An automated object-oriented approach to facilitate core infrastructure of a Smart City: a comparative study between Bhopal, India and Trondheim, Norway

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ABSTRACT: Smart cities are cities that provide core infrastructure and give a decent quality of life to its citizens. Core infrastructure includes adequate water supply, assured electricity supply, sanitation including solid waste management, health and education etc. Since cities have always lacked open space, roof area of buildings can be used to provide infrastructure. For example, solar Photovoltaic (PV) Systems can be installed on rooftops of residential, commercial or industrial premises and the electricity generated from such systems could either be entirely fed into the grid or used for self consumption. Given the importance of roof area, this research emphasized on the automated extraction of urban roof area in both tropical and Nordic urban environments to compare and contrast the set of rules needed for their automated delineation. Bhopal City, India and Trondheim City, Norway are selected as study areas because they represent Tropical and Nordic urban environment respectively. An existing set of rules for automated extraction of urban roof areas of Bhopal city was developed in 2016 using object-oriented classification tools, available through eCognition Developer (V. 8.7.2). A smaller residential neighbourhood in Bhopal city has been selected as Test Site and World View 2 stereo pairs & multispectral images were used as input data. After successful extraction of urban roofs of Bhopal city, the method was applied to extract residential roofs of Trondheim city from high resolution orthophotoes. Several adjustments were needed due to the morphological differences between the roofs of two different cities. Visual comparison with the manually delineated roof area confirms the success of this revised automated method in two different environments. The quantification of roof area further helped to estimate solar energy potential through rooftop PV of these two cities.

1. INTRODUCTION:

The harvesting of solar energy still encounters many barriers in Norway. Recent Norwegian energy policies (Olje- og Energiedepartment, 2016) identify wind and hydropower as the most suitable Renewable Enrgy Source (RES) for the country and relegate solar energy to a marginal role. Despite the fact that in Norway, the sun provides an amount of energy 1500 times higher than that currently used (Andresen, 2008; Halvorsen et al., 2011; Nord et al., 2016), the energy production from solar systems is still low compared to neighboring countries (Merlet and Thorud, 2015). However, the number of installations has been growing in recent years: During the last decade, a significant interest in solar technology investment has been registered in the country. The number of large-scale solar energy projects has increased, both in private and public buildings. Automated and semi-automated methods to extract area available for rooftop solar PV panel installation can aid in this process (Saha et. al., 2016).

An automated object-oriented classification tool was developed by Saha et. al. (2016) to recognize and digitize the total roof area of Bhopal city, Madhya Pradesh. Object-oriented classification is used to identify specific shapes in data sets. This is based on both the pixel values in a raster dataset and on the contextual information between pixels and extracted objects (Saha et. al. 2016). From the DEM, the topographic variation and its derivatives (values of aspect and slope) were analyzed using eCognition Developer (v.8.7.2). The software performed a multi-resolution segmentation followed by a classification based on a set of rules. Polygons that represent the individual drumlins were then extracted, visualized and statistically compared to those identified via manual digitization. A good agreement between the two methods showed that the automated method is reliable (Saha et. al. 2016).

This automated extraction is partly supervised: an initial set of rules is defined to recognize the object (rooftop area) of interest. Afterwards it can produce consistent and repeatable results. The aim now is to assess whether the method by

Saha et. al. (2016) is both robust and flexible enough to be easily adjusted and applied to an orthophoto with a higher resolution of 4cm and with the challenges of a Nordic environment, including the rooftops' (1) orientation, and (2) typology.

Automatically delineated objects can also be updated and combined with other thematic data in a Geographical Information System (GIS), which provides a wide range of applications for spatial analyses. A reliable tool to automatically extract geometric information from any object could assist the mapping of, for instance, private gardens in urban areas (Mathieu et. al., 2007), neighborhoods with low and high socioeconomic status (Stow et. al., 2007).

2. BACKGROUND WORK

As the concept of Smart Cities is gaining attention in academia, business and government, scholars and professionals have been proposing a large number of technologies and applications using in situ and mobile sensors, but use of GIS/Remote Sensing (RS) techniques on satellite images remains surprisingly limited. Smart city applications often address questions associated with energy consumption and mobility, and sometimes public health, too (mainly to do with air and water quality). Bonafoni et. al., (2016) remote sensing technique to analyze the urban heat island effect on the city of Terni, Central Italy and proposed sustainable strategy in designing smart cities: foreseeing both mitigating urban heat islands and evaluating the renewable energy efficiency. Saha (2017) has provided a remote sensing based framework integrating multiple aspects of a smart city. In her research, she has extracted urban roof areas from high resolution satellite images of Bhopal city, Madhya Pradesh, India using automated technique developed through object-oriented classification method. Roof area data, thus extracted was further used to estimate potential for rooftop solar PV which is one of the important pillars of smart city development in India.

Lobrocco et. al., (2016) has analyzed solar accessibility of Norwegian residential housed using parametric modeling software. Windows -based NURBS modeler Rhinoceros (McNeel Robert and Associates, 2015) and Grasshopper (Davidson, 2013) have been used to control the geometric parameters (e.g., buildings' height, exposure and orientation of buildings' façades and distance between the analyzed buildings). To date, however, a remote sensing technique has not been used to extract urban roof area of Nordic environment.

3. THE STUDY AREAS: TROPICAL AND NORDIC CITIES

Bhopal city of Madhya Pradesh is chosen as tropical case study city. Residential areas within the city boundary have been digitized using Bhopal Master Plan (2021) as reference and a small test area has been selected from amongst these areas (Figure 1A.a). The selected test area is a gated residential neighbourhood developed by a private developer namely 'Minaal Residency' (Figure 1A.a). The test area covers 0.89 sqkm of the area and has a population of 7344. There are five types of plot areas, but the residential is in the form of plotted row housing, the height varying from two to three floors (Figure 1A.b &c). Without tall trees and high rise buildings, roofs of residential buildings of the test site have the potential to get ample sunlight. Since it is a planned neighbourhood, the test site is favourable for automated extraction of building rooftops.

Trondheim city of Norway is chosen as a Nordic case study city (Figure1 B. a). Since the Test Area of Bhopal is purely residential, the Test Area within Trondheim Municipality is deliberately chosen as a residential area namely 'Steindal'. Unlike the Test Area of Bhopal Steindal contains buildings with different typology and orientation (Figure1B. b, c, d).

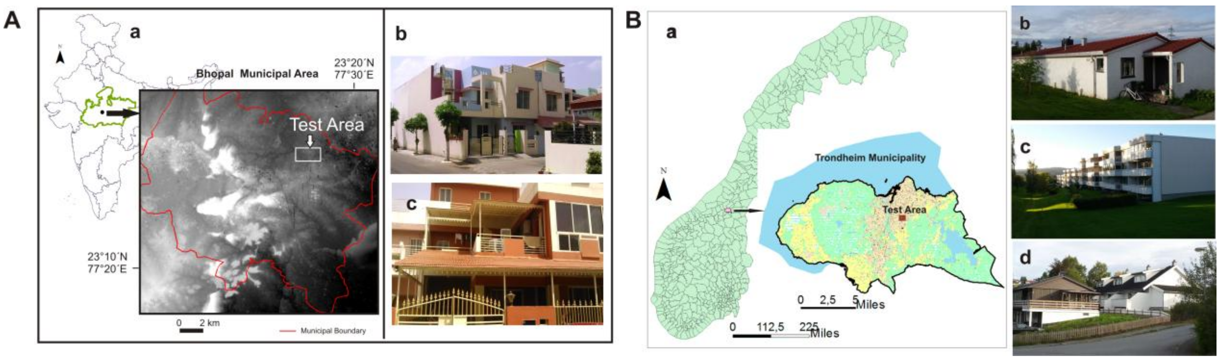

Figure 1. A. Location of tropical case study site in India-'Minaal Residency'. B. location of the Nordic case study site in Trondheim-'Steindal'.

4.DATA USED:

In this study, World View 2 (WV2) stereo pairs and multispectral imagery from Digital Globe Inc. has been used as base data for automated extraction of urban roofs of Bhopal City. Stereo images are those when same area has been photographed with high resolution cameras installed at different angles.

For Steindal, Orthophotos with 4 cm spatial resolution and shape files of building footprints were acquired from the Norwegian Mapping Authority (www.kartverket.no). Layers of DSM & DTM of 25cm resolution were acquired from Trondheim Municipality (www.trondheim.kommune.no).

5. OBJECT-ORIENTED ANALYSIS OF ROOF AREA

5.1. Tropical case study area –Minaal Residency

The method to build a set of rules to delineate the perimeter of roof area using object-oriented classification tools is explained in detail in Saha et. al. (2016). Automated extraction of roof area comprised of four steps: 1) Image pre-processing, 2) Production of reference map, 3) Automated extraction of total roof area using object-oriented classification.

5.1.1. Image Pre-Processing

As rooftop and roads are composed with similar material they are seen the same way by satellite sensors. Elevation data plays a major role to segregate rooftops from roads. To get Elevation data, WV2 stereo pairs with 0.5 m spatial resolution are processed to produce 2 m Digital Surface Model or DSM (Figure 2A). A DSM represents the elevation of every natural and/or artificial object like building, vegetation, etc. as seen by sensor above the earth. The DSM is further filtered to produce DTM (Figure 2B) which shows the bare earth elevation. The DTM then is subtracted from DSM to produce nDSM (Figure 2C) which shows the height of the objects standing over the earth's surface. A reference map has been produced by performing on-screen digitization of building footprints of the test area in eCognition Developer software itself.

5.1.2. Production of Reference Map

Multispectral image with 2 m spatial resolution from WV 2 is used for this purpose. As the dwelling units in the test area are row housing units, individual units are not visible in satellite image (Figure 3A). Each block consists of 8 to 36 houses/dwelling units and such blocks are separated by circulation paths. During digitization, each block is digitized as a single polygon and considered for total roof area extraction. These are being referred as building polygon. When manually digitized polygons are overlaid on the top of nDSM layer, it was found that building polygons at nDSM contains more area around the edges (Figure 3B). They are termed as North and East Edge (Figure 3B).

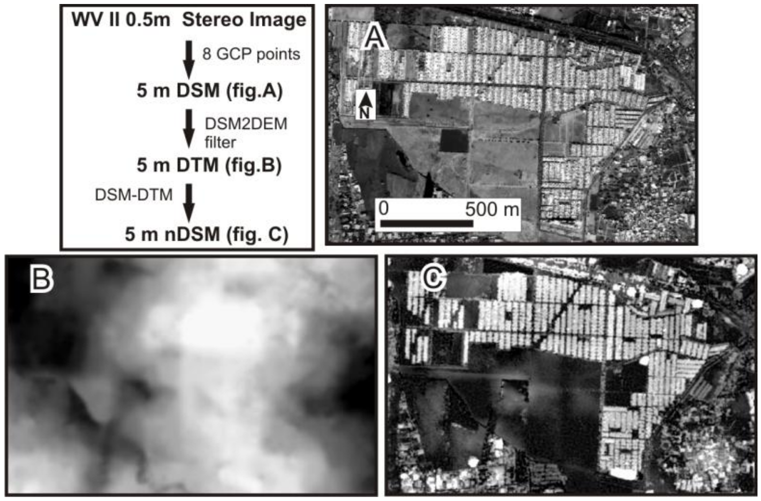

Figure2. Flow chart describes image preprocessing with images showing intermediate outputs.

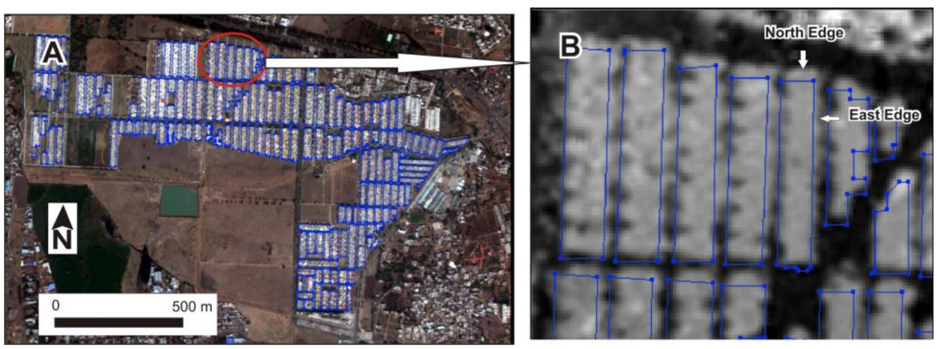

Figure3. Preparation of reference data: (A) Building polygons are digitized on top of multispectral image; (B) Digitization of each block as single polygon

5.1.3. Automated Extraction Of Total Roof Area Using Object-Oriented Classification.

The edge breaks are then detected from the Relief Shaded image and Near Infra Red band using a Sobel Edge Detection algorithm available through Rolta Geomatica. It created an image with high pixel value where there is an edge (Figure 4A&B).The edges were then classified under the class East Edge and North Edge using membership function of layer values and orientation (Figure 4.C). The classified objects were then converted to vector files. Using vector files as the thematic layers, roof area was extracted as individual polygon for each block using information regarding building height and contextual information like Relative Border to East and North Edges (Fig. 4D).

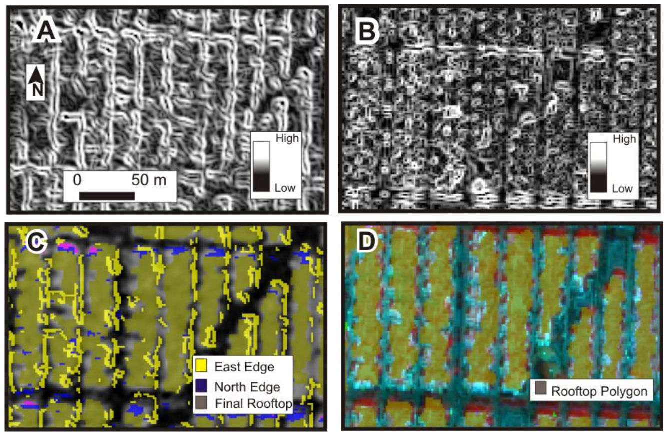

Figure4. automated extraction of building polygons, A. East edge derived form Relief shaded image, B. North Edge derived from Near Infrared BandC. North Edge and East Edge classes, Building polygonsare extracted in relation to Edges D. Individual polygon for each block

5.2. Nordic Case Study Area – Steindal

The process of roof extraction of Nordic city of Trondheim involved two steps: 1) Image pre-processing, 2) Automated extraction of total roof area using object-oriented classification.

5.2.1. Image Pre-Processing

Since both DSM (Figure5A) and DTM (Figure 5B) are obtained from Trondheim Municipality, the image pre-processing starts with subtracting DTM from DSM and generating nDSM (Figure5C). Unlike the Test Area of Bhopal, individual roof area of buildings of Steindal is visible in the high resolution Orthophoto (Figure 5D). As a result, the methodology of automated extraction focused on extracting individual polygon for each roof.

5.2.2. Automated Extraction of Total Roof Area Using Object-Oriented Classification.

For being part of the Nordic region, every building at Steindal has a chimney in its roof. Via an initial manual analysis, it is found that chimneys and the boundary of roofs have a different reflectance value over Red band. To accentuate the edge effect the Sobel Edge Detection filter is run on Red band which produces an image with higher value where there is the chimney and roof boundary (Figure6A).

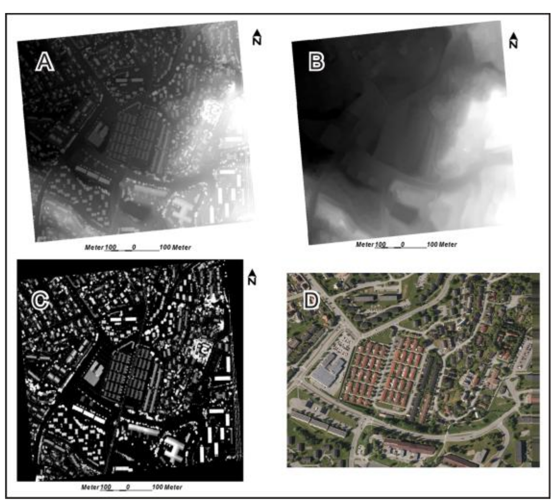

Figure 5. Image pre-processing

Because trees and houses have the same height at Steindal, it is necessary to segregate trees for smoother extraction of roof area. The same initial manual analysis mentioned above revealed that trees have different slope than the roof. DSM is further processed to generate slope layer (Figure6B).

Figure 6. A. Red Edge layer derived from red band, B. Slope layer derived from DSM.

Then the derived layers of nDSM, slope and Red_Edge layer are stacked with orthoimage and Merged Image was produced.

The process of automated extraction starts with performing Chessboard Segmentation on Merged Image (Figure7A). Chessboard Segmentation cuts the scene into equal squares of a given size (cognition Developer, 2014). Image objects representing chimneys and trees are separated using the membership function of edge layer and slope respectively (Figure 7B). Second level of analysis starts with Multiresolution (MS) segmentation on nDSM (Figure 7C). The MS segmentation starts with single image objects of one pixel and merges them iteratively, pair-wise 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 assigning weight to shape and compactness criteria (eCognition Developer, 2014). In this case, larger weight was assigned to coloure (refer flow chart of figure 7) to ensure that height information of nDSM is fully utilized.

Image objects representing the roof area are classified as “Roof” thresholding the height information (Figure7D). The resultant image contained individual polygons under “Roof” class which are further converted to vector file, namely Roof.shp and used in accuracy assessment. The above methodology described in the flow chart with images showing intermediate outputs in figure7.

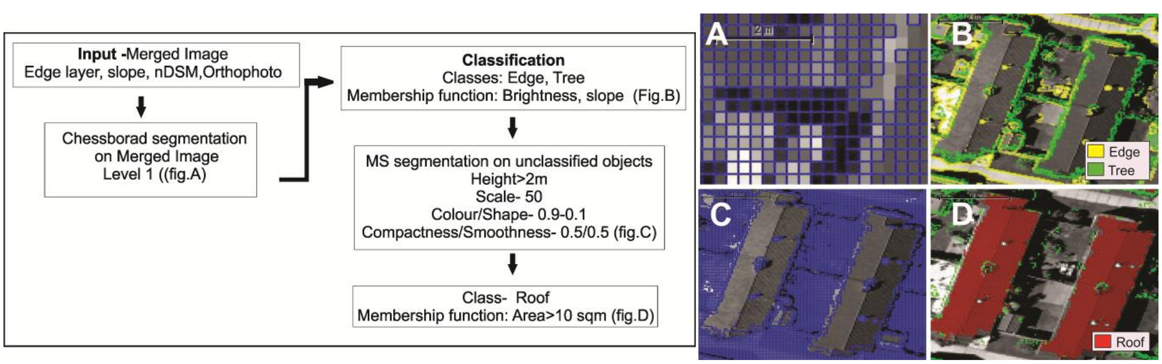

Figure 7. Flow chart describes automated extraction of roof area (see text for detail) with images showing intermediate outputs.

6. EVALUATING THE RECOGNITION METHOD

6.1. Tropical Case Study Area –Minaal Residency

The accuracy of assessment involves checking the accuracy of per-object intersection of the classification. For this purpose, automatically extracted rooftops of the test area of Bhopal, India 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 (Saha et. al., 2016).

Since the objective of this research is to quantify available rooftop areas for PV installation, accuracy assessment is performed by comparing the area extracted by the automated method with that of reference maps. It is found that the proposed object oriented method was able to extract 83.47% of manually digitized roof area. Table1 shows the detail of this visual comparison (Saha, 2016).

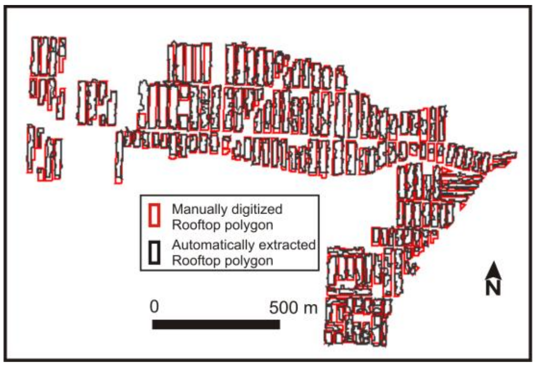

Table1: Comparison between manually digitized and automatically extracted rooftop polygons

	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

Figure8. Visual comparison between automated and manually extracted drumlins

6.2. Nordic Case Study Area – Steindal

In the case of Steindal, Trondheim, Norway, reference roof polygons are already available from Trondheim authority. For the purpose of visual comparison, reference polygons are overlaid on automatically extracted polygons (Figure9A). According to the figure, automated method identified most building polygons mapped by manual method in its original location. For Steindal also, accuracy assessment is performed by comparing the area extracted by the automated method with that of reference maps. It is found that the proposed object oriented method was able to extract 76% of manually digitized roof area. Table2 shows the detail of this visual comparison.

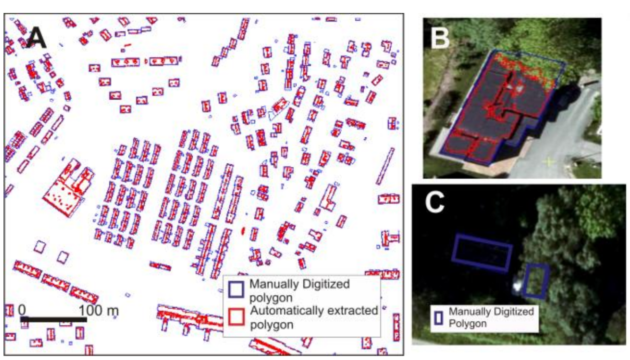

Table2: Comparison between manually digitized and automatically extracted rooftop polygons

	Manually digitized rooftop polygons	Automatically extracted rooftop polygons
Total number of polygons	430	378
Total Area (sqm)	49035.27	37529.93
Percentage to total area	100	76%

Figure 9. A. Visual comparison between automated and manually extracted rooftop polygons, B &C. Automated method did not extract the roofs which are covered with vegetation.

Close visual inspection reveals that the proposed method is better for mapping real time data compare to the manual method because it can exclude the roof area which are covered with vegetation at that point of time (Figure9.B and C).

7. ESTIMATING SOLAR ENERGY POTENTIAL FROM ROOFTOP PV

7.1. Tropical case study area –Minaal Residency

Method to estimate the solar energy potential through rooftop solar PV using roof area data is explained in detail in Saha et. al., (2016). Having obtained the total roof area of a region, it was necessary to reduce this area to that which could be available for solar photovoltaic applications, in order to determine the potential power output. A reduction process started through selecting a reduction factor of 0.3 reported in literature (Saha, 2017). Using the reduction factor, area available for solar panel installation is obtained (Saha, 2017).

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:

APV = 0.3∗ARoof………. (Equation 1)

The derived value is then used to calculate solar energy output/day via equation:

E = Imd *e * APV ………. (Equation 2)

Where 'Imd' is the mean daily global insolation on a horizontal plane, 'e' is the module efficiency, 'APV' is the roof area available for PV installation. Table 3 describes details of the calculation.

Table 3. Estimation of per capita energy output for Minaal Residency

Potential solar energy output for the Test area (kWh/day)	Potential Per-capita energy output from the Test Area (kWh/day) *	Per-capita energy consumption (kWh/day)
76342.50	10.39	3.91
*calculated by dividing potential solar energy output for Steindal with a total population of Minaal Residency which is 7344.		

7.2. Nordic case study area – Steindal

To estimate the solar energy potential of Steindal, same procedure is applied except the reduction factor. Because the automatically extracted total roof area is already excluded from the area covered by the chimney, vegetation and other objects, the total area is itself the available area for solar PV installation. As a result, no reduction factor is and the roof area available for PV installation (APV) is the total roof area (ARoof) .

APV = ARoof ………. (Equation 1)

APV= 37,529.93m^2

Having obtained available roof area for Steindal, potential solar energy output/day is calculated using Equation 2. 'imd' for Trondheim, Norway is 2.53kWh/m^2/day; 15% is considered for 'e' as it is the minimum module efficiency offered by the leading PV producers in the Nordic region. Table4 describes details of the calculation.

Table 4. Estimation of per capita energy output for Steindal

Potential solar energy output for the Steindal (kWh/day)	Potential Per-capita energy output from the Test Area (kWh/day) *	Per-capita energy consumption (kWh/day
14,257.96	15.00	25.82
*calculated by dividing potential solar energy output for Steindal with a total population of Steindal which is 950.		

8. CONCLUSION AND WIDER IMPLICATIONS

This paper, for the first time, compares the outcomes of an automated method to extract urban roof area using DSMs from two different environments: a Tropical and a Nordic setting. The object oriented classification tool under evaluation was developed by Saha et. al. (2016) using eCognition Developer and based on a set of rules.

We show in this work that an expertise-based modification of this tool is necessary to successfully recognize the same type of urban roof in different climatic conditions. Because the urban roof typology of Minaal residency is flat, the variations of slope and elevation play a relatively small role in recognizing the objects compared to the variations of building shadows. The set of rules for automated object recognition used for the Tropical roofs, thus mainly focuses on variations in building shadows. In contrast, Nordic roof area of Steindal are a combination of both flat and pitched roofs and show a wider variety in slope and roof material, for example material used in chimneys and boundaries are different from the main roof. As a result, the automated extraction of these roofs is based more dominantly on the recognition of variation in slope, elevation and reflectance pattern in Red band. With a supervised approach in modifying the tool to its environment, we find that the tool is reliable and flexible.

The extracted roof area is further reduced to acquire the available roof area for solar PV installation and the potential of this available roof area for solar energy production is estimated using specifications and company stated output capacities of multi-crystalline solar photovoltaic modules. As rooftop solar PV is one of the major sources of clean energy it is gaining huge importance in Smart City planning. The proposed and researched method for rooftop extraction, presented in this paper, would help with Smart City projects by reducing the time required for estimation and calculation of solar energy potential through rooftop solar PV at any spatial scale.

9. ACKNOWLEDGEMENT

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