International Journal of Scientific & Engineering Research, Volume 11, Issue 5, May-2020
ISSN 2229-5518

Reviewing the Pertinence of Sentinel-1 SAR for Urban Land Use Land Cover Classification

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Abstract— Conventional approaches for urban land use land cover classification and quantification of land use changes have often relied on the ground surveys and urban censuses of urban surface properties. Advent of Remote Sensing technology supporting metric to centimetric spatial resolutions with simultaneous wide coverage, significantly reduced huge operational costs previously encountered using ground surveys. Weather, sensor's spatial resolution and the complex compositions of urban areas comprising concrete, metallic, water, bare- and vegetation-covers, limits Remote Sensing ability to accurately discriminate urban features. The launch of Sentinel-1 Synthetic Aperture Radar, which operates at metric resolution and microwave frequencies evades the weather limitations and has been reported to accurately quantify urban compositions. This paper assessed the feasibility of Sentinel-1 SAR data for urban land use land cover classification by reviewing research papers that utilised these data. The review found that since 2014, 11 studies have specifically utilised the datasets. The reviewed studies demonstrated that, features representing urban topography such as morphology and texture can easily and accurately be extracted from Sentinel-1 SAR and subjected to state-of-the-art classification algorithms such as Support Vector Machine and ensemble Decision Trees for accurate urban land use land cover classification. Development of robust algorithms to deal with the complexities of SAR imagery is still an active research area. Furthermore, augmentation of SAR with optical imagery is required especially for classification accuracy assessments.

Index Terms— Sentinel-1; Synthetic Aperture Radar; Feature Extraction; Land Use Land Cover; Classification; GIS, Remote Sensing.

1 Introduction

Carbon dioxide, water vapour and industrial gases are highly localised in vegetation biomass and within urban compositions of asphalt, concrete, industrial and automobile fumes, and these gases are responsible for altering the ozone layer's thermodynamic stability and contributing to global climate change effects [1], [2]. Adverse climate change effects to urban dwellers include; increased urban temperatures leading to intensification of urban heat island phenomenon [3], and health hazards resulting from automobile and industrial emissions [4]. Anthropogenic activities are well-known drivers of urbanisation and climate change effects therefore, accurate quantification and monitoring of changes in urban landscapes is an important prerequisite to minimisation of greenhouse gas emissions, sustainable urban planning and climate change management [5]. However, the complexity of urban composition poses a significant challenge that requires flexible and robust Land Use Land Cover Classification (LULC) methods [6]. More so, it is evident that where the LULC method succeeds in one geography, generalisation to another does not yield similar successful results [3].

Recent studies have reported increased influence of Remote Sensing (RS) on urban LULC studies [7]–[9]. Several features that describe urban areas such as the natural and man-made objects, surface morphology, height of objects and textural information, can be recorded and extracted from the RS imagery [10]. Earlier studies suggested that vegetative and geometric features are most effectively extracted from optical imagery and microwave RS imagery respectively [11], [12], thereby requiring fusion of optical and microwave imagery in order to effectively conduct urban LULC study. However, due to susceptibility of optical imagery to adverse weather conditions, recent studies have tested and confirmed the utility of only microwave RS imagery for urban LULC. For example; [13] tested several machine learning algorithms for urban LULC using Sentinel-1 Synthetic Aperture Radar (S1-SAR) datasets over Istanbul and achieved an overall accuracy of 85.17%. Similarity, [14], reported overall classification accuracies of 88.8% when multi-season S1-SAR imagery were used to delineate vegetative areas. Therefore, the significance of RS imagery form S1-SAR cannot be understated.

Although, S1-SAR was recently (first mission in 2014) launched by the European Space Agency (ESA), its Interferometric Wide (IW) swath and dual-polarised channels, provides single source sensor data where significant urban features can be extracted for land-based targets [13], [15]. S1-SAR imagery are also acquired with limited weather interference and independent of solar illumination, with a near-global coverage and operating at centre wavelength of 5.067cm larger than most atmospheric aerosols. Additionally, the optimum spatial resolution of 10m and a 6-day repeat interval, allows for time-series monitoring of urban energy processes such as sprawl, temperature and pollution [4]. Despite the opportunities presented by S1-SAR imagery, there exists limited information about its adoption and generalisation urban LULC domain.

In this review paper, we reviewed journal articles that have been published since 2014. The review aimed to identify papers that have utilised S1-SAR data to extract urban features for urban LULC studies. We relied on the Google Scholar and Web of

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ISSN 2229-5518

Science; which are respectively free and for-profit indexing service, as the source of the review articles. The contributions of this review are; (1) documenting the utility of S1-SAR data for urban LULC since its launch in 2014, (2) determining the features of significance to urban LULC extractable from S1-SAR data, (3) assessing the performance of urban LULC methods using S1-SAR data..

2 Review Methodology

Optimising structured search results on a journal database require customised use of keywords, arranged and concatenated with appropriate wildcards. Our review methodology followed a three-staged process. At onset, computerised search queries were executed, followed by manual abstract review of search results, and concluded with a full review of the paper. In the first-stage, three main keywords for the search strings are targeted namely; (1) Sentinel-1 SAR, (2) urban land use land cover classification and, (3) urban feature extraction.

Table 1. shows the details of search strings and query results. A total of 904 publications were obtained from the two journal

TABLE 1
Structured Queries and Resulting Number of Publications from Google Scholar and Web of Science

Publication Repository	Structured Search Strings	Search Results	Abstract Review Results
Google Scholar	"Sentinel 1 ǀ Sentinel-1 ǀ SAR ǀ Synthetic Aperture Radar" AND "Land Use Land Cover Classification" AND "Feature Extraction"	3	3
	"Sentinel" AND "Land Use Land Cover Classification"	394	
	"Sentinel" AND "Urban Feature Extraction"	12	
Web of Science	(Sentinel 1 OR Sentinel-1 OR SAR OR Synthetic Aperture Radar) AND (Land Use Land Cover Classification) AND (Feature Extraction)	70	37
	(Sentinel) AND (Land Use Land Cover Classification)	393	
	(Sentinel) AND (Urban Feature Extraction)	32	

Note: Queries were executed on 27 Dec 2019

indexing service providers. In the second-stage, focus was narrowed to publications for which at least a LULC task was performed, resulting into 73 publications (3 from Google Scholar and 70 from Web of Science). Upon manual review of the 73 publication abstracts, 40 publications (listed in Reference section) specifically utilised at least a SAR dataset (either; Sentinel-1, RadarSAT, terraSAT, etc) for a LULC and/or feature extraction task. The 40 publications formed the basis for this review paper.

3 Datasets, Case Studies and Test Locations

The use of SAR datasets for earth studies is not a new research paradigm. Enormous archives of SAR imagery from both commercial and open-access SAR satellite missions have existed to date and continues to drive research. Details and reference to resourceful information about SAR missions, data providers and applications are found in [9]. Some notable sources include the European Remote Sensing (ERS-1 & -2), Advanced Synthetic Aperture Radar (ASAR), Spaceborne Imaging Radar-C/X-Band Synthetic Aperture Radar (SIR-C/X-SAR), Japanese Earth Resources Satellite (JERS-1), RADARSAT-1&-2, Advanced Land Observation Satellite (ALOS-1).

However, specific to Sentinel-1 SAR (S1-SAR) datasets, our review revealed limited literature confirming its adoption and

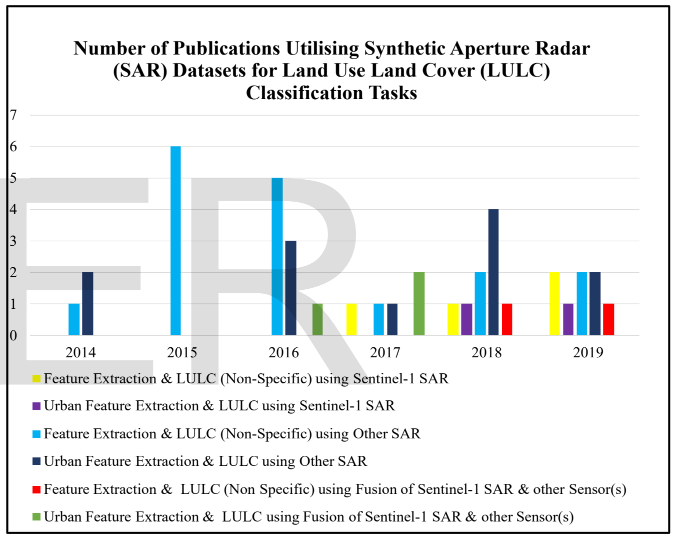

Fig. 1. Number of Publications and their LULC Classification Scopes.

use for urban LULC studies. To date, as shown in Fig. 1 and Table 2, 11 case studies have utilised S1-SAR for feature extraction and/or LULC, of which only 5 are specific to urban LULC. However, Table 2 confirms two significant information about S1-SAR; (i) the flexibility with which S1-SAR can be utilised alongside other datasets and (ii) its ability to be ingested using latest machine- and deep-learning algorithms. These proves that S1-SAR is a new and promising data alternative with great potential to improve accurate characterisation of urban neighbourhoods and quantification of land use and land cover changes.

Notable case studies demonstrating the utility of S1-SAR data include; in Bukina Faso, West Africa and Reunion Island in the Indian Ocean [16], where fusing S1-SAR with optical imagery improved the synergy between spatial and temporal dependencies in tropical climatic conditions for the delineation of built-up areas as well as other LULC classes. Similarly, the utility of S1-SAR datasets in Berlin, Germany, improved the

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accuracy of identifying water, urban and forest covers although at the expense of agricultural land covers [17]. The significance of Berlin case study is that the performance of S1-SAR for LULC classification depended on only the thresholds applied to SAR polarisation rather than the dataset itself. Consequently, a single S1-SAR data can be utilised in different LULC tasks using different thresholds.

Although, vegetation has high reflectance in the optical frequencies thereby requiring optical imagery, stems and branches from high plants have significant scatters in the microwave frequencies allowing for optimal identification and classification as demonstrated in the LULC case of Cameroon [16] and Amazonian forest [18]. One key strength of any LULC task (method or data) is its ability to be generalised from one geography to another with similar results. For S1-SAR, it has been shown that a single city-based LULC task [19] can be generalised to global scale urban LULC tasks [8], [10]without degrading the results.

TABLE 2
REVIEWED ARTICLES THAT UTILISED SENTINEL-1 SAR (S1-SAR) FOR LAND USE LAND COVER (LULC) CLASSIFICATION

LULC Type	Test Location	Datasets	Feature Extraction Methods	LULC Classification Methods	Reference
Urban LULC	Beijing, Chengdu & Nanchang cities of China	S1-SAR, ERS-2 & ENVISAT	KTH-Pavia (combines Spatial Indices and GLCM)	KTH-SEG (classification) & SVM (post-classification)	[2]
	Beirut (Lebanon) & Damascus (Syria)	Landsat, S2 & S1-SAR	Polarimetry equations	RF	[3]
	Istanbul, Turkey	S1-SAR	Polarimetry equations, PCA, KernelPCA and Autoencoder	K-means clustering	[13]
	Tehran, Iran	Landsat-8, ALOS-2 & S1-SAR	Polarimetry, GLCM & PCA	SVM, ML & PCT	[20]
	Global Cities	S1-SAR	Polarimetry, GLCM, & Morphology	Canonical Correlation Forests	[10]
Agric LULC	Northern Xinjiang, China	S1-SAR and S2	Polarimetry, Vegetation Indices & GLCM	CART, RF and SVM	[21]
	Bokito, Cameroon	S1-SAR & RapidEye	Polarimetry, Vegetation Indices & GLCM	RF	[14]
	Papua Region, Indonesia	S1-SAR	Polarimetry equations	Gaussian, kNN, SVM & RF	[1]
	West Java Province of Indonesia	S1-SAR	GLCM	ANN	[19]
General LULC	Koumbia, Burkina Faso & Reunion Island, France	S1-SAR & S2	Deep learning (RF, ConvLSTM, TWINNS & RF_TWINNS)		[16]
	Berlin neighbourhoods, Germany	S1-SAR	Polarimetry & GLCM	Multiresolution Segmentation in eCognition	[17]

4 METHODS FOR URBAN FEATURE EXTRACTION FROM S1-SAR

Urban conurbations are characterised by mixed compositions of man-made metallic and concretised structures as well as plant, water, vegetation and bare land covers. The geometric forms of man-made urban features and biochemical proprieties for other features have different scattering and dielectric properties in the microwave frequency [15]. From the recorded S1-SAR imagery, several urban features can be extracted that accurately classifies urban areas. These features include; (1) textural information describing spatial variations of the urban neighbourhoods, (2) polarimetric information used for retrieval of geometry and dielectric information for urban compositions and (3) morphological profiles of urban scenes that describe physical and socio-economic characteristics of local neighbourhoods [10], [22]. In recent studies, the use of coherence information from dual-polarimetry has led to improved estimation of polarimetric features form S1-SAR imagery [16].

Generally, methods for feature extraction from S1-SAR isolate homogenous pixels along the spatial and grey-level dimensions from single-polarised imagery. However, higher order polarimetry is capable of more detailed characterisation of targets. Consequently, dimension reduction algorithms are adopted prior to extraction of segments [7]. Vector-based dimension reduction methods such as Kernel Fisher Discriminant, Principal Component Analysis and Independent Component Analysis, computes imagery matrix that ignores spatial locations of pixel neighbourhoods [23]. Since coherency and thus multi-polarisations SAR are essential, [24] proposed the use of polarimetric decomposition algorithms such as Pauli, Cloud, Freeman-Durden and Krogager that incorporates pixel proximity information in the decomposition processes. To cope with high SAR dimensions in general (due to multi-polarisation or time-series), a detailed framework was proposed by [25], where the registration and pixel-matching of the slave and master imagery are first attained using progressive binary partitions and subsequently the feature's pixel-level time series and its spatial correlation are matched.

4.1 Local Statistical Feature Extraction

Local neighbourhood statistical parameters such as the mean, median and standard deviation are essential features for describing urban landscapes. Extraction of local statistical features are generally categorised into histogram-based and distribution-based methods [26]. In either method, features such as maximum, minimum, skewness, kurtosis, mean, median, variance, average energy, are extracted from the S1-SAR imagery intensities, by fitting a distribution (e.g. Rayleigh, Gamma, Gaussian, Wishart, etc) on the intensity histogram.

4.2 Textural Feature Extraction

Textural features are constituted from spatial variations of the recorded S1-SAR backscatters due to the heterogenous urban landscapes. Whereas homogeneous fields such as vegetation-covers have textural homogeneity, urban features show varying textural variations. There are several textural feature extraction methods for S1-SAR including; the Neighbourhood Correlation Images (NCI) and Object Correlation Images (OCI) [27] and the Grey-Level Occurrence Matrix (GLCM) method [28]. GLCM is generally is well-known in literature and frequently used for bench matching studies because it is more efficient in reporting correlation degree between pixel pairs in order to ascertain intensity, uniformity, homogeneity and energy among others. GLCM's major limitation is that it focuses on single-dimensional S1-SAR datasets and suffers from difficulty to identify low backscatter urban features from grey-scale. A second drawback of GLCM is its second order statistics nature, thus, it is affected by distance and direction of the neighbourhood pixels. Despite drawbacks, GLCM is a stable and popular textural feature extraction method. To address the drawbacks,

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ISSN 2229-5518

different sets of GLCM statistics should conducted to reflect different distances. Also, Fast Fourier Transform methods such as in [29] has been reported to be more effective for 2D S1-SAR complex image spectra.

A more efficient solution to GLCM's second order statistical problems include the works of [30] which combines GLCM matrices with Multilevel Pattern Histogram (MLPH) features to extract both local and global structural information. In essence, since textural patterns in the imagery have different sizes and intensity levels, MLPH captures the pattern size distributions by a varying intensity-based windows, with similar intensities forming a local structure. The pixel-wise moving window is computationally intensive, therefore, [22] computed feature-specific semi-variogram to obtained variograms of distinct shapes and parameters in advance. The variograms once combined with GLCM matrices in a fuzzy set theory, not only describes the spatial characteristics but also to improves the fuzzy belongings for low backscatter imagery [31].

4.3 Morphological Feature Extraction

Morphological methods are useful for extraction of S1-SAR features at pre-processing stages [10] or removal of "salt and pepper" noises as a post-classification step [22]. In urban settings, where mixed pixel problems are often encountered, the strength of mathematical morphological method as being both pre- and post-processing methods provide the ideal spatial-spectral context of urban neighbourhoods. Central to mathematical morphology method are the opening and closing operations [13]. The standard opening and closing operations are repetitive and uses a customised pixelated structure defined by a radial distance to remove unwanted structures in the case of opening or to fill structural gaps in the closing operation. As a result, the resulting feature sets are often larger than the input image. By using a reconstruction operators methods [10], an enforced opening, eliminates image objects smaller than structuring element without altering the shape of those objects and during closing, the preserved image objects are reconstructed, thereby reducing the number of opening and closing iterations while preserving shape during feature extraction.

4.4 Polarimetric Features.

The multi-polarimetric channels of S1-SAR imagery aids in effective retrieval of shape, orientation, and presence of moisture information from the backscatter coefficients. The standard S1-SAR formula; (1) used for normalised coherence calculations and (2) used for relative phase calculations) are sufficient in extracting polarimetric and coherence information from the Sentinel-1 SAR datasets [1].

$$\left(\frac{\langle S_{VH}S^{*}{}_{VV}\rangle}{\sqrt{\langle |S_{VH}|^{2}\rangle\langle |S_{VV}|^{2}\rangle}}\right) \tag{1}$$

$$actan2(\langle S_{VH}S^{*}{}_{VV}\rangle) \tag{2}$$

Where; $|S_{VH}|^2$ and $|S_{VV}|^2$, are the intensity of the VH and VV channels respectively and the complex conjugates of VH and VV are donated by the asterisk (*).

Although, increased polarimetry lowers the effective spatial purity of the backscatters, the dual-channel polarimetry provided by S1-SAR sufficiently balances the spatial and polarimetric requirements [10], [24]. Also, the dual polarisation allows for accurate discrimination of specular and diffuse surface scatters and as a result, they are essential in describing the urban patches using simple measures such as mean, median, and standard deviation [32].

5 Methods for Urban Land Use Land Cover Classification

Land Use Land Cover Classification (LULC) is an established domain, however the dynamics of human activities and uncertainties in climatic conditions continue to challenge researchers and planners, consequently resulting into new inventions or refinement of existing LULC methods. Common LULC methods operate on pixel basis and therefore termed pixel-based methods. Others, leverage on spatial homogeneities within the imagery to perform segment-based or object-based classification. Both Pixel-based and Object-based methods for LULC, and their hybrid variants are detailed in Reference [17] of [27]. These methods are categorised into supervised, unsupervised or hybrid according to the level of user engagement during the classification process.

5.1 Determination of Classification Classes

The optimal choice of a representative LULC classes is an essential step in the classification process. In its simplest form, LULC classes are binary (presence or absence) however, in urban landscapes where multi-class phenomenon are prevalent, the classes can be determined in several ways including; (i) an advance determination using prior knowledge of the study area or pre-existing data [17], [33], (ii) reliance on standardised class determination schemes such as Local Climate Zone in [10], and (iii) automatic class assignments using natural distribution of features within the imagery such as the use of quaternion autoencoder in [34]. In the works of [35], an automatic assignment of classes is possible in SAR imagery of different scales. Specifically, Table 1 of [35] summarises state-of-art class assignment schemes common with their optimal multiclass categories and hierarchies.

5.2 Pixel-Based Classification Methods

Pixel-based classification methods for SAR imagery follow a two-step procedure that starts with obtaining a difference imagery pixel-by-pixel followed by classifying the target image using change statistics from the difference imagery [27]. The common methods for obtaining difference imagery include; image differencing (3), variants of image ratioing (4), and regression analysis (5). In the case of the former two methods, the difference image ($I_{(x,y)}$) is determined from time-variant reference (I_{master}) and target (I_{slave}) imagery. Whereas for Image regression, ($I_{(x,y)}$) is a linear function of reference image (I_{master}) taken at different time. Although, the use of pixel intensity can be sufficient to obtain the difference image, thresholding the difference image (from image differencing or backscatter coherence or log-ratio intensities) is recommended in order to isolate changing regions from the Threshold Imagery (6). Thresholding method is highly dependent on the applied threshold (τ) and independence of spatial relations of pixels.

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ISSN 2229-5518

$$I_{(x,y)} = |\, I_{master} - I_{slave} \,| \tag{3}$$

$$I_{(x,y)} = \sum_{i,j=1}^{x,y} \left(r1 \left(\frac{I_{master}}{I_{slave}} \right) + r2 \left(\frac{I_{slave}}{I_{master}} \right) \right) \tag{4}$$

$$I_{(x,y)} = a(I_{master}) + b \tag{5}$$

$$\text{For:} \quad T_{(x,y)} = \begin{cases} 1, & I_{(x,y)} \geq \tau \\ 0, & \text{Otherwise} \end{cases} \tag{6}$$

Where;

$\forall r1, r2 \geq 1$; r1 and r2 are independent normalisation constants; a and b are regression parameters of unknowns.

$(i, j) \forall W_{(x,y)} |\, (i, j) \leq (x, y)$; a window (i, j) is applied over each imagery pixel (x, y) recursively.

Furthermore, in pixel-based methods, generation of meaningful classification results requires additional pre-processing and post-processing steps such as filtering, morphology operations and clustering. Also, the effects of speckle noise on low thresholding values are enormous as compared to higher thresholds. However, higher thresholds diminish the number of features detected. Therefore, these methods (Image differencing, ratioing and regression) require careful configurations and are not robust to speckle noise or variations in radar backscatters and patterns of texture.

5.3 Object-Based Classification Methods

Optimal representation of geographical objects within urban structure requires groupings of pixels according to different aspects such as, spatial, temporal, spectral and inhibited geometry [36], [37]. Existence of several LULC classes with variable reflectance, limits the functionality of pixel-based methods. In object-based classification methods, image objects (formed by groups of individual but contextually related pixels) are the functional unit of analysis. These units are richer in information such as texture, shape, and spatial relationships with neighbouring objects. Object-based classification methods typically starts with extracting image-objects, which is achieved by segmentation or stratification of the images that may be applied using external information to like parcel boundaries image segmentation. Once the image-objects have been identified, use of training datasets with the image-objects results into a developed classification hierarchy (a trained model for classification) that can then be applied to the last stage of classification.

Several methods for classification exist to date. These methods are highly dependent on the classification scales (generalised, higher-order or local scales). In a study conducted by [38], rule-based classification algorithm (RB) outperformed other classification methods such as support vector machine (SVM), K-nearest neighbour (KNN) and pixel-based decision tree (DT) in a generalised urban LULC study. However, confirmed by [10], the dependence of RB on categorical datasets and generalised rules generally affects it prediction quality. As such, in cases of local-scales where urban heterogeneity is prominent, SVM, DT and ensemble DT such as Random Forest (RF) and Canonical Correlation Forest (CCF) have been found to improve classification accuracy [10], [24], [39].

Table 3 summarises the recent and state-of-the-art object-based classification methods that utilised SAR datasets for urban land use land cover classification.

TABLE 3
OBJECT-BASED CLASSIFICATION METHODS USING SAR DATA FOR LAND USE AND URBAN LAND COVER CLASSIFICATION

Segmentation Method	Class Determination Method	Classification Method	Reference
Quaternion Autoencoder	Multiclass based on Quaternion Autoencoder	Unsupervised, Quaternion Self Organising Map (SOM)	[34]
SLIC & OPF clustering Texture	Multiclass based on intensities & prior knowledge	Supervised, Multilayer Perceptron ANN	[27]
K-means clustering	Multiclass based on multilevel distribution coding model	Unsupervised, Maximum Likelihood based on Wishart Distribution	[36]
K-means clustering	Multi-class based on intensities and prior knowledge	Unsupervised, Kohonen Method based on Neural Networks and Credal theory	[33]
Tensor Local Discriminant Embedding (TLDE)	Multi-class based on intensities and prior knowledge	Supervised, Nearest Neighbour and Support Vector Machine	[37]

6 CONCLUSIONS

In conclusion, Table 2 summarises the 11 articles out of the total 40 reviewed articles that directly extracted urban features from Sentinel-1 Synthetic Aperture Radar (S1-SAR) datasets for urban Land Use Land Cover (LULC) classification. Although, S1-SAR datasets are mainly used for geometric feature extraction, its utility as a new alternative data source for urban LULC classification is superior. Notable urban features recommended by the reviewed papers for extraction and use in urban LULC classification included; polarimetric, morphological and textural features. This review further identified the use of Local Climate Zone (LCZ) classification scheme for selecting standardised urban classes as effective method that evades the challenge of assigning generalised LULC classes across different urban areas at global scales. In summary, progress in the use of S1-SAR for urban LULC classification is a promising research area however, accurate performance require; (i) choice of more than one classification algorithm such as Support Vector Machine (SVM) and ensemble Decision Trees (DT), given that, there was no agreement on a single superior classification algorithm by the reviewed papers, (ii) the use of a standard class-assignment scheme in which case LCZ was preferred for global or large geographic-based studies, and (iii) augmenting S1-SAR with other high resolution optical imagery was recommended for accuracy assessments. Furthermore, the development of cloud-based supercomputing infrastructures such as Google Earth Engine [40] significantly reduces the bottlenecks of high computational power experienced in urban studies. Given that S1-SAR is currently ingested and accessible in Google Earth Engine, future works should explore the functionality of a single-source supercomputing platform for data ingestion, analyses and customised applications development.

International Journal of Scientific & Engineering Research, Volume 11, Issue 5, May-2020
ISSN 2229-5518

ACKNOWLEDGMENT

The authors wish to thank colleagues and management at the respective affiliated institutions for computing, space and other resources accorded during the period of conducting this work. Special appreciation goes to Alfred Alumai, PhD, through whom, earlier work in urban sprawl assessment (https://doi.org/10.1016/j.ejrs.2018.01.008) supported by Muni University Small Research Grant and Digital Globe Foundation Satellite Imagery Grant, spurred this work and the ensuring researches.

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