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Satellite imagery to select a sample of rooftops for a PV installation project in Jeddah, Saudi Arabia

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Abstract. A region-based convolutional neural network image segmentation approach (Mask R-CNN) was applied to identification of flat rooftops from satellite imagery in the city of Jeddah in Saudi Arabia. The model was trained on a small sample of rooftops (202) digitized from a 0.5 m resolution image (covering 0.21 km^2) and then was applied to an independent area 4.5 km away. The precision and recall of the model were 0.98 and 0.96 respectively in terms of identifying rooftops in the independent area. A spatially stratified sample of rooftops was drawn from those identified by the model and the median roof area of the sample was not significantly different from the area as a whole. The results, although at a small scale, demonstrate the effectiveness of this approach for selecting buildings with appropriate rooftops for solar photovoltaic (PV) installation, in the context of closely spaced flat-roofed buildings, without requiring cadastral mapping or LIDAR datasets.

1. Introduction

In hot, humid areas such as the city of Jeddah on the Red Sea coast of the Kingdom of Saudi Arabia (KSA), demand for electricity for air conditioning is very high, driven in part by low historic electricity prices. Despite an abundance of solar resource there is an extremely low level of penetration of rooftop-mounted photovoltaic (PV) electricity generation, with its potential benefits of reducing consumer electricity bills in addition to reducing carbon dioxide emissions. In addition, KSA has an ambitious programme to diversify its economy from fossil fuel production and install 58.7 GW of renewable energy generation capacity (including 40 GW of PV) by 2030, starting from a base of almost exclusively oil- and gas-based electricity generation [1].

The work presented in this paper is part of a study in Jeddah, KSA, aimed at evaluating the effectiveness of installing rooftop PV arrays, with or without energy storage, at reducing air-conditioning electrical demand at the household level, known to make up around 70% of household electrical demand in KSA [2]. In the study, a number of buildings will have PV arrays installed (the ‘intervention’ group) and a similar number will simply be monitored for energy demand (the ‘control’ group). The relative change in electrical demand of the two groups will compared over a period of approximately two years or more.. Previous studies have indicated that rooftop PV could make a significant contribution to domestic loads [3,4], the former based on aggregate data at the national level and the latter, a detailed case study of a single villa in Jeddah.

In order to select buildings for the study, a probability-based sample will be drawn from the population of residential buildings in the city (in the wider city region, comprised by housing unit, approximately 57% apartments, 8% villas, 32% traditional homes and 3% other types [3]) and the building/rooftop owners will be approached to take part in the study. It is expected that the performance and utilization of rooftop PV systems will vary according to location in the city, partly due to unmeasured socio-economic variables and partly due to physical variables such as the urban heat island effects and differences in dust accumulation depending on exposure to prevailing winds [5–7]. To ensure that the sample is spatially balanced, a spatially stratified approach will be used i.e. spatial units will be used as a variable to stratify the sample [8]. The advantages of this approach are that possible effects of spatial autocorrelation are avoided when compared to systematic (grid-based) sampling; and that there is no possibility of large unsampled areas, compared to simple random sampling from a list.

The challenge in this case is that LIDAR or detailed cadastral mapping datasets are not publicly available in this location (unlike in e.g. [9]) and therefore it is necessary to infer the presence of domestic buildings (and suitable rooftops for PV installation) directly from satellite imagery. An additional requirement is that the roof area is automatically evaluated during the sampling process. To efficiently carry out this task at scale and to enhance the reproducibility of the work, the process should be automated.

A previous study in KSA [10] used a manual selection process investigating individual buildings to consider shading effect of rooftop furniture such as HVAC units, plant rooms, and satellite antennae on PV modules. They then used a GIS approach to extent the analysis to the scale of city of Al-Khobar. They covered the residential part of the city investigating 33,000 residential units. They conducted a field survey to confirm the available PV rooftop areas estimated from a high (0.5 m) spatial resolution GeoEye image. A regression model based on a sample of 70 households was produced in order to identify the area available for rooftop-mounted PV. Finally, PVSOL software was used to evaluate the impact of shading on the final areas selected. They concluded that up to 28% of rooftops in the city were available for PV application. They claimed that due to the similarities in structural and architectural features in the region, their model is applicable to the Gulf Co-operation Council (GCC) countries. Also highlighted was the importance of Utilization Factor, i.e. the proportion of roof area available for mounting PV modules when all access requirements, structural and shading restrictions have been applied.

For the present work we aim to automate the process of rooftop identification using the latest development in region-based convolution neural networks for segmentation of images, the Mask R-CNN model [11]. This model has previously been used to identify building footprints in USA, China, France and Sudan [12,13] and was found to perform well in situations where buildings are closely spaced from or joined to (or overlapping) other buildings. Note that we are employing an existing model to a new location and our contribution is limited to training the model, examining the results and using them to select a spatially balanced sample of rooftops from those identified by the model. We have not addressed the Rooftop Utilization Factor in the present work which is limited to identifying rooftop outlines.

2. Methods

To train the Mask R-CNN model, a block measuring 630 m by 340 m (0.21 km^2) in postal code area 23462 of Jeddah was chosen at random and the flat areas of rooftops manually digitized from a WorldView® 02 image. The pixel size was 0.5 m and only the red channel was used in order to reduce processing requirements, given that the blue and green channels did not improve contrast between rooftops and other features, when compared to the red channel (Figure 1). In this present work, the rooftops were always digitized as rectangles, regardless of more complex rooftop layouts. More accurate digitization and segmentation of rooftops will be the subject of further work. In total, 202 rooftops were digitized (Figure 2), with a pseudo-median roof area of 376 m^2, $CI_{95}\{365,386\}$ m^2. The digitized rectangles were converted to a raster with 0.5 m resolution, which was split into 128 by 128 pixel chips for training purposes (with X and Y strides of 64 pixels) and the rooftop areas were coded as 1 with all other areas coded as 0. All processing was carried out using ESRI ArcGIS Pro® 2.7.1 using the Spatial Analyst and Image Analyst toolboxes. The preparation for the training step was carried out in the projected map space (UTM 37N, WGS84 and units of m) and the original raster cell resolution of 0.5 m was used.

The Mask-RCNN model was trained using the ESRI ArcGIS arcgis.learn python module which depends on the PyTorch and fast.ai libraries [14,15]. The model contains the pre-trained Resnet50 CNN model (which allows layers to be skipped to ensure better training), in addition to the part trained on the input dataset [16]. The number of epochs used to train the model was 40, after which the optimal learning rate was automatically determined by the model to be in the range of 6×10^{-6} to 6×10^{-5}.

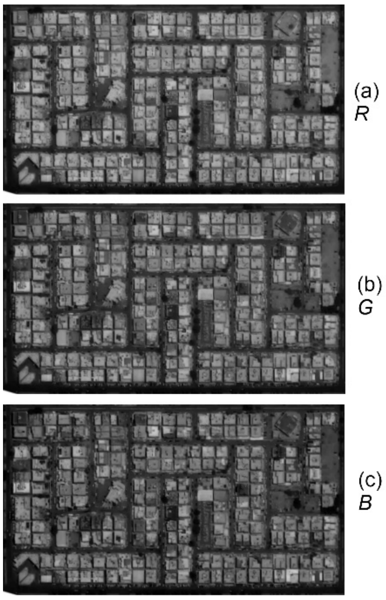

Figure 1. RGB channels of training image with γ=0.4, indicating little difference in contrast of rooftops between the channels

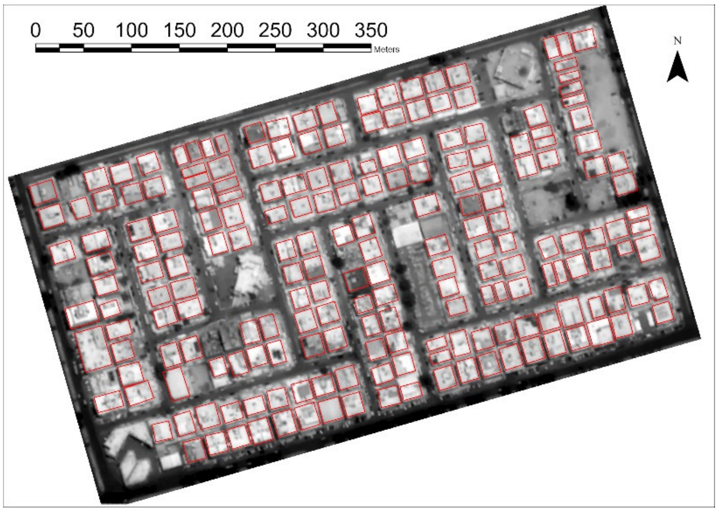

Figure 2. Training image in postal code area 23436 of Jeddah with rooftops digitized as rectangles (red).

3. Results

3.1. Model validation

Ten percent of the input image chips were used for within-sample validation (Figure 3), giving an average precision score of 0.77 during the training process. Figure 4 indicates that the training and validation losses decreased and converged over the subsequent epochs of training, with the validation loss slightly greater than the training loss, indicating a well-behaved model without excessive variance. Note that the 'loss' function in this context is the sum of the binary cross-entropy (negative of log probability) of various model components [17].

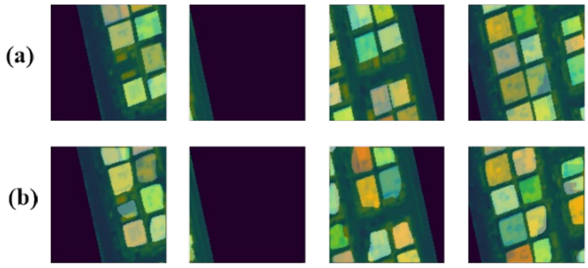

Figure 3. Image chips in validation set (a) as digitized (b) as detected by the model

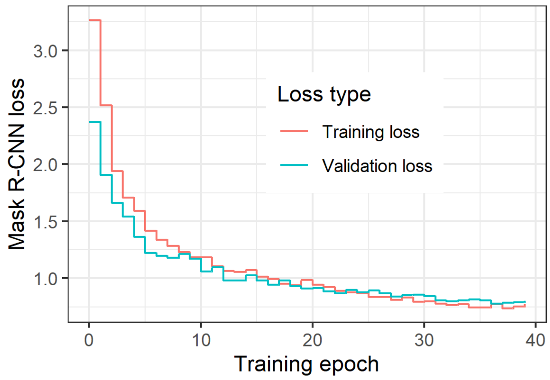

Figure 4. Values of Mask R-CNN model loss function versus epoch.

3.2. Application to an independent area

The trained model was then applied to an area within another postal code area in Jeddah, 23345 (4.5 km from the training area in area 23462, see Figure 5 below).

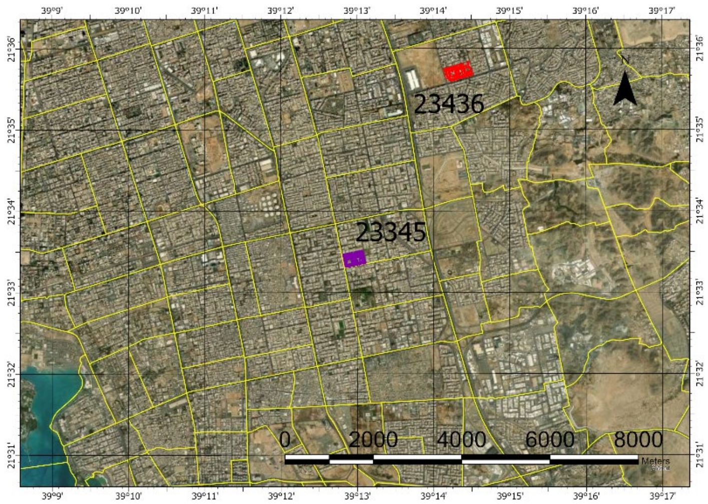

Figure 5. Map of part of the city of Jeddah, with the northern highlighted area (red) indicating the training area (postal code 23436) and the southern highlighted area (purple, postal area 23345) indicating the independent area for testing the model.

The result of applying the model to the new area are shown in Figure 6. The model correctly detected 128 distinct rooftop footprints with pseudo-median plan area of 436 m^2 $CI_{95}\{425,447\}$ m^2 (one sample Wilcoxon rank sum test). For these rooftops, the polygon generated by the model intersected more than half of the true area of the rootop ('Intersection over Area' or IOU > 0.5). On inspection of the imagery and also street level photographs, there are three rooftop footprints that have not been identified by the model (false negatives, magenta arrows in Figure 6). In addition, there are two rooftops that have been incorrectly identified as separate when they are in fact part of one roof. These are indicated by cyan arrows – here counted as false negatives as IOU ≤ 0.5. Note that although this work is focused mainly on domestic buildings, the model training did not attempt to segment between different building types and part of the roof of a mosque (two false positives - yellow arrow) has been identified; a next step in the analysis will be to distinguish between building types.

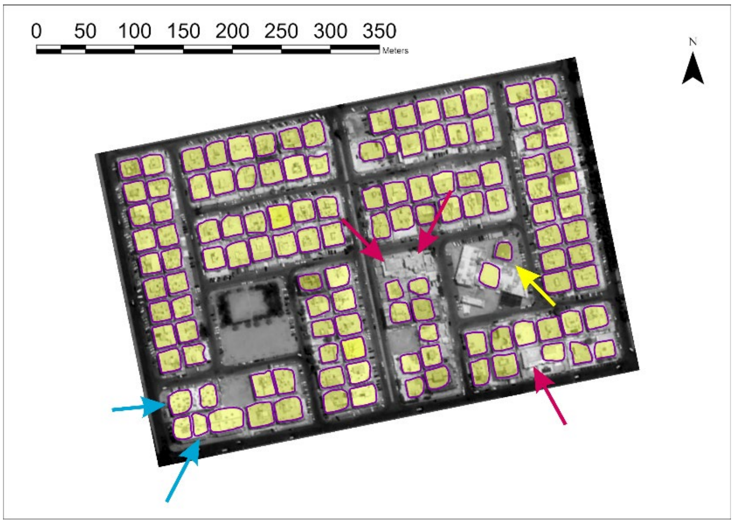

Figure 6. Image in postal code area 23345 of Jeddah with identified rooftops indicated by yellow shaded areas bounded by purple lines. 'False negative' rooftops indicated by magenta arrows; improperly segmented - blue arrows; parts of mosque - yellow arrow

Therefore for this simple binary case and small sample, the model identified 121 true positives, the precision was 121/(121+2) = 0.98 and the recall was 121/(121+5) = 0.96.

3.3. Spatial sampling

In order to test the method for sampling buildings, a spatially stratified sample of ten buildings was generated from the rooftops identified in the previous section. The centroids of the rooftops were extracted as points, which were in turn used to generate polygons which each contained approximately N/n = 128/10 ≈ 13 rooftop centroids (with 13±1 centroid per polygon allowed). This was carried out automatically using ESRI ArcGIS Pro® 2.7.1 Geostatistical Analyst toolbox. One centroid was then randomly selected from each polygon to give the final sample of ten rooftops (see Figure 7). The distribution of the sampled rooftop areas is given in Figure 8 and was not significantly different from the population (Wilcoxon rank sum test p=0.36).

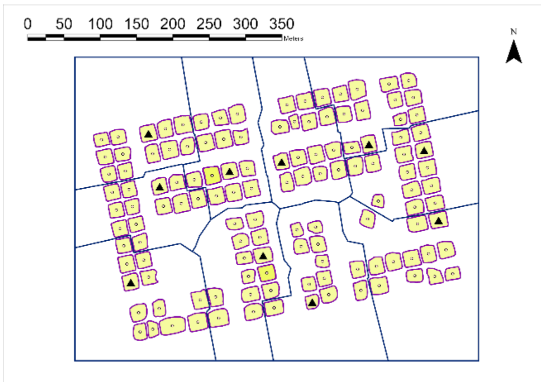

Figure 7. Spatial stratification of identified rooftops, with automatically generated balanced polygons (blue lines). Randomly selected rooftops indicated by solid black triangles.

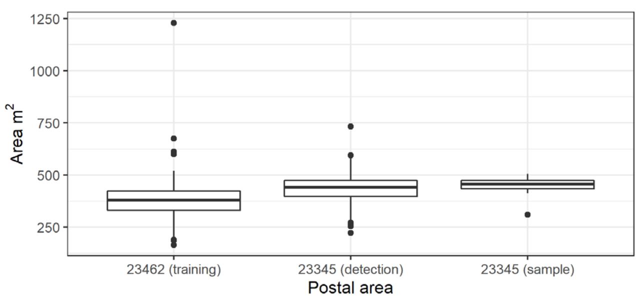

Figure 8. Comparison of distributions of area of rooftops (left: training set, as digitized; centre: independent set n=128; right: sample from independent set n=10)

4. Conclusion and further work

The Mask-RCNN model has been shown to be appropriate for identifying rooftop areas in the context of closely spaced, flat-roofed buildings in Jeddah, KSA. This facilitates spatially stratified random sampling in a context where a cadastral map is not available, and also provides an estimate of roof area and hence potential PV capacity of the rooftops. Future work will train models using more accurately digitized rooftop footprints, accounting for shading from obstacles on the roofs, and different building types in order to improve the accuracy of estimates of rooftop Utilization Factor for PV installations.

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