The potentials of Sentinel-2 and LandSat-8 data in green infrastructure extraction, using object based image analysis (OBIA) method

S M Labib and Angela Harris

School of Environment, Education and Development, University of Manchester, Manchester, United Kingdom

ABSTRACT

Green infrastructure (GI) mapping and monitoring is crucial in urban areas, and remote sensing is widely used to accomplish the task. Improved moderate resolution Sentinel-2A (10 m) and LandSat-8 (15 m) images, in place of commercial satellite images, enable GI mapping with little to no cost. Considering so, the objective of this paper is to evaluate the potential of GI feature extraction of Sentinel-2A (S2) and LandSat-8 (L8) (freely available images) using the Object Based Image Analysis (OBIA) method. The advantage of using OBIA over pixel-based analysis has been investigated primarily with very high resolution images. Using OBIA, bottom up (i.e. Multiresolution) and top down (i.e. Spectral Difference) segmentation were implemented using eCognition to obtain image objects for both S2 and L8 images. Then, rule-based classification was performed to extract GI areas from the objects. NDVI, NDWI, NIR/R ratios were utilized in rule set development, after several trial and error process. Both S2 and L8 provided acceptable extraction of GI for urban areas. However, with an overall accuracy of 71.24%, S2 was more effective when extracting GI areas. Shadows along roads and high rise buildings caused some inaccuracy in classification.

Introduction

Urban development has resulted in higher rates of vegetation and water body disappearance over the last few decades. Covering soil with impervious surfaces is considered a major threat to overall living conditions in cities (Blaschke, Lang, & Hay, 2008). Monitoring change in land cover through a focus on green infrastructure (GI), Green and blue areas such as urban parks, natural vegetation, waterbodies; in cities has become a widely researched area of investigation due to the massive impact land use can have on a city’s environment, ecology, health and wellbeing (Gill, Handley, Roland Ennos, & Pauleit, 2007; Norton et al., 2015; Tzoulas et al., 2007). For such monitoring, optical satellite images are used extensively. Several pixel-based methods (e.g. supervised, unsupervised), Object-based image analysis (OBIA) and hybrid approaches (e.g. Supervised with Support Vector Mechanisms – SVM) have been widely explored, using either very high spatial resolution (e.g. IKONOS, QuickBird) or moderate resolution (e.g. Landsat 7 ETM+) images (Wieland, Torres, Pittore, & Benito, 2016; Zhang, Feng, & Jiang, 2010).

Variation in spatial resolution provides contrasting results between commercial satellite image-based results and freely available satellite images such as Landsat. Prior to the launch of Sentinel-2 (S2) and Landsat-8 (L8) programmes, very high resolution (VHR) commercial images were usually better than moderate resolution images (Ouyang et al., 2011; Radoux & Defourny, 2007). Thanks to these programmes, both S2 and L8 have improved the spatial resolution of freely available satellite images. This provided the opportunity to map GI more accurately without any cost for purchasing VHR images. Sentinel-2 provides 10-m resolution for visible and near infrared (NIR) bands, and Landsat-8 provides a 15-m panchromatic band with 30-m visible and NIR bands that can be updated to a 15-m resolution using pan sharpening (Drusch et al., 2012; Roy et al., 2014). Several studies have compared the differences and potentials between these two freely available satellite data resources, such as Novelli, Aguilar, Nemmaoui, Aguilar, and Tarantino (2016) compared the performance of L8 and S2 in detecting greenhouse gas. Mandanici and Bitelli (2016) explored the primary differences in spectral variation and correlations among different bands as well as combinations of bands for various uses. These studies have indicated the potential better performance of different sensors based on purpose and under different radiometric conditions. However, investigations are needed to understand which image resource provides better results when working with GI and how well S2 and L8. Despite the 5-m variation in spatial resolution
between S2 and L8, it was initially hypothesized that both approaches would provide similar results when using OBIA to extract vegetation and water bodies in urban areas.

The selection of OBIA method has been considered carefully over the traditional pixel-based method. OBIA is relatively recent in practice, and the method already proposed several advantages over the pixel-based methods; such as, consideration of spatial auto-correlation, improved image class, contextual consideration, integration of ancillary data in the process (Blaschke, 2010; Blaschke et al., 2014; Liu & Xia, 2010). OBIA is becoming more and more popular among the scientific community, and in fusion with several high-end classification methods, such as random forest (RF), rule-based classification, SVM, this method has transcend into a more robust method for image classification due to its ability to segment detail objects, consideration of the contextual setup, ability to accommodate expert rules in its classification (Blaschke et al., 2014). Additionally, the opportunity to semi-automate the process of classification for same sensors enable it more efficient and time saving for future monitoring (Blaschke et al., 2014; Hussain, Chen, Cheng, Wei, & Stanley, 2013; Novelli et al., 2016; Ouyang et al., 2011).

The basic idea of this comparison is to add evidence in the body of knowledge, regarding the effectiveness of these freely available data sources. This study is more focused to evaluate differences between S2 and L8 when extracting GI information from dense urban fabric; however, concern regarding the use of rule-based classification and accuracy of classification has been taken into consideration. Additionally, OBIA method implantation has been done carefully opposed to pixel-based classification; as pixel-based evaluation has been investigated for S2 and L8 separately, there is a gap in identifying how they perform in case of OBIA while extracting GI-related features.

Study area and data

A dense urban core of Dhaka city, Gulshan-1 area, has been selected as study area for this research (Figure 1a). Geographically it is located between 23° 46’ 32.76” N to 23° 47’ 5.12” N latitude and 90° 25’ 18.43” E to 90° 24’ 43.66” E longitude.

This study area is typical of urban land use with mixed conditions in Dhaka city, Bangladesh. The area includes a lake, making it suitable to explore the extraction of both green and blue areas. This area has mixed land use, with high-rise building for both official and institutional use, along with some vegetation cover by the side of lake and roads (Figure 1b). The area has several high-rise buildings along the road network with mixed land use (Figure 1c). However, in relation to the study area there is no available updated information for vegetation and water bodies in the city’s 2010 Detail Area Plan (DAP) by RAJUK (City planning authority) (Figure 1b) (Labib, Rahaman, & Patwary, 2014). The selection of this area not only adds updated information for this region, but the research can also lead to a

Figure 1. (a) Dhaka city map (black circle indicates study area); (b) Land use map (Labib et al., 2014); (c) Google Earth image showing roads and buildings.
Once the OBIA has been established.

For this study, S2 and L8 images were utilized, and these were downloaded from Earth Explorer. The details of image acquisition and related information are listed in Table 1. Images are Level-1C products, and geometric and top-of-atmosphere (TOA) correction has been provided. Both images contain less than 10% cloud coverage (CC) in the larger image, and 0% CC over the study area. The images were captured during the afternoon (after 16:00:00); hence, the presence of shadow noise is highly likely due to sun angle and the existence of high-rise buildings in this area. Both S2 and L8 images were acquired on 2 February 2017 because of the presence of shadow and less cloud cover during winter season in the study area region. This ensured more visibility and less interactivity with cloud cover, as well as provided the opportunity to explore the effects of shadow.

The raw L8 data have been captured by OLI_TIRS sensor, and there are nine bands of images downloaded within the compressed files; they are: Coastal aerosol (430–450 nm), blue (450–510 nm), green (530–590 nm), red (640–670 nm), NIR (850–880 nm), shortwave infrared-1 (1570–1650 nm), shortwave infrared-2 (2110–2290 nm), cirrus (1360–1380 nm) and panchromatic (15 m resolution) (Novelli et al., 2016; Roy et al., 2014). For S2, there are total 12 bands: Coastal aerosol (443 nm), blue (490 nm), green (560 nm), red (665 nm), NIR (842 nm), four vegetation red edge bands (bands 5,6,7 and 8A), water vapour (1375 nm), short wave infrared-1 (1610 nm), short wave infrared-2 (2190 nm), cirrus (1376 nm) (Drusch et al., 2012; Kaplan & Avdan, 2017). In this study, only blue, red, green and NIR bands have been utilized for both sensor types, and for L8 the panchromatic band is used to optimize the cell size for the visible bands. The main reason behind selecting these bands is their wide acceptance in extraction of GI elements (Jensen, 2009; Jensen & Cowen, 1999). Additionally, it is understandable that, these bands are mostly affected by atmospheric effects (Campbell & Wynne, 2011); however, the intention was to explore how these freely available data perform under the presence of atmospheric effects. Hence only TOA has been considered for image corrections before conducting segmentations and classifications. Furthermore, Short-wave Infrared and other bands have not been considered; as for OBIA, the major focus was provided on the difference in spatial resolution for this study. As the main concern for openly available data images are, the low spatial resolution, for example, most of the LandSat data have either 30 m or 60 m spatial resolution.

In addition to these data, GIS data (i.e. DAP Data) is utilized in doing validation and comparisons of the results. DAP data was created during 2008–2010 using total station by the city planning authority. The data calibrated and published in digital format (i.e. Shapefile) in year 2010 with scale 1:3960 (Representative Fraction). In this case, polygon-shape files were utilized for the comparisons. These data were the most authentic database for the time period, as the city planning authority have checked and validated these data with proper filed visit and other observations they have collected during the process of database creation.

Furthermore, for the validation of the results; reference data (28 points) was collected using Trimble GPS System (GeoXH, with 10 cm accuracy, details of the location and actual land class are presented in Table 1, Supplementary Document). Detailed land cover type and shadow information was collected for the corresponding reference points.

**Methods**

Considering the shortcomings of pixel-based methods (i.e. lack of consideration for spatial auto-correlation, presence of salt-and-pepper and emphasis on spectral value), OBIA has been considered more robust (Blaschke, 2010). Thus, OBIA was applied, based on the work flow outlined in Figure 2. The process of OBIA is followed by rule-based classification to extract the GI areas at the final stage. The details of different stages are discussed in following sections.

**Pre-processing**

In this study, both S2 and L8 images are TOA corrected and geo-referenced. However, for both, geo-correction has been conducted based on GPS tie points. Additionally, to meet with existing shapefile (Polygons) of the study area (collected from local planning authority, RAJUK), projection transformation was conducted, and all files were projected to a UTM system (previously Bangladesh Transverse Mercator – BTM). Using the existing shapefile, spatial subsets of S2 and L8 images for the study area were obtained. The shapefile used in this case (the

### Table 1. Sentinel-2 and Landsat-8 image details for the study area.

| Satellite       | Sensor          | Pixel size (m) | Date (time)     | Product level | Sun angle | Sun zenith |
|-----------------|-----------------|----------------|-----------------|---------------|-----------|------------|
| Landsat 8       | OLI_TIRS        | 30 (15 m Pan chromatic) | 2 February 2017 (16:24:51) | Level-1T      | 144.292   | 42.281     |
| Sentinel-2A     | MSI             | 10 (Bands 2, 3, 4, 8), 20, 60 | 1 February 2017 (16:38:25) | Level-1C      | 149.755   | 46.417     |
circle shown in Figure 1b, 1c) has a radius of 500 m (m). After obtaining the subsets, 1050 m length and width square size images were obtained for the blue, green, red, NIR and pan-sharpen bands of S2 and L8. All these bands (blue, green, red and NIR) were combined into a single image using layer stacking in ENVI (Version 5.3) for further processing. For L8 data to be compared with S2 data with close spatial resolution, pan-sharpening process has been implemented to ensure that the composite image of L8 has spatial resolution of 15 m (Pushparaj & Hegde, 2017). In this case, ESRI algorithm (pan-sharpening method – ESRI, Zhang & Mishra, 2014) based on spectral modelling for data fusion has been utilized to sharpen the image. The process is conducted in ArcGIS. Pan-sharpening process has been conducted in ArcGIS as other data sets (e.g. Shapefile) were all integrated in ArcGIS, and the process was computationally efficient in ArcGIS. Finally, a layer-stacked image of S2 and a pan-sharpened image of L8 were used for the further processes.

Image segmentation

In this study, both bottom up algorithms (i.e. Multiresolution Segmentation (MRS)) and top down (i.e. Spectral Difference Segmentation (SDS)) were utilized to get acceptable segmentation results for OBIA method (Kaplan & Avdan, 2017; Novelli et al., 2016). For segmentation, the process eCognition Developer (version 9) was utilized. This software and its developed algorithms are widely used in different OBIA studies (Blaschke, 2010; Schultz et al., 2015). In this particular study, MRS and SDS were applied together.

MRS algorithm follows sequential region merging, starts at the single pixel level and mutually similar neighbouring pixels form smaller segments. The segments grow and pixels are grouped until a “heterogeneity threshold” is reached. The variance threshold is a function of image layer weight, scale parameter, shape (defines the weight of colour when segmentation) and compactness (defines the closeness of pixels in an object, compared to the circle) (Details can be found in Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). However, selection of weight, scale parameter and shape is matter of experimentation to achieve acceptable segmentation with clear differences among objects (Aguilar, Saldaña, & Aguilar, 2013). In this case (both for S2 and L8), the NIR band of the stacked images is given a weight of two, where other bands are given weight of one, as both water and vegetation are more sensitive to NIR bands (Kaplan & Avdan, 2017). The scale parameter defines the maximum standard deviation of homogeneity criteria based on the weighted image layer. In this case, image type scale values between 10 and 150 were experimented with using a trial and error process to find the best scale for S2 and L8 at the selected image extent. The final scale values are listed in Table 2. In addition, scale, shape and compactness values between 0 and 1 were experimented with, and considering the urban context, higher compactness

| Algorithm | Segmentation attributes | Sentinel-2 (S2) | LandSat-8 (L8) |
|-----------|-------------------------|----------------|---------------|
| MRS       | Layer weight (blue, green, red, NIR) | 1, 1, 1, 2 | 1, 1, 1, 2 |
|           | Scale parameter         | 13             | 17            |
|           | Shape                   | 0.5            | 0.6           |
|           | Compactness             | 0.9            | 0.7           |
| SDS       | Maximum spectral difference | 65             | 68            |

Figure 2. Workflow of OBIA and validation.
and moderate shape values were found to be effective for both S2 and L8. Final values of compactness and smoothness are listed in Table 2.

In addition to the MRS algorithm, SDS algorithm was applied in the segmentation process. This is a widely used segmentation algorithm in case of extracting urban-vegetation-related information (Puissant, Rougier, & Stumpf, 2014). This algorithm allowed image objects to be merged based on spectral mean values below a given threshold and help improve the segmentation accuracy (Kaplan & Avdan, 2017). After several experiments with values (40–100) for maximum spectral difference, the selected values in Table 2 were found to provide suitable merging of image objects during the segmentation. Finally, applying MRS and SDS together at the same level of the segmentation process was completed.

Classifications and merge

The image objects developed in the segmentation stage needed to be classified to find the vegetation and water objects. Several classifications methods are integrated in eCognition including: K-nearest neighbour (KNN), SVM, decision tree (DT), assign class based on membership function (MF) and fuzzy classification (Haiyan et al., 2017; Ouyang et al., 2011; Puissant et al., 2014). Several OBIA studies have utilized DT, SVM, RF approaches to classify segments into different classes. These classification methods mostly follow supervised decision rules and often aided by data pattern using machine learning, and these methods lack in integrating expert-based human knowledge in the classification process (Lang, 2008; Mather & Koch, 2011). A growing argument has risen in recent studies, indicating the gap between image object domain and human language-centred class development, in turn indicates the importance of ontology in remote sensing (Haiyan et al., 2017). This implies, expert-based knowledge in classifying and interpreting image objects are often overlooked, but the use of expert knowledge of context, and spectral characteristics of object can bridge the gap of image object classified by machines and interpreted by humans (Andrés, Arvor, Mougenot, Libourel, & Durieux, 2017). Therefore, the integration of semantic knowledge in image classification becoming a way of implementing ontology in the remote-sensing studies, and several studies have experimented with semantic rule-based classification approaches to further improve image classification with expert knowledge (Andrés et al., 2017; Damien, Durieux, Andrés, & Laporte, 2013). Using remote-sensing experts’ knowledge of study area (contextual knowledge), and spectral characteristics of different bands as well as band ratios; the experts formulates semantic relations and therefore make MFs based on semantic rules for different types of land classes. For vegetation, non-vegetation, water and built-up areas Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Brightness, Red Edge (NIR/R) are found considerably important to express expert rules. In addition, the MF also integrates the experts’ contextual knowledge to relate the spectral characteristics in the classification process (Andrés et al., 2017; Belgiu, Hofer, & Hofmann, 2014; Damien et al., 2013; Haiyan et al., 2017).

In this study, MF-assigned classification was implemented using expert knowledge about the spectral characteristics and contextual relations of vegetation, water and built-up land cover in the study area. MF function-based classification is more rigorous to develop using trial and error (Figure 2, red arrow indicates the trial and error process) to obtain a more realistic classification that mimics the semantic rules developed based on expert knowledge of the study area objects. This process provides better results compared to nearest neighbourhood, DT and maximum likelihood methods (Haiyan et al., 2017; Laliberte, Justin Koppa, & Rango, 2006; Ouyang et al., 2011). Additionally, semantic rule-based MFs are not yet widely utilized with S2 or L8 data (e.g. like RF, KNN, ML classifications are experimented in several papers). Thus, there are scopes for experiments to integrate ontological expressing in classifications of S2 and L8 data.

The MFs were developed for three major classes: vegetation, water body and built-up area; additionally, for possible shadow conditions, a different MF has been formulated. As the focus was to extract GI infrastructure, special consideration was given to vegetation and water-related indices such as NDVI, NDWI, NIR/R (Belgiu et al., 2014; Haiyan et al., 2017; Kaplan & Avdan, 2017). Additionally, with field observation (contextual knowledge) and VHR satellite images from Google Earth, shadow was considered to be an important aspect in this study. However, instead of using shadow removal algorithms developed for VHR images (Luo, Wang, Shao, & Deren, 2015; Zhang et al., 2010), a shadow classification was used in order to understand the level of complexity shadow creates for S2 and L8 when conducting feature extraction.

Both for S2 and L8, developing the MF for vegetation and built-up areas involved the use of NDVI and NIR/R ratio values. For water body, NDVI, NDWI and visible brightness values were utilized collectively to provide a MF (Belgiu et al., 2014; Haiyan et al., 2017; Kaplan & Avdan, 2017; Toure et al., 2016). However, for shadow class, only a NIR/R ratio was found to be useful. The range of values for these indices were combined together with “AND”, “OR”
logic, after several trial and error processes (Andrés et al., 2017; Doustfatemeh & Baleghi, 2016; Ouyang et al., 2011). In this case, for S2 and L8, the threshold values had similarity. Additionally, when developing the MF, area, perimeter and shape indexes were considered to understand the variations among objects (Zhang et al., 2010). Ancillary GIS data from RAJUK was used as a reference to determine land use type and help identify threshold values during trial and error. After selecting appropriate threshold combinations and values, the classification was conducted and several classes were merged. Finally, the merged classes were exported to GeoTIF files and imported into ArcGIS for mapping and validation (Blaschke et al., 2008).

**Validation of the classified images**

Validation of the OBIA process is still a matter of debate among different researchers, as it has been argued that there is uncertainty in accuracy assessment when using OBIA due to how segmentations and classification accuracy assessments are handled (Liu & Xia, 2010). However, in this study, segmentation accuracy is visually judged (Novelli et al., 2016) by experts’ knowledge of the study area in contextual settings. In this regard, visual interpretations were made comparing with VHR images, in particular compared with Google Earth images (Dorais & Cardille, 2011; Elwood, 2011) and DAP GIS data. The outline of water bodies, and buildings are visually explicit in both Google Earth images and ancillary DAP data (i.e. Polygons), and these help the analyst to identify the segments. However, classification accuracy was assessed quantitatively using error matrix (Haiyan et al., 2017). Finally, the classification is compared with already existing GIS auxiliary data; this enables to compare the classifications quality in terms of the contextual aspect. Using GPS points with class attributes (i.e. vegetation, water, built-up, shadow cover), confusion matrix for S2 and L8 classified images was produced (Tables 2 and 3, correspondingly in supplementary document), and corresponding user accuracy (UA), producer accuracy (PA), overall accuracy (OA) along with Kappa values were estimated.

| Classification | Sentinel-2 (S2) | LandSat-8 (L8) |
|---------------|----------------|----------------|
| Built-up      | 1.00           | 0.75           |
| Water         | 0.67           | 0.80           |
| Vegetation    | 0.88           | 0.70           |
| Shadow        | 0.50           | 0.80           |
| OA            | 71.41%         | 67.85%         |
| Kappa         | 0.68           | 0.57           |

**Results and discussions**

**Segmentation comparisons between Sentinel-2 (S2) and LandSat-8 (L8)**

The segmentation results for the S2 and L8 images of the study area are presented in Figure 3. As illustrated in Figure 3(b), segments developed for L8 are quite small in scale, and they are not well developed for water bodies. Some of the segments often do not represent a whole object, and rather show combinations of objects. In contrast, segments developed for S2 (Figure 3d) are better fitted with water bodies and buildings and considered a good fit for vegetation areas when comparing the false colour composite (FCC) (Figure 3c). As well as segments for S2 are more related to specific objects, and they are clearly distinguishing the objects with clear boundaries. It is clear that even with optimized parameters, L8 segments are not as well developed as S2 segments. While the L8 segments have moderately good fit to the boundaries of vegetation and water, they do not result in good fit for buildings (compared with FCC, Figure 3a). In this case, the reasons might be the lines running in segmentation algorithms, which are more focused on scale and image detailing. With 5 m higher spatial resolution, S2 sale parameters (the scale input for OBIA parameter in eCognition) are relatively smaller than L8 parameters, and these influence the processes of MRS and SDS algorithms (Benz et al., 2004; Blaschke, 2010). It can be argued that the spatial resolution and higher optimization of S2 parameters also positively influence the image segmentation process, while L8 data have limitations compared to S2 data.

**Classification comparisons between Sentinel-2 and LandSat-8**

The L8 classified image is illustrated in Figure 4(a), and the S2 classified image is presented in Figure 4(c). Compared to L8, S2 classifications are smoother and less pixelated. This might be again the result of the 5-m difference in pixel size between S2 and L8 (after pan-sharpening). For both classification, the rules are relatively well fitted and provide realistic extraction of GI objects in the study area. However, the S2 classification has misclassified several built-up and vegetation classes as water (Figure 4c) where shadow was dominant (Figure 3c). L8 also misclassified some areas in the same zone, but the number is relatively less compared to S2 (Figure 4a). The misclassification raises the question of reliability of the GI feature extraction; in this regard it can be argued that when using freely available satellite data sources with less or minimum pre-processing such as no shadow removal, it is possible to have less reliable data. Therefore, the users have to be careful while
reporting these results, as well as possible support of ancillary data might help to increase the reliability of the results.

Considering so, after overlaying with ancillary GIS data, it was found that L8 has over or under-classified water body area, while S2 results are highly accurate in terms of feature extraction and boundary delineation. Additionally, S2 also has better identified the vegetation areas and shadow areas. In this case, comparison of class areas is presented in Figure 5. Figure 5 illustrates the percentage of each class extracted by different images. For S2, built-up areas cover 55.26% of the whole area, while for L8 47.75% areas are built-up. This shows S2 has extracted more hard surfaces areas (e.g. buildings, roads) than L8; this is probably because S2 segmentations are more accurate than L8 for buildings and hard surfaces. However, major class differences in area are observed in case vegetation and shadow classes. S2 extracted only 15.02% area covered with vegetation or green spaces; in contrast, L8 shows 28.27% area covered with vegetation. From visual observation of Google Earth images, and field visit, it has been observed that vegetation is less dominant in this particular study area; thus, it can be argued that L8 has over-classified vegetation. Additionally, S2 image showed 8.15% area as shadow cover, while for L8 shadow cover is around 5.13%. This is also crucial; the study area has more shadowed locations along the roads, where high-rise buildings caused shadows, and L8 often failed to address this condition. Finally, S2 has marked 21.57% of the area as waterbodies, while L8 has marked 18.84% as waterbodies. This shows that L8 clearly underestimated the water areas, and often misclassified this with vegetation class.

In addition to these, often misclassification of water is also observed along the roads (Figure 4b, d). In this case, as mentioned earlier, high-rise buildings on both sides of a road cause dark shadows that have the reflectance values within the range of reflectance values of water. This finding is consistent with other studies (Luo et al., 2015; Zhang et al., 2010). This indicates that S2 can be a better competitor to the costly VHR images, while keeping in mind the possible problems with

Figure 3. (a) FCC for L8 pan-sharpened image (NIR, R, G); (b) image object segments (total 558) for L8, moderate fit with vegetation and water, poor fit to buildings; (c) FCC for S2 image (NIR, R, G) shows higher clarity, the middle zones of the image show dark areas indicating tall buildings, that shows water-type pixel value due to possible presence of shadow; (d) image object segments (total 589) for S2.
shadow and its removal. In general, S2 provided better classification of vegetation and water compared to L8, and it is more consistent with existing GIS data. In this case, an argument can be made on the use of semantic rule-based classifications; that is, the rule-based classification can be a way forward to develop area-specific algorithms to extract features from objects, rather than performing classification again and again. Thus, semantic rule-based classifications might help to better automate the process of classification, and this can allow to integrate expert knowledge in the area of remote sensing. In addition to GI areas, S2 also shows

Figure 4. (a) L8 classified image; (b) GIS data overlay on L8 classified image; (c) S2 classified image; (d) GIS data overlay on S2 classified image.

Figure 5. The difference in land classes observed from S2 and L8 classification.
the presence of new built-up areas along the water-bodies, which are not apparent in existing GIS data, which are approximately 7 years old, as the data was created between 2008 and 2010, and published in the year 2010. Further validation of this classification was done based on accuracy assessment results.

**Accuracy assessment**

The accuracy assessment test results are presented in Table 3. It is quite clear that S2 has better UA and PA for built-up, water and vegetation classes compared to L8. S2 has low performance in terms of shadow class but greater PA accuracy for water and vegetation. The OA of S2 is considerably higher than L8. However, the kappa for S2 is again higher than L8, despite being less than the standard acceptable threshold of 0.75. The L8 kappa value is considerably lower and indicates less credibility for L8 extractions in all the classes.

The initial assumption of equal performance has been proved wrong, and S2 performed better than L8, with higher accuracy. Results show that S2 can be used in GI mapping in urban areas with 71.41% accuracy. However, S2 classification is highly vulnerable to shadow conditions and resulting misclassification, where L8 has considerably lower classification accuracy. Shadow has been found to be a major noise in this study both for S2 and L8. Due to its slightly higher spatial resolution, S2 has more difficulty with shadow noise compared to L8. Previous research using IKONOS or QuickBird has resulted in 80–95% accuracy (Ouyang et al., 2011; Toure et al., 2016; Zhang et al., 2010). Considering the cost of other methods and the availability of S2, it could be considered an effective substitute if further improvements are made in terms of image processing and classification methods.

**Conclusion**

In this paper, the utility of freely available Sentinel-2 and LandSat-8 data in extracting GI has been investigated using the OBIA method. The analysis found that S2 performs better than L8, despite errors due to shadow and classification weakness. Further improvements can make S2 images more robust in feature extraction using OBIA. Algorithm development for shadow removal specific to S2 and modifications of existing VHR shadow removal algorithms for both S2 and L8 could further improve the OBIA method. OBIA works quite well with S2 and L8; however, further improvement of rule-based classification with SVM, use of RF classifications, segmentation accuracy assessment and use of more ground-truth data for accuracy assessments still need detailed investigation.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

**ORCID**

S M Labib @ http://orcid.org/0000-0002-4127-2075

Angela Harris @ http://orcid.org/0000-0002-2184-0274

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