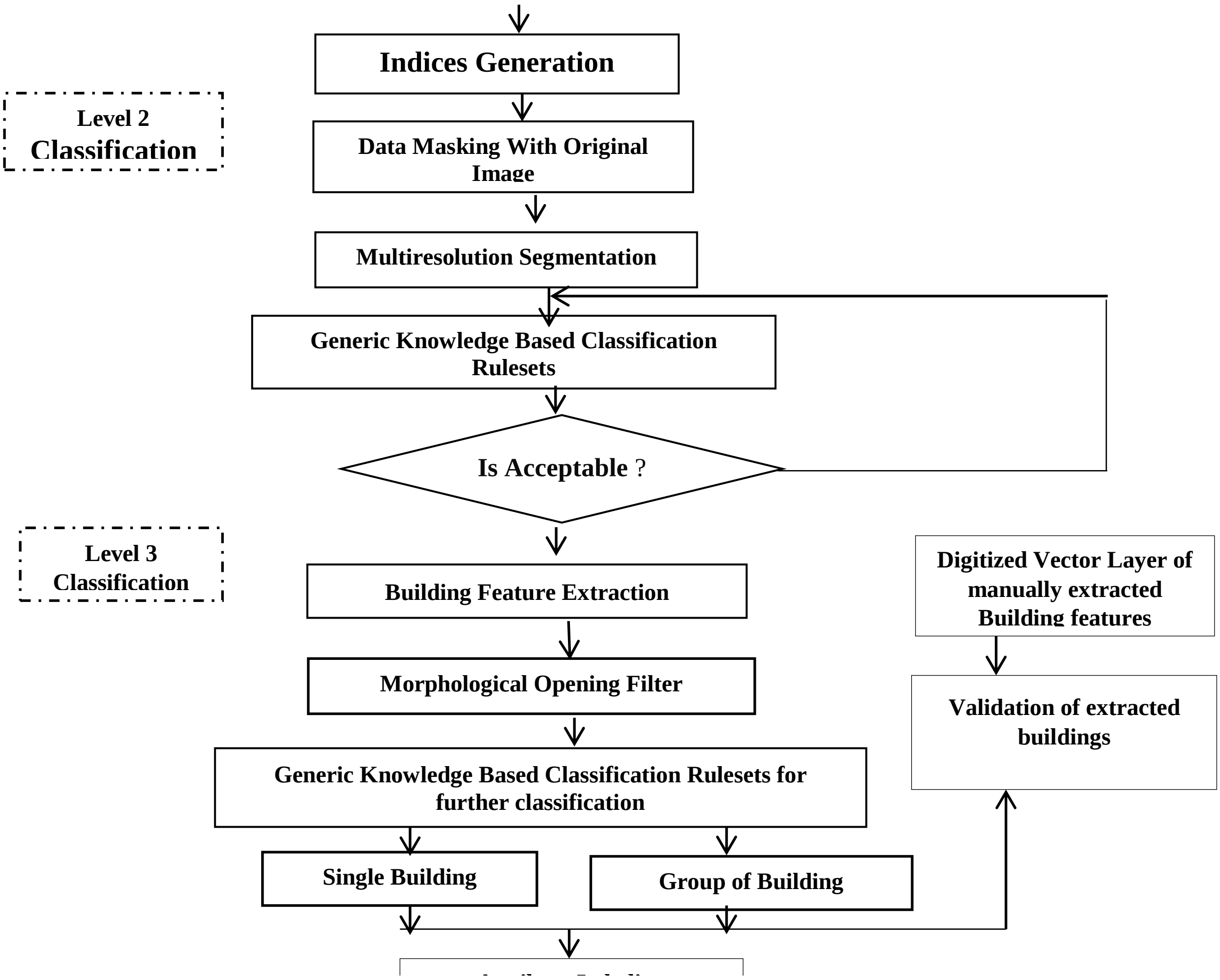


Figure 3: Methodology

At the first stage, High resolution dataset is separated into built-up and nonbuilt-up area using Normalized Difference Vegetation Index (NDVI).The equation of NDVI index is given below:

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

The extracted masked imageries are integrated with the original image to get only the built-up area from the full landscape area. The second stage of extraction uses object based approach and knowledge based approach into which built-up area is further separated into linear and nonlinear features. Buildings usually appear in a nonlinear shape, therefore at the third stage of classification, extracted nonlinear features are further classified as two classes. i.e. building and non-building. Use of morphological filtering is implemented for the refinement of classes and further separation of buildings into generalized two classes as single building and group of buildings.

Here, the building features are having irregular geometrical structures. Therefore, the generalized rulesets depicts the categorization of built-up area two main classes as- 1) Dense built-up region, 2) sparse built-up region.

In dense populated area; two type of pattern can be illustrated as a) regular, b) irregular pattern, slop and complex areas. The regular pattern area can extract the individual buildings in appropriate manner. In irregular area, it is very difficult to detect the boundaries using very high resolution datasets. These features are extracted as a patch/group instead of separate buildings.

Depending on the location and sparse urban structures, the buildings appears as individual features. These buildings are extracted as ‘single buildings’. At this time, the geometrical edge of buildings also plays vital roles in feature extraction using generic transferable rulesets.

RESULTS & DISCUSSION

The result of this paper using hierarchical knowledge based approach is illustrated below. At level 1 extraction, NDVI index were used as initial separation of built-up and nonbuilt-up area. Figure 4 illustrates the extracted built-up area in three different test cases.

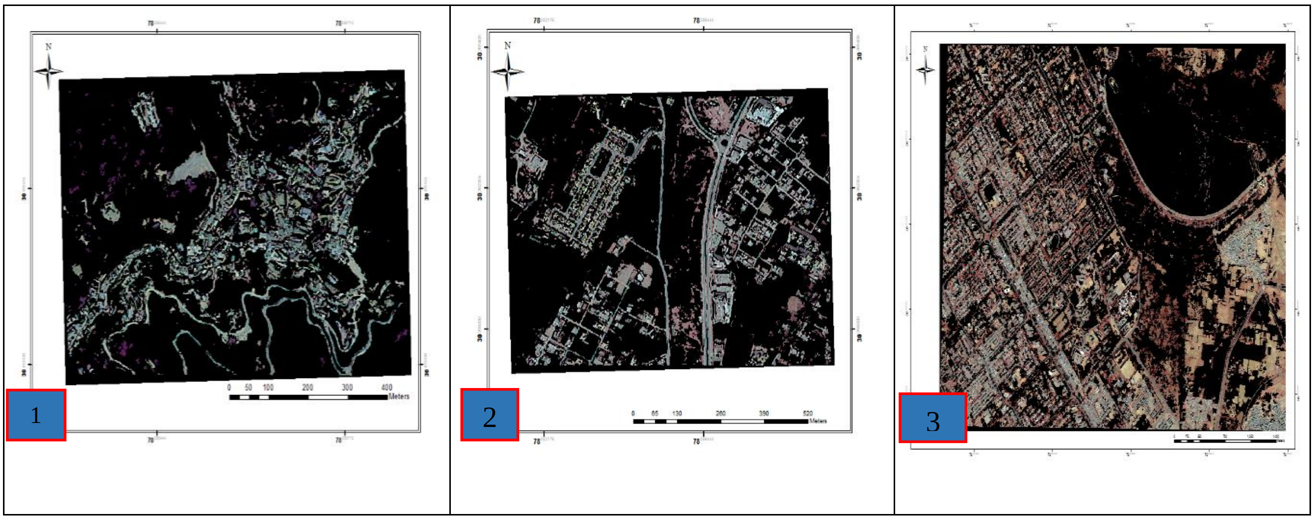


Figure 4: Buildup area extraction at 1st stage of Classification 1)hilly Area ,2)Flat Area, 3)Planned Area

The second stage of automatic extraction of building implements multi-resolution segmentation. Parameters such as scale of 30, shape of 0.2 and compactness of 0.6 is used for the optimum segmentation of homogeneous built-up regions. The extracted built-up area is further separated into linear and nonlinear areas. Since, buildings have nonlinear geometric characteristic, and therefore, considered for detailed stage of classification. Figure 5 demonstrates nonlinear building feature extraction. Figure 5 demonstrates nonlinear building feature extraction.

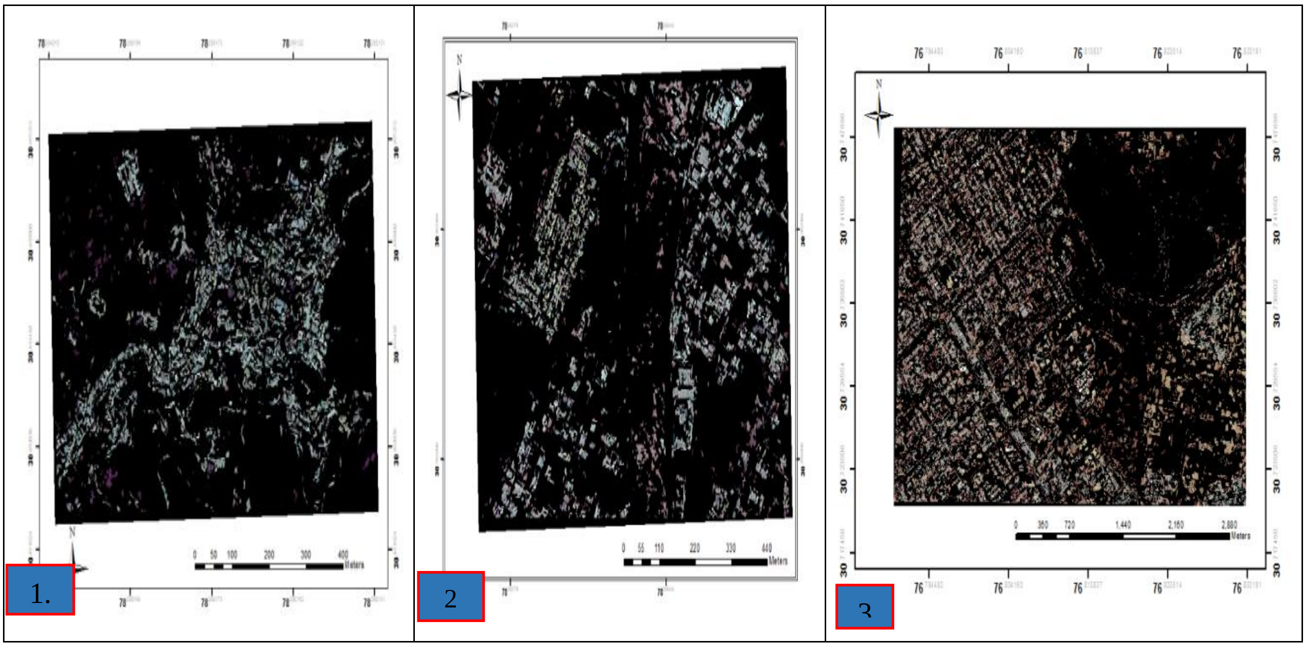


Figure 5: Nonlinear building feature extraction at 2nd stage of Classification of 1)hilly Area ,2)Flat Area, 3)Planned Area

The outcome of nonlinear building extraction is further classified into generalized two categories i.e. single building and group of buildings. The data from second stage is imported in MATLAB computing program for further refinement and attribute labeling using morphological opening filter. Here, spatial, spectral and relational properties are utilized for the detail generalized categorization of building features. Figure

6 expresses the outcome using knowledge based rules for 3rd level of building extraction.

Single Building	Group of Building	Classified Building output

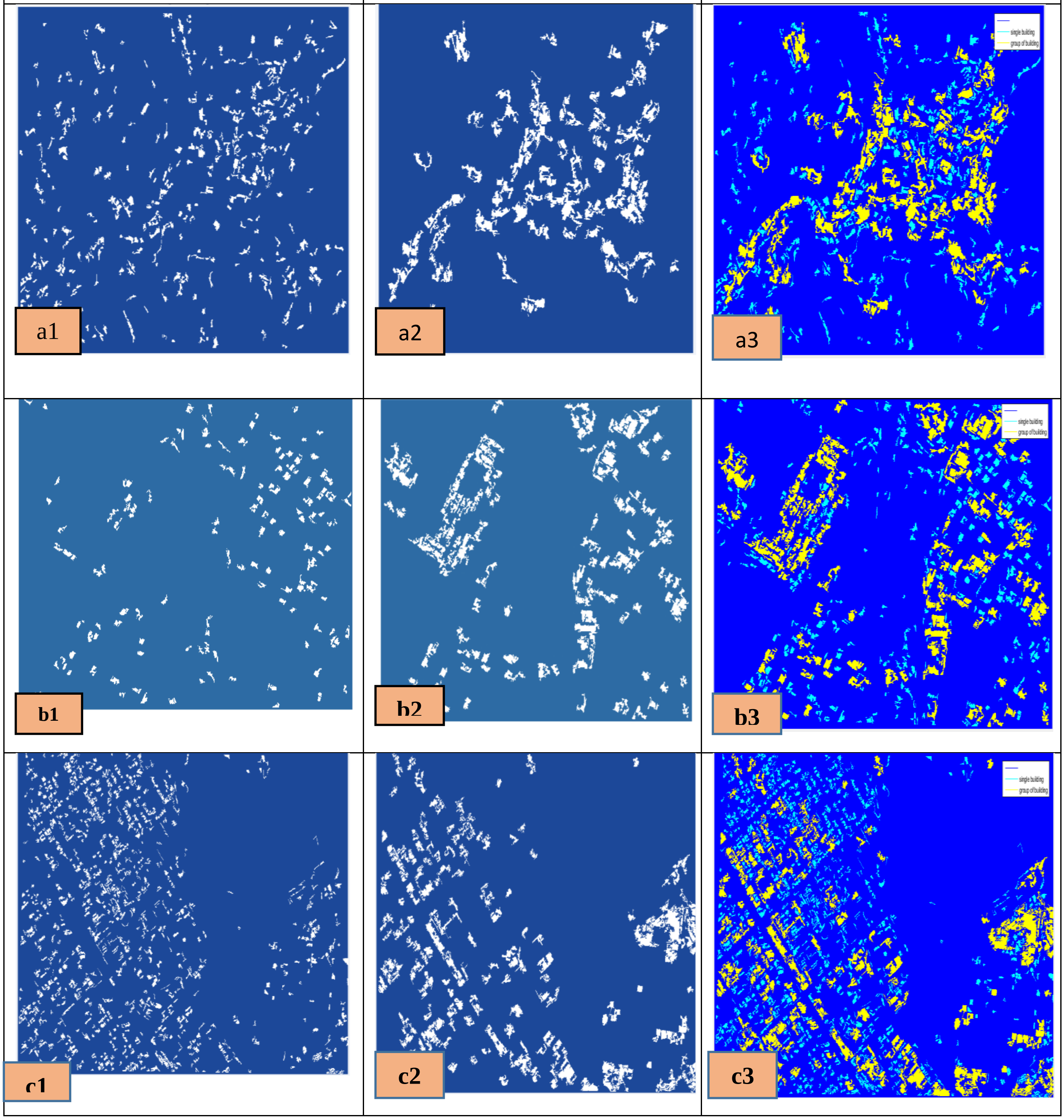


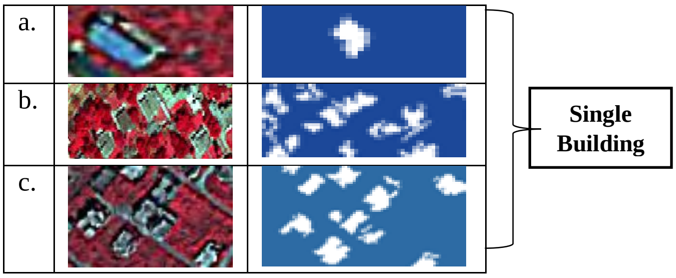
Figure 6: Types of buildings at final stage of classification single building (a1,b1,c1),Group of building(a2, b2, c2),classified output(a3, b3, c3)of 1)hilly Area ,2)Flat Area, 3)Planned Area

For analysis and validation of the extracted features, the manually digitalized vector layer is considered. The accuracy of building features is based on the amount of accurately extracted features. Here, samples of the test sites are taken for evaluating the accuracy in three different terrain areas.

Validation of different terrain cases:

The original terrain area and its associated extracted building features are explained below.

1. *Sparse Built-up Area:*

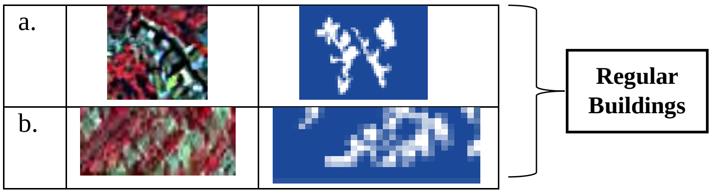


As the urban structure is sparse in this case, the building features can be detected easily. Here, figure represent the raw satellite data and extracted building feature of (a) hilly area (b) Planned area (c) flat area.

2. *Dense Built-up Area:*

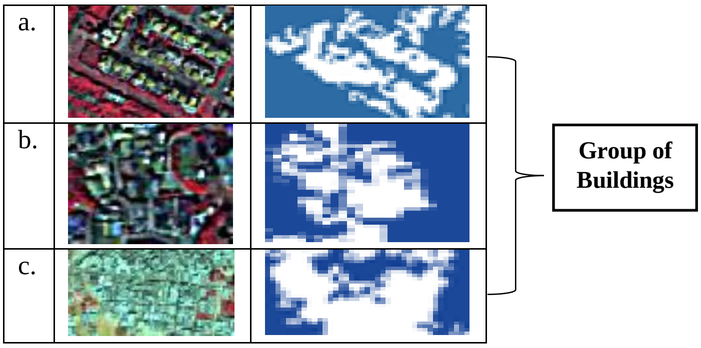
2.1 Regular built-up Area

In this case, as the urban structure is having regular pattern, the buildings feature can be extracted in dense built-up area.



The slope and complexity plays important role in building extraction. Figure, depicts the extracted regular buildings of (a)hilly area(b)Planned area

2.2 Irregular Built-up Area



The irregular built-up area is very critical to extract with high resolution area since this area consist of high amount of compactness and complexity in buildings features. Therefore, the feature can be extracted with the group of buildings instead of individual buildings. Here, figure shows the irregular extracted building feature of (a) flat area(industrial area)(b)hilly area(c)slum area.

The comparative analysis of the overall calculated accuracy of three test sites is given in figure 7

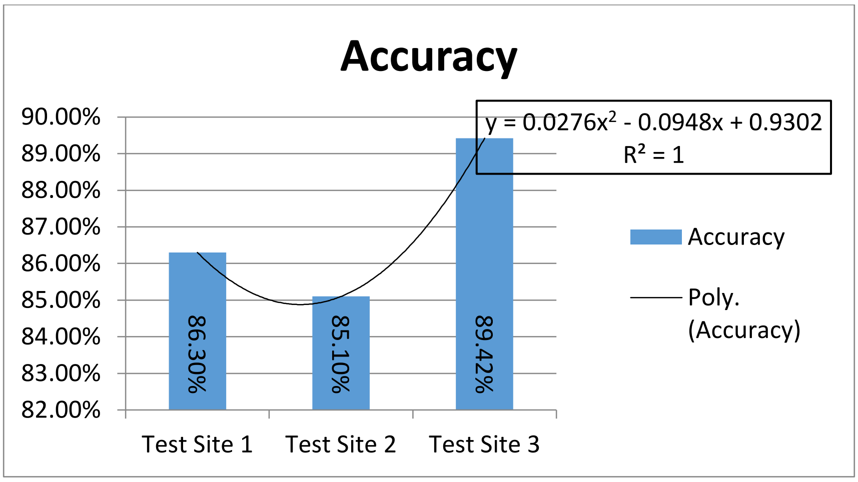


Figure 7: Accuracy assessment

The calculated accuracy shows that the generic knowledge based rulesets is highly applicable to planned area with the accuracy of 89.42%.

As, different terrain cases area having there complexity and associated issues; it is very difficult to use generic techniques for classification and extraction of building features. Therefore, generalized technique is of importance. The rulesets used for hierarchical stage classification for building feature extraction is given below:

The RMSE value of the equation (R^2=1) interprets that, the applied rules are fitting the equation.

1st Stage: Separate built-up area from the landscape area with the ruleset as:

NDVI<0.6 & NDBSI<0.11

2nd Stage: Separate Nonlinear Buildings from entire built-up area with the ruleset as:

NDVI<0.38 & NDBI>0.11 & Length<26 & L/W>1 &Area<250

3rd Stage: Association rules and Morphological rules to classify the extracted building feature as single building & group of buildings.

CONCLUSION

This paper proposed an automatic approach for building feature extraction and classification using combination of object oriented, knowledge based and morphological filters. An automatic approach also focuses on generic rule based classification which can be transferable to other optical datasets of similar spatial resolution. These rules were implemented with the use of spatial, spectral and sematic properties. The overall accuracy of this method is depending on terrain area or test cases.

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