Journal of Geomatics Vol 10 No. 2 October 2016

An object-oriented approach to quantify available roof area for solar PV installation: Case of Bhopal city, Madhya Pradesh, India

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Abstract: This paper proposes an automated method to quantify available roof area for solar Photovoltaic (PV) installation. Quantification will help to estimate the energy potential from rooftop solar PV which is necessary to solve the problem of energy crisis in Indian cities. The method of automated extraction has been built for a residential neighborhood of Bhopal city, using object-oriented classification available through eCognition Developer software. For this purpose, 2m Digital Surface Model (DSM) was generated from World View (WV) 2 stereo pair and used as a base data along with multispectral image of WV 2. Roof area obtained from automated extraction was visually and statistically compared to those identified via manual digitization. High agreement between two methods confirmed potentiality of the proposed method.

Keywords: Photovoltaic potential, Object-oriented classification, Digital Surface Model (DSM)

1. Introduction:

Cities are the focal points of regional economic development having predominance of financial, educational, technological and industrial sectors. Each of these sectors needs constant supply of energy to function properly. For sustainable urban development, renewable energy supply is necessary because they are clean, safe and abundant. Among the available clean energy sources, solar energy has the highest global warming mitigation potential (Ramachandra, 2011). Photovoltaic (PV) power system is one of the leading approaches in solar energy based applications. To mount PV panels large areas are needed but cities always lack open spaces. If PV panels are located far from the city, it would require additional investment in infrastructure for transporting the electricity. A long distance between the power plant and the consumer also means higher transmission losses (Vardimon, 2011). In this context, rooftops of city building can provide excellent location for installing PV modules. Production units can be small and located on top of residential buildings. Larger systems can be located on top of commercial or industrial buildings. Rooftops provide free available area, eliminating the need to use extra land area and since electricity is generated close to the consumer, transmission loss is also minimal. Another advantage which might be significant is that placing panels on a building's rooftop can decrease the solar heating of the building (Vardimon, 2011).

An important question is how to estimate the potential of PV solar electricity of a city? To address this question, quantification of available roof area is necessary. This paper proposes an automated method to extract total rooftop area of a residential neighbourhood of Bhopal city. The method uses object-oriented classification available through eCognition Developer (v. 10). Data used is 0.5 m resolution stereo imagery and 2m resolution multispectral image of World View (WV) 2 sensor. After having total roof area, area available for installing PV panel is derived by applying standard which considers factors such as shading, other uses, PV panel efficiencies and average solar insolation in the region.

2. Background

2.1. Related work

Several authors have applied GIS techniques to extract rooftop surface area for assessing solar PV potential (Ramachnadra et al., 2014; Santos et al., 2014; Kodysh et al., 2013; Verdimon, 2011; Wiginton, 2010; Hofierka, 2009; Izquierdo et al., 2008). Verdimon (211) used buildings' polygon obtained through digitization of orthophotoes of Israel; Wiginton (2010) applied ArcGIS extension, Feature Analyst on high resolution orthophotos of Ontario, Canada; Hofierka (2009) created a 3-D city model using digital orthophoto and digital elevation data of Bardejov city in eastern Slovakia with a spatial resolution of 1m; Izquierdo et al. (2008) used the Spanish cadastre plug-in for Google Earth™ to segregate building roof areas; Ramchandra et al. (2014) estimated rooftop solar photovoltaic potential of Uttara Kannada, India, by digitizing rooftop area in selected villages using Google Earth images. Santos et al. (2014) and Kodysh et al. (2013) used Light

Journal of Geomatics Vol 10 No. 2 October 2016

Detection and Ranging (LiDAR) data to estimate solar radiation potential on rooftops of residential buildings in Lisbon, Portugal and multiple buildings of in Knox County, Tennessee, USA respectively.

Unfortunately, these studies are not directly applicable to estimate available roof area for installing rooftop PV for Bhopal due to following reasons: (1) high resolution orthophotoes and LiDAR data are not available for Bhopal; (2) cadastre plug-in for Google Earth™ is not available for India; and (3) on-screen digitization on Google Earth is extremely time consuming and subjective.

Object-Oriented (O-O) classification has been used for urban feature extraction (Herold, 2002; Giada, 2003; Shackelford and Davis, 2003). Aldred (2011) in particular, used O-O classification for extracting urban rooftop at the University of Aldred (2011) in particular, used o-o classification for extracting urban rooftops of West Ontario campus in Canada using IKONOS data with 93.5% accuracy. This classification approach has not been used to extract Indian urban rooftop for the purpose of estimating solar energy potential from rooftop solar PV. This paper proposes an automated method through object-oriented classification for extraction of residential roof area to estimate the solar energy potential of a residential neighbourhood of Bhopal city, India.

3. Test site and data description

The test site is a gated residential neighbourhood developed by a private developer within Bhopal Municipal Corporation (BMC) area (fig. 1). The residential neighbourhood namely Minal Residency covers 0.89 km^2 of area and has 4000 dwelling units. The neighbourhood has row houses with one/two stories structure.

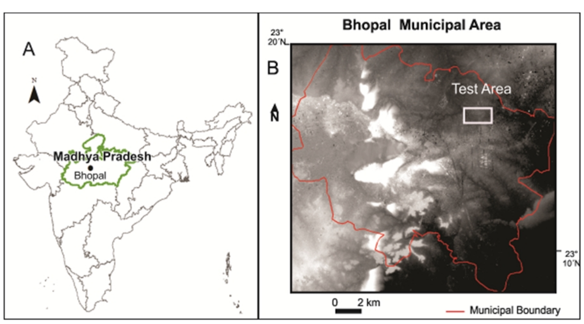


Figure 1: (A) Location of Bhopal city within Madhya Pradesh; (B) Location of test site within BMC

In this study, WV-2 stereo imagery from Digital Globe Inc. is used as base data for automated extraction. Besides, multispectral image of WV-2 is also used. Specifications of the data are given in Table 1.

Table 1: WV-2 data and test site description

Coordinate system	UTM Zone 43N WGS84 ellipsoid
Date of Acquisition	7th February 2013 Time: 05:43:09
Upper Left corner	77d22'54.1124"E 23d16'56.4422"N
Lower Right corner	77d28'43.8749"E 23d11'02.6396"N
Spectral Bands (Spatial Resolution and band width)	50 cm Panchromatic (0.45-0.90µm) 2m Blue (0.445-0.516µm) 2m Green (0.506-0.595µm) 2m Red (0.632-0.698µm) 2m Near-infrared (0.757-0.853µm)

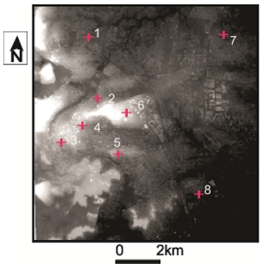
4. Methodology

4.1 Image preprocessing

As both rooftops and roads are composed of same material i.e. concrete, they appear spectrally similar in satellite images. The elevation data plays a major role in segregating rooftops from roads. To get elevation data, WV-2 stereo pairs are processed to produce Digital Surface Model or DSM. A DSM represents elevation of every natural and / or artificial object like building, vegetation etc. as seen by sensor above the earth. The process of automated DSM generation in Orthoengine by Rolta Geomatica V.10 mainly involves image matching which is selecting a matching point in one image, finding its conjugate point in the other (stereomate) image and computing 3D position of the matched point in object space. Accuracy of the 3D position is determined by a math model which is set to Rational Function Model (RFM). RFM uses polynomial coefficients, often called Rapid Positioning Capability (RPC) data. RPCs are generated from onboard instruments and are provided by vendor with stereo data. Sometimes the accuracy of the sensor-oriented RFM is not sufficient. Additional information like Ground Control Points (GCPs) is required to ensure a fairly desirable level of geo-positioning accuracy (Wang et al., 2011). To refine the math model, first order polynomial was used for which minimum number of GCPs required is 4 per image (Geomatica, 2003). Eight GCP points are collected for each stereo pair using high performance DGPS with about 50 cm horizontal accuracy and 8 m vertical accuracy. The

Journal of Geomatics Vol 10 No. 2 October 2016

GCPs are acquired in UTM projection and WGS 84 datum. Fig.2 shows location and details of GCP points.



Point Id	Ground X (m)	Ground Y (m)	Ground Z (m)
1	746006.842	2574867.251	441.84
2	750797.659	2566958.602	421.00
3	745827.012	2570418.639	465.60
4	745786.104	2570704.408	467.45
5	745762.614	2571041.961	473.49
6	745456.419	2572141.582	458.41
7	745043.543	2571249.787	469.96
8	7444410.645	2570747.630	460.00

Figure 2: Location and details of GCP points

The DSM with 2 m spatial resolution (fig 3A) of Bhopal city produced by Ortho Engine (v.2013) is further filtered to generate Digital Terrain Model (DTM) (fig. 3B) using DSM2DEM algorithm available in Rolta Geomatica. The algorithm strips buildings and trees from the DSM to produce a bare-Earth DTM. The subtraction of the DTM from the DSM of the same scene is called a normalized DSM or nDSM (fig. 3C):

$$nDSM = DSM - DTM$$

This derived layer of nDSM is then combined with 2m multispectral data from WV-2 (fig. 3D) and the new five-layer dataset "Merged Image 1" (fig. 3E) is used for all subsequent analysis in eCognition Developer.

4.2 Production of the reference map

A reference map was produced by performing on-screen digitization of building foot prints of the test area in eCognition Developer software itself. 2m resolution Multispectral image from WV-2 is used for this purpose. Because the dwelling units in the test area are semi-detached bungalows, individual units are not visible in satellite image (fig. 4A). Each block consists of 8 to 36 houses separated by circulation path appears as individual units (fig. 4A). During digitization, each block is digitized as single polygons (fig. 4B) and considered for total roof area extraction. They are referred as Building Polygon in the following sections. Total 164 polygons were digitized and saved in vector format (fig. 4B). The manually digitized polygons were used as reference to assess the accuracy of automatically extracted building polygons.

4.3 Determining the rule set for automated extraction of building polygons

When manually digitized polygons are overlaid on the top of nDSM layer during reference data preparation, it was found that blocks within nDSM includes area outside the edges (fig. 4B). To exclude this erroneous inclusion it was necessary to define boundaries for Building Polygons to be extracted. They are termed as North and East Edge (fig. 4B). The method for automated extraction is performed in two steps, namely (i) Automated extraction of edges as thematic layer and (ii) Building polygons are extracted as individual objects using thematic layers as reference.

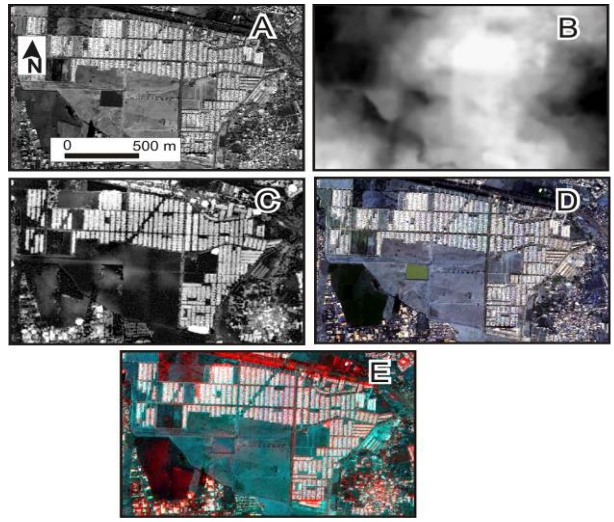


Figure 3: Preprocessing of data (A) DSM; (B) DTM; (C) nDSM; (D) 2m WV multispectral image; (E) Merged image 1

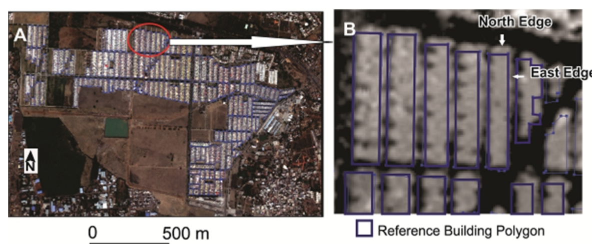


Figure 4: (A) Each block of the test area consists of 8 to 36 houses; (B) Manual digitization of reference building polygon

4.3.1 Building thematic layers: Thematic layers provided in O-O classification in eCognitionare the vector or raster files providing underlying information for efficient classification. To extract east edges, relief shaded image is prepared from DSM using illumination angle perpendicular to building orientation. Sobel-edge detection algorithm is run on relief shaded image to accentuate the East Edge. It creates an image with high pixel value where there is an edge (fig. 5A). Multiresolution (MS) segmentation was performed to extract edges as objects (fig. 5B). MS segmentation in eCognition Developer starts with single image objects of one pixel and merges them iteratively, pairwise and then in pairs of sets, into larger units until an upper threshold of homogeneity is locally exceeded. This homogeneity criterion is defined as a combination of spectral homogeneity and shape homogeneity. This calculation can be influenced by modifying the scale parameter: higher values result in larger image objects, while smaller values yield smaller image objects. The homogeneity criteria can be customized by weighting shape and compactness criteria (eCognition Developer, 2014).The objects are then further classified using membership function of layer values and orientation (fig. 5C). The classified objects were then merged and converted to a vector file named "East Edge.shp" (fig. 5D).

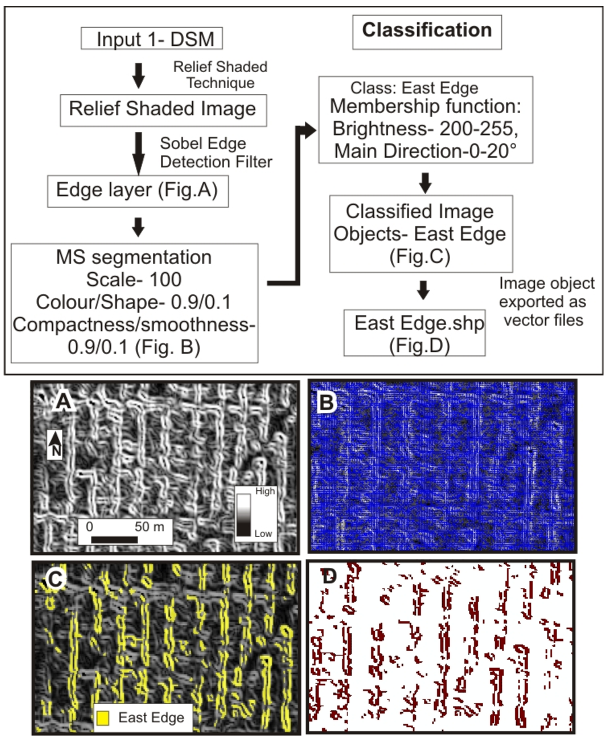


Figure 5: Flow chart describes building of thematic layer for identification of East Edge (see text for detail), with images showing intermediate outputs

North Edge is shadow areas of each block (fig. 4B). To mark shadow areas more prominently, edge detection filter is run on Near InfraRed (NIR) layer of multispectral image which produces an image with higher value where there is a shadow (fig. 6A). This edge layer is segmented using MS segmentation (fig. 6B) and then classified using membership function for layer value and orientation (fig. 6C). The classified objects exported into "North Edge.shp" file (fig. 6D).

4.3.2 Creating individual polygons for building blocks: The second level of analysis started with merging the nDSM, Edge layers, Multispectral image to "Merged Image 2". MS segmentation is performed on

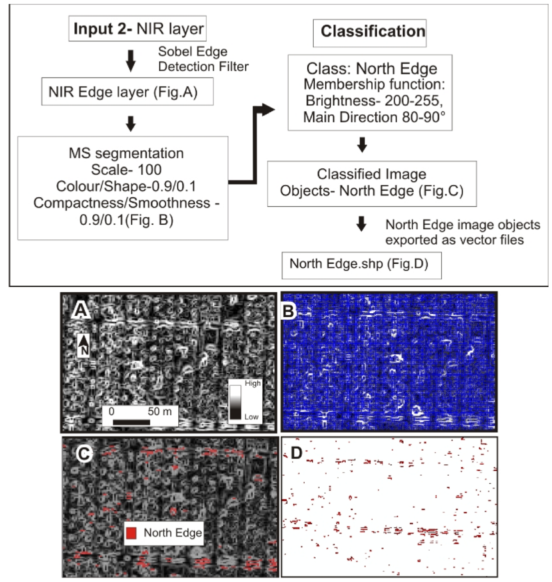


Figure 6: Flow chart describes building of thematic layer for identification of north edge (see text for detail), with images showing intermediate outputs

this dataset, using East Edge.shp and North Edge.shp as thematic layers. To obtain maximum information from vector layers, the scale parameter was set high (500) whereas shape and compactness were emphasized by setting them at 0.9 and 0.5, respectively (fig. 7A). After extracting East and North boundaries for building polygons as objects they are classified by setting threshold for edge value under the class East Edge and North Edge (fig. 7B). The unclassified objects are then further segmented using MS segmentation. nDSM layer was given maximum weightage to extract image object layers for building polygons. Objects for building polygons were then classified using information regarding building height and contextual information like Relative Border to East and North Edges. The newly created class is named as "Final Rooftop" (fig. 7C). The Roof Area class contains individual polygon for each block. Lastly, the ''Close Image Object'' operation of the morphology algorithm was used to fill any gaps within building polygons (fig. 7D), simply by taking any as-yet unclassified pixels enclosed within the ''Final Rooftop'' class and adding them to that classified Rooftop area. The resultant image contains individual polygons under "Rooftop Polygon" class, which are further converted to vector file namely RooftopPolygon.shp and used in accuracy assessment.

Since the rooftops are extracted as polygons the total roof area is also extracted automatically. The total roof area for the neighbourhood as extracted by the proposed method is 0.29km^2 or 290,000m^2.

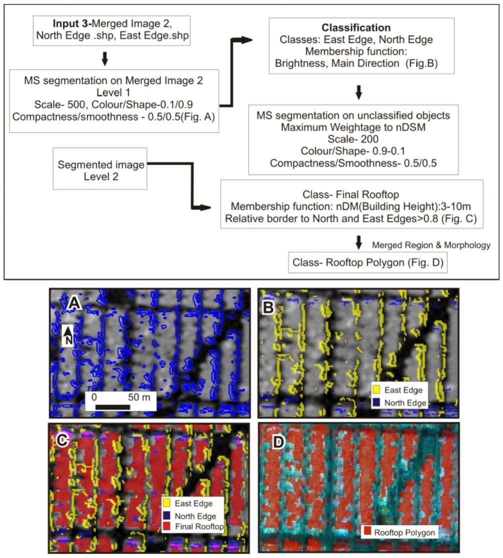


Figure 7: Flow chart and corresponding images are showing the automated extraction of building polygons. (A) A first round of segmentation toward extraction of edges; (B) North Edge and East Edge classes are shown in blue and yellow respectively; (C) Building polygons are extracted in relation to Edges; (D) Individual polygon for each block is extracted for entire test area

4.4 Estimating suitable roof area for PV panel installation

Having obtained total roof area for a region, it is necessary to reduce this area to that which is available for solar photovoltaic applications, in order to determine potential power output. There are many factors which influence the fraction of available roof area, including shading, location of heating, cooling instruments, orientation etc. The primary focus of this paper is to develop a correct estimate of the total roof area in the region; a separate simulation or statistical analysis for obtaining reduction factors was outside the scope of the project and thus related literature (Pillai and Banerjee, 2007;Sharma, 2015) was utilized to obtain approximate areas available for PV. The lowest fraction for residential building obtained from the literature is 0.30. This allows for the calculation of the fraction of unshaded roof area which is unused for other purposes, including panel servicing and installation.
Thus, the roof area available for PV installation (APV) is the total roof area (ARoof) multiplied by the reported and chosen fraction as indicated below:

$A_{PV} = 0.3 * A_{Roof}$ ……… (equation 1)

Thus, for the test area,
$A_{PV} = (0.3) * 0.29$ sq.km = 0.087 km^2 or 87000 m^2.

Thus, total roof area available for rooftop solar PV panel installation is 0.087 km^2 or 87000 m^{2}for the test site. Using available roof area, solar energy potential through rooftop PV can be estimated by taking standard dimension and wattage of rooftop PV panels.

5. Accuracy assessment

The accuracy of assessment involves checking the accuracy of per-object intersection of the classification. For this purpose, automatically extracted rooftops are overlaid on the top of manually digitized polygons or reference polygons (fig. 8). The comparison shows that automated method identified all manually mapped Rooftops in its original location. It means the proposed automated method achieved 100% success in basic recognition.

Since the objective of this research is to quantify available rooftop area for PV installation, accuracy assessment is performed by comparing area extracted by automated method with that of reference map. It is found that the proposed object oriented method was able to extract 83.47% of manually digitized roof area. Table2 shows the detail of this visual comparison.

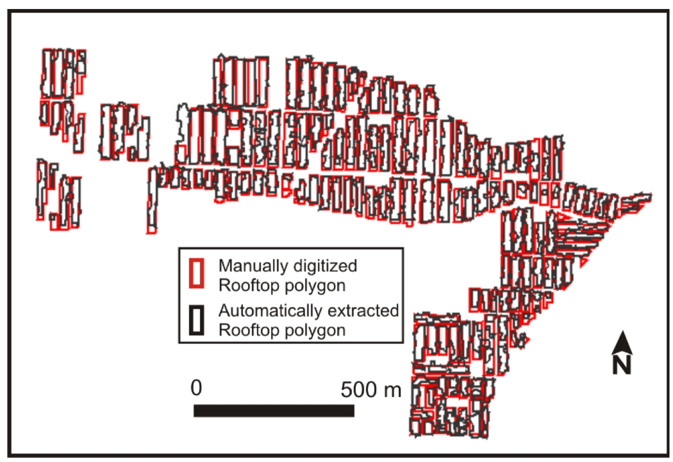


Figure 8: Visual comparison between automated and manually extracted drumlins

Table 2 shows automated method extracted more polygons compared to manual method. This is because in automated method, some building blocks are extracted through multiple polygons rather than one continuous polygon (fig.9A). There are also cases where only 20% of manually digitized area is covered by the automated method (fig. 9B). That is the reason why total area extracted by automated method is lower than the manual method.

Table 2: comparison between manually digitized and automatically extracted Rooftop polygons

	Manually Digitized Rooftop polygons	Automatically Extracted Rooftop polygons
Total Number of polygons	164	186
Total Area (sqm)	349236	291528
Percentage to total area	100	83.47%

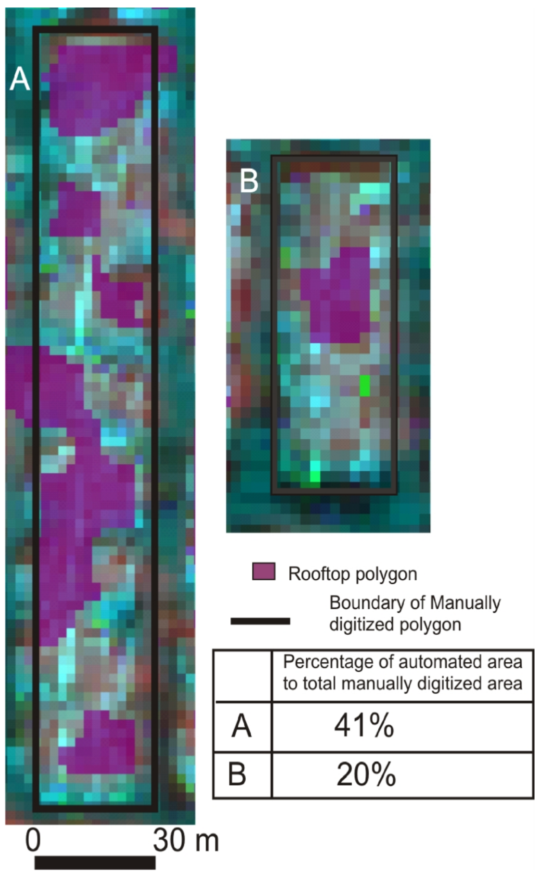


Figure 9: (A) Building polygons extracted in multiple image object; (B) Only 20% of manually digitized area is covered by the automated method

This might have happened because of the error within elevation data which have propagated through the process of deriving nDSM from DSM. As a result, there is a variability of nDSM values within building polygons. Image objects having less than threshold value for nDSM (see section 4.3.2) have been excluded during classification.

6. Discussion

In this research an effort is made to test the high-level object-oriented image analysis technique for the automated extraction of urban rooftop from very high resolution satellite image. Since the test area contains semi-detached row houses and nDSMcould not be produced for less than 2 m, total roof area is extracted for each block rather than individual dwelling unit. Since, the objective of this research was to extract potential roof area for rooftop PV installation, the accuracy of the proposed method was assessed in terms of its capacity of extracting roof area mapped by manual method. The success rate of the automated method is 83.47% but it can be further improved by reducing the error in elevation data.

Although, the present paper tests the object-oriented methodology only over a residential neighbourhood, the next stages of research are to (1) test the method over a much larger area (such as entire Bhopal city) (2) test how will this form of analysis holds up in dealing with less regularly oriented urban rooftop (given most Indian cities have haphazard pattern of building orientation).

The proposed method provides a means for identifying those parameters that are indicative of urban rooftop type in any given area that can be used to automatically recognize all similar urban rooftop in a particular area. This provides a better, quicker, more objective, and repeatable alternative to fieldwork and manual digitization. Quick area estimation for rooftop PV installation will lead to successful implementation of solar rooftop policies launched by Govt. of India.

7. Conclusion

In this research, an effort was made to test the high-level object-oriented image analysis technique for the automated extraction of urban rooftop from very high resolution satellite image. The success rate of the automated method is 83.47% and it can be further improved by reducing the error in elevation data. Correct area estimation for rooftop PV installation will lead to successful implementation of solar rooftop policies launched by Govt. of India.

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