

## **The Use of Remote Sensing and GIS for Land Use and Land Cover Mapping in Eswatini: A Review**

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DOI: <http://dx.doi.org/10.4314/sajg.v10i2.13>

### **Abstract**

*Remote sensing and GIS are often used to assess spatiotemporal variations for land use/land cover (LULC) monitoring and classification. While LULC monitoring and classification has been undertaken in Eswatini, little attention has been given to ascertaining covered thematic areas, methods of image classification, and approaches and techniques for improving classification accuracy. This paper summarises and synthesizes the progress made in the Kingdom of Eswatini regarding the application of remote sensing and GIS in LULC monitoring and classification. Eight thematic areas (water resources mapping; land degradation; forestry; wildfire detection; urban expansion; crop production; disease surveillance; general mapping) dominate evaluated LULC studies, employing three LULC classification methods (classic; manual; advanced). While some studies include strengths and weaknesses of LULC classification techniques applied, others do not. This review shows that only two advanced classifiers (random forest; object-based) were identified from the reviewed articles. In addition, reviewed studies applied only two approaches (use of multi temporal data; fine spatial resolution data) and three techniques (use of ancillary data; post-classification procedure; the use of multisource data) for improving classification accuracy. Furthermore, the review finds that limited LULC investigations have been covered in Eswatini with a specific focus on the Sustainable Development Goals (SDGs). As such, this review recommends 1) the inclusion of higher resolution imagery for mapping purposes, 2) the adaptation of strengths and weaknesses for any image classification technique employed in future publications, 3) the use of more varied approaches and techniques for improving classification accuracy and area estimates, 4) inclusion of standard errors or confidence intervals for error-adjusted area estimates as part of accuracy assessment reporting, 5) the application of advanced image classifiers, and 6) the application of Earth Observation (EO) Analysis Ready Data (ARD) in the production of information for the support of the SDGs.*

**Keywords:** *Earth Observation; LULC; classification approaches and techniques, remote sensing and SDGs*

## **1. Introduction**

The continuous monitoring of the Earth's surface through remote sensing technologies is an essential source of spatiotemporal data for deriving useful land use/land cover (LULC) information (Mudau, Mhangara & Gebreslasie, 2014; Phiri & Morgenroth, 2017). Furthermore, the use of land use and/or land cover classification is an important means for monitoring environmental variations. Thematic maps, which are outputs from LULC classification are key for the formulation of effective land management, planning and urban policies (Hlatywayo & Masvosve, 2015; Rimal *et al.*, 2017).

The advancement of technology has resulted in the provision and integration of remote sensing derived data with other forms of data that assist in the production of meaningful information. This is further enhanced by initiatives that provide access to remote sensing (and other) data, such as the automated Landsat data processing system, which facilitates the provision of globally consistent Analysis Ready Data (ARD) for earth observation through an application known as the Global Land Analysis and Discovery Analysis Ready Data (GLAD ARD) tool (Potapov *et al.*, 2020). Furthermore, the notable collaboration between Earth Observation (EO) data scientists and statisticians to produce official statistics offers increasing opportunities for novel future LULC studies globally, including those for the Kingdom of Eswatini (formerly known as Swaziland). Some important contemporary initiatives that promote the integration of EO data and non-remotely sensed data include Digital Earth Australia (Dhu *et al.*, 2017), and Digital Earth Africa (DEAfrica) (Agrawal, 2019). DEAfrica is an advanced technological initiative aimed at providing access to free satellite data, also referred to as EO data at an ARD stage through data cubes. Digital Earth Africa also comes with analytical tools and high-performance computing (HPC) infrastructure meant to facilitate easy access and analysis of large volumes of EO data, specifically Sentinel 2 and Landsat series imagery, without necessarily downloading these to the analysts' local hard drive (Agrawal, 2019). Earth Observation data is part of big data (data that is characterized by high volume, velocity and variety), requiring high management capabilities (Baumann *et al.*, 2015). To demonstrate the relevance of EO data in the production of LULC statistics, the Departamento Administrativo Nacional de Estadística (DANE) in Colombia validated the accuracy of the classification of their study (United Nations, 2017). The validation was performed by creating a confusion matrix for different LULC classes, which showed a precision of 92.5%, 91.4% and 86.8% for the years 2005, 2010 and 2015 respectively at a 95% confidence interval. The authors concluded that the results were satisfactory and that the project has potential to be replicated in other areas. With the advent of DEAfrica, there is a potential for similar studies in future in Africa, including for Eswatini.

In 2015, the United Nations agreed on 17 Sustainable Development Goals (SDGs) (United Nations, 2015). In line with Vision 2022 of the National Development Strategy (NDS) and Strategy for Sustainable and Inclusive Growth 2030 (SSDIG), Eswatini is committed to the implementation of the SDGs, as well as Africa's Agenda 2063 (Ministry of Economic Planning and Development, 2019). In addition to the opportunities presented by the advancement in remote sensing technology and the initiatives promoting access to such technologies and concomitant data (discussed above), there is evidence that many of the global SDGs indicators cannot be successfully measured without the

inclusion of EO data (Paganini, 2018; Walter, 2020), as illustrated by the efforts of the United Nations Global Working Group on Big Data for Official Statistics (United Nations, 2017). Well-managed natural resources ensure sustainable food security (SDG 2), clean water supply (SDG 6), and forest use (SDG 15), among others. For Eswatini, for example, SDG 2 and SDG 6 are a national priority, with SDG 11 a cross cutting issue (Ministry of Economic Planning and Development, 2019), and their achievement can be supported by the use of remote sensing approaches and EO data. In addition, many SDG indicators require high quality, timely and accessible data in order to be achieved (Anderson *et al.*, 2017). Furthermore, EO data provide information for SDGs through the reduction of survey costs while simultaneously providing data at more explicit geographical levels (Paganini, 2018; Walter, 2020), supporting the implementation of the SDGs targets. For example, the Australia Bureau of Statistics has since 2014 used EO data for estimating crop yields and for the production of official environmental statistics, with such statistics ultimately informing SDG indicators (Halderen *et al.*, 2016). In South Africa, the government, aiming to reduce hunger and other deprivations associated with society and the environment (Cumming *et al.*, 2017), monitors and manages its natural and human-built resources partially through the use of EO data and remote sensing methods. For example, Mudau *et al.* (2020) used SPOT 6 satellite imagery to detect built-up from non-built up areas, providing detailed information for monitoring the urban built environment, with such results contributing to, *e.g.* SDG 11. Furthermore, land cover, land use and land cover change are among the statistics that can be derived from EO data (United Nations, 2017).

In Eswatini, various studies on LULC have been undertaken using remote sensing and Geographic Information Systems (GIS). Little work has been done to assess the different methods of LULC classification, thematic areas addressed, and classification accuracy assessments done for such studies completed within Eswatini. This review does not attempt to conduct a review of remote sensing methods, approaches, and classifiers in LULC mapping, since these have been done elsewhere (*e.g.* Costa *et al.*, 2018; Sepuru & Dube, 2018; Bégué *et al.*, 2020). Rather, we summarise and synthesise available remote sensing and GIS studies for Eswatini, identifying the types of classifiers used and how these compare to advanced classifiers found in literature, establishing covered thematic areas, and compare classification approaches and technologies for improving classification accuracy to those of recent literature. Furthermore, this paper contributes towards existing literature and promotes the use of remote sensing and GIS data for LULC investigations in Eswatini, as well as the adoption of these technologies towards realisation of the SDGs (specifically 2, 6, 11, and 15). As such, this paper advances knowledge relating to LULC classification, its uses, applications, and implications in Eswatini, while placing such studies within the context of the SDGs and their realisation.

This paper provides a brief overview of Eswatini (2. Study Area), followed by the results derived from the reviewed articles (3. Review). The identified themes are also presented in this section. This is followed by an evaluation of remote sensing classification methods (4. Classification Methods in Remote Sensing), a discussion of the results and interpretation thereof (5. Discussion), as well as areas of suggested future research (6. Future Directions).

## 2. Study area

Eswatini is a landlocked country located in Southeastern Africa (Figure 1). The country is mostly bordered by the Republic of South Africa on the North, West and partly Southeast. Towards the East, the country borders the Republic of Mozambique. Its approximate land area is 17 364km<sup>2</sup>, lying between latitudes 25°43'S and 27°19'S and longitudes 30°47'E and 32°08'E. The country has four administrative regions and four agro-ecological zones. The agro-ecological zones are based on elevation, topography, geology, and soils, as well as climatic conditions. On average, the country's altitude is 1,200m above sea level. Eswatini has dry winters and wet summers, with the annual rainfall highest in the Highveld (1,000-2,000mm) and lowest in the Lowveld (500-900mm). The Highveld temperature is relatively cold, while temperatures in the Lowveld reach around 40°C in summer (World Meteorological Organization, 2011). With an approximate population of 1.1 million, about three quarters reside in the rural areas where subsistence farming is predominantly practiced (Central Statistical Office, 2017).

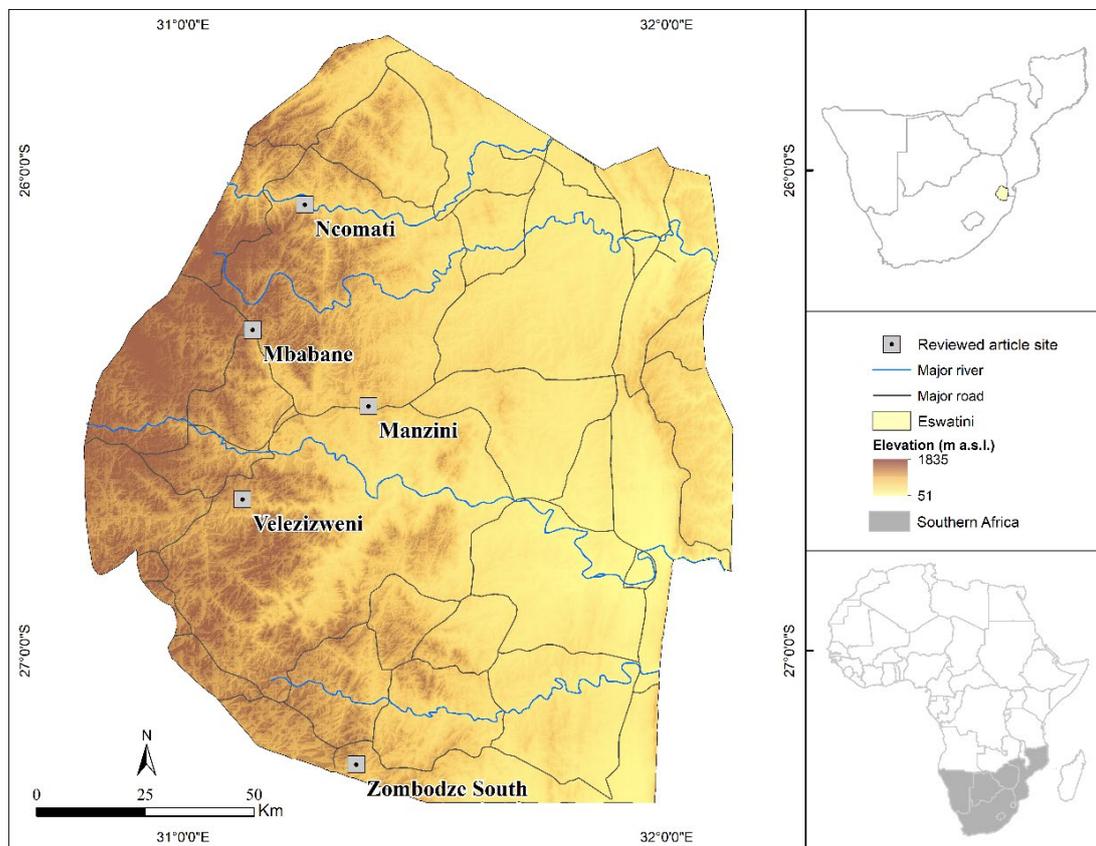


Figure 1. Location of Eswatini, depicting some of the specific study areas from the reviewed articles.

## 3. Review

Table 1 lists evaluated research articles (n=15) focusing on LULC change studies conducted for Eswatini. A majority (n=8), of the reviewed articles used Landsat imagery, three used aerial photographs, two used RapidEye imagery, one used Worldview-2 imagery, and one study used

Moderate Resolution Imaging Spectroradiometer (MODIS) data. Notably, while Radar has some advantages compared to optical remote sensing, including the capacity to acquire images in all weather conditions and day or night (Markert *et al.*, 2018), none of the reviewed articles used imagery from this remote sensing technique. In all the reviewed studies, only one study applied remote sensing classification on land use, whereas 11 studies applied remote sensing classification on land cover, while four studies combined remote sensing classification techniques on both land cover and land use. Seven of the studies applied classic classification, while four used manual classification. The remaining four studies applied advanced classification. These classification categories are explained in Section 4 of this paper.

Only five studies highlighted limitations or implications for future research, while ten did not. Similarly, only four studies made recommendations for future research. In two research papers, the authors recommended that further research should be done to produce more enriched findings on specific subjects, while in the remaining two studies a suggestion to include ancillary data in future studies was made.

This review establishes that LULC classification methods applied by different researchers in the reviewed Eswatini articles can be grouped into three categories (manual, classic and advanced LULC classification), and eight thematic areas that can be broadly classed into natural resource management (1: water resource mapping, 2: land degradation mapping, 3: forestry, 4: wildfire detection), urban monitoring (5: urban expansion), agriculture (6: crop production), health monitoring 7: (disease surveillance), and other mapping (8: general mapping). Manual or visual classification is a result of image interpretation based on recognition of objects, from an aerial view, through the use of visible image properties such as the differences in tones, shapes, texture, sizes, colour and patterns to delineate land cover (Phiri & Morgenroth, 2017). Classic classifiers assume that the dataset has a normal distribution, and that statistical parameters such as the mean vector and covariance matrix generated from the training samples are representative of the sample. As such, classic classifiers are largely dependent on the accuracy of the parameters estimated by the model while the lack of capacity to integrate spectral data with ancillary data is a limitation (Lu & Weng, 2007; Salah, 2017). In comparison, advanced classifiers do not assume that the dataset has a normal distribution, and do not consider statistical parameters to compute class separation. These type of classifiers are suitable for the integration of ancillary data into a classification procedure and for handling complex landscapes (Maxwell, Warner & Fang, 2018). Their categories are explored in Section 4 of this review. The eight identified themes are discussed in greater detail in the subsections below.

Table 1. A list of reviewed articles with variables of interest.

Author(s)	Title	Classification	Type of classifier	Data	Spatial resolution (m)	Temporal resolution (days)	Limitations/gaps mentioned: Yes/No	Implications for future research indicated: Yes/No
		LC/LU/ Both						
Cohen <i>et al.</i> (2013)	Rapid case-based mapping of seasonal malaria transmission risk for strategic elimination planning in Swaziland.	Land cover	Advanced	Landsat ETM	30	16	No	No
Dlamini (2011a)	Application of a Bayesian network for land-cover classification from a Landsat 7 ETM + image.	Both	Classic	Landsat ETM+	30	16	Poor classification of roads and rocks.	Inclusion of ancillary data to improve classification accuracy.
Dlamini (2011b)	Application of Bayesian networks for fire risk mapping using GIS and remote sensing.	Land cover	Classic	MODIS imagery	1	500	BN inability to allow feedback loops.	Real time fire risk analysis possible if there is improved data quality.
Dlamini (2014)	Probabilistic graphical models for feature-based detection.	Land cover	Classic	WorldView-2 imagery	2	1.1	No	No
Dlamini (2017)	Mapping forest and woodland loss in Swaziland: 1990–2015.	Land cover	Classic	Landsat TM and OLI	30	16	No	A need to evaluate forest cover dynamics over longer period to determine drivers.
Dlamini & Mabaso (2011)	Effect of Infrastructural development on land use and cover of urban areas in Swaziland; case of Mbabane.	Both	Manual	Aerial photograph	1:50,000	-	Inaccurate change detection due to poorly produced topographic maps.	No
Dlamini <i>et al.</i> (2015)	Assessing the relationship between environmental factors and malaria vector breeding sites in Swaziland using multi-scale remotely sensed data.	Both	Advanced	RapidEye satellite image	5	1	No	No
Franke <i>et al.</i> (2015)	Earth observation in support of malaria control and epidemiology: monitoring approaches.	Land cover	Advanced	RapidEye satellite image	5	1	No	No

Khalili (2007)	Monitoring of Incomati River Basin with Remote Sensing.	Land cover	Manual	Landsat 7 ETM+	30	16	No	No
Manyatsi <i>et al.</i> (2008)	Mapping of soil erosion using remotely sensed data in Zombodze South, Swaziland.	Land cover	Classic	Landsat ETM and Digital aerial photo	30	16	Field crops classified as moderate vegetation.	No
Mkhabela <i>et al.</i> (2005)	Early maize yield forecasting in the four agro-ecological regions of Swaziland using NDVI data derived from NOAA's AVHRR.	Land cover	Classic	NOAA-AVHRR	1100	16	Limited availability of NDVI data weakened model.	Inclusion of rainfall, temperature and solar radiation could improve model performance.
Muyambi (2016)	Strengthening the National Protected areas system in Swaziland Swaziland Land Cover, Land Cover change analysis and vegetation types for 1990, 2000, 2010, and 2015.	Land cover	Advanced	Landsat TM, ETM and OLI	30	16	No	No
Sidorchuk <i>et al.</i> (2001)	Gully erosion modelling and landscape response in the Mbuluzi River catchment of Swaziland.	Land cover	Manual	Aerial photograph	1:30,000	-	No	No
Tengbeh (2006)	Crime analysis and police station location in Swaziland: a Case study in Manzini.	Land use	Manual	Orthophoto, topographical maps, and street guides.	Un-identified	-	No	No
Tfwala <i>et al.</i> (2012)	Assessment of Land Degradation at Velezizweni, Swaziland.	Land cover	Classic	Landsat ETM	30	16	No	No

### **3.1. Water resources mapping**

Different LULC classification methods have been used for monitoring and identifying water resources using remotely sensed data in various countries (e.g. Kaplan & Avdan, 2017). Mapping water resources using EO data can improve information generation in areas where there are limited infrastructure resources for *in situ* measurements and instruments. In Eswatini, Khalili (2007) manually digitised the extent of the reservoir of the water body at Incomati River Basin using Landsat Enhanced Thematic Mapper plus (ETM+) imagery. While manual digitisation is a time-consuming process, the researcher argued that it minimises classification errors. The digitised output was validated with water level data obtained from the Department of Water and Sanitation of South Africa (Khalili, 2007).

### **3.2. Land degradation mapping**

This theme focuses on using remote sensing and GIS technologies to monitor and quantify land degradation (e.g. Mararakanye & Nethengwe, 2012; Ahmad & Pandey, 2018). In a study to assess land degradation at Velezizweni, Tfwala, Manyatsi & Wang (2012) used Landsat ETM+ imagery and aerial photography to manually digitise training data polygons for the development of different land cover spectral signatures. In Zombodze South, Manyatsi & Ntshangase (2008) used both reflectance and Normalized Difference Vegetation Index (NDVI) values to determine the extent of land degradation. These authors provided producer's accuracy and user's accuracy values for all the different classes in addition to a KHAT statistic of 78%, attributing inaccurate classification of field crops to the medium spatial resolution of the ETM+ imagery used. Improvements in spatial resolution of the latest satellite platforms such as PlanetScope (3-4 m resolution) will ensure that crop fields can be mapped with higher accuracies, thus, providing useful information such as agricultural statistics that can assist the government to improve policy implementation and food security.

### **3.3. Forestry**

LULC mapping with a forestry application makes use of satellite data captured through different remote sensing sensors to monitor, classify, and quantify forest coverage (Wulder, 1998). In mapping forest and woodland loss for the period 1990-2015 in Eswatini, Dlamini (2017) used Carnegie Landsat Analysis SystemLite (CLASlite) software to extract data from satellite images to identify forest from non-forest areas and used Google Earth™ images in the validation process. While the classification was successful, Dlamini (2017) suggested a need to evaluate forest cover dynamics over a longer period to determine the spatiotemporal developments and their drivers.

### **3.4. Wildfire detection**

EO data derived from remote sensing rather than field surveys is now commonly used to map the occurrence of fire on grasslands ecosystems (Buthelezi *et al.*, 2016). In Eswatini, Dlamini (2011b) applied a Bayesian Network (BN) model, a supervised classification parametric artificial intelligence (AI) approach, to map fire risk areas. The author enhanced the classification process by including additional data such as altitude, soil class, annual temperature, mean annual rainfall, and other data. Dlamini (2011b), as already noted by Korb & Nicholson (2004), stated that strengths of the BN model include its capacity to use incomplete datasets and its cost effectiveness. However, the BN model is unable to allow for feedback loops, and Dlamini (2011b) concluded that with the improvement of data collection, near real time fire risk analysis could be possible in future. Advanced Fire Information System (AFIS) and Global Wildfire Information System (GWIS) are examples of existing fire detection systems.

### **3.5. Urban expansion**

Satellite data can be applied to the monitoring of urban expansion (*e.g.* Mohammadian, Tavakoli, & Khani, 2017). In order to determine the extent of the result of development caused by infrastructure on land use and land cover in Mbabane, Dlamini & Mabaso (2011) used scanned topographic maps and a set of colour aerial photographs to manually digitise different LULC within the Mbabane city boundary for the years 1976, 1992, and 2006 through ArcMap 9.3. The authors, as already noted by Kraak & Ormeling (2003), highlighted the reliability of on-screen manual digitisation, but also acknowledged its tedious and time-consuming nature. Furthermore, the topographic maps used for digitisation contained inconsistencies that subsequently resulted in poor classification and inaccurate change detection analysis.

### **3.6. Crop production**

Geospatial technologies are now commonly used in precision management of agricultural crops (*e.g.* Panda, Hoogenboom, & Paz, 2010). In Eswatini, Mkhabela & Mashinini (2005) utilised NOAA, AVHRR, NDVI data for forecasting maize yield in the four ecological zones of the country. Mkhabela & Mashinini (2005), as already noted by Baez-Gonzalez *et al.* (2002), acknowledged that the presence of atmospheric effects associated with satellite images had negative implications on the analysis. The authors also cited limited availability of NDVI data for the country as a factor that weakened their model, noting that the model could be improved by including more NDVI and maize yield data. They further recommended the inclusion of additional data on rainfall, temperature, and solar radiation. These datasets can be easily obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) World Radiation Data Centre (WRDC), National Aeronautics and Space Administration (NASA) and other sources. For instance, Zhang *et al.*, (2016) successfully compared reanalysis climate data with surface observations using data from the ECMWF.

### **3.7. Disease surveillance**

Here advances in remote sensing and GIS are used to apply geospatial tools to public health related studies (Dhewantara *et al.*, 2019). In Eswatini, Cohen *et al.* (2013) used a gridded 100m resolution population map and Landsat ETM image to map seasonal malaria transmission risk areas. The researchers used NDVI and Normalized Difference Water Index (NDWI) (classic classification methods) to identify water bodies (potential breeding sites for malaria vectors), using GIS to establish the potential risk areas for malaria transmission. In a different study to support malaria control and epidemiology monitoring using EO, Franke *et al.* (2015) conducted land cover classification using eCognition software, applying the advanced classification method of object-based supervised classification. Accuracy assessment was done to validate the classification technique and an overall accuracy of 80.7% and Kappa coefficient of 0.78 were provided. Similarly, Dlamini, *et al.* (2015) used high resolution RapidEye satellites imagery, land surface temperature and emissivity, rainfall estimates (RFE), and digital elevation model (DEM) datasets to create LULC classification in the malaria-endemic regions of Eswatini, by applying the advanced classification method of object-based supervised classification. The authors further supplied an overall accuracy of 80.7% and a Kappa coefficient of 0.78 for the classification of water bodies and wetlands.

### **3.8. General mapping**

The final theme concerns itself with the mapping of various land cover types and land use changes (*e.g.* Szabó *et al.*, 2019). In a study in Eswatini, Dlamini (2011a) applied the BN model on Landsat 7 ETM+ images to perform LULC classifications. Dlamini (2011a) noted that the BN model can indicate which variable contributes most to the classification accuracy, is able to classify medium spatial resolution with little confusion and misclassification, and is easy to program and adopt to other remote sensing problems. However, Dlamini (2011a), as already noted by Jensen (2001), stated that the BN model requires continuous data to be discretized first, and that the model could not accurately classify some roads or granite rocks, as already observed by Stefanov *et al.* (2001) and Herold *et al.* (2003), due to the similarity of spectral signatures with roofing materials of buildings. The author recommended the inclusion of additional data such as DEMs or texture information for future studies, arguing that these could improve classification accuracy. In another study by Dlamini (2014), the BN model was used to successfully classify invasive alien plants in Eswatini using Worldview-2 imagery. The success of the BN model classification approach lay in its probabilistic strength to identify unique phenological or reflectance values based on spectral properties, allowing for the differentiation of individual plant species. Dlamini (2014) concluded that the findings of his study could be applied to broader applications in remote sensing.

Muyambi (2016) in turn employed object-based classification and on-screen manual digitisation on Landsat TM, Landsat ETM+, and Landsat OLI imageries to generate a land cover classification for years 1990, 2000, 2010 and 2015 and ending by performing change detection analysis for different land cover features. Muyambi (2016) further performed accuracy assessment, which employed high-

resolution Google Earth™ imagery and a ground truthing exercise as a map reference. An overall accuracy of 85.71% and a Kappa coefficient of 83.86% for the 2015 land cover classification map were provided. However, the author indicated that this approach generally requires the researcher to have thorough knowledge about the study area. Figure 2 is a 2015 land cover map for Eswatini generated by Muyambi (2016). In comparison, Tengbeh (2006) used visual and manual classification techniques to identify different land use classes in a study aimed at analysing crime and police station location in Manzini, Eswatini. In digitising the different land use classes through ArcGIS, Tengbeh (2006) used topographic maps, digital street guides, aerial photographs, and direct field observation. Finally, the researcher created nine land use feature classes.

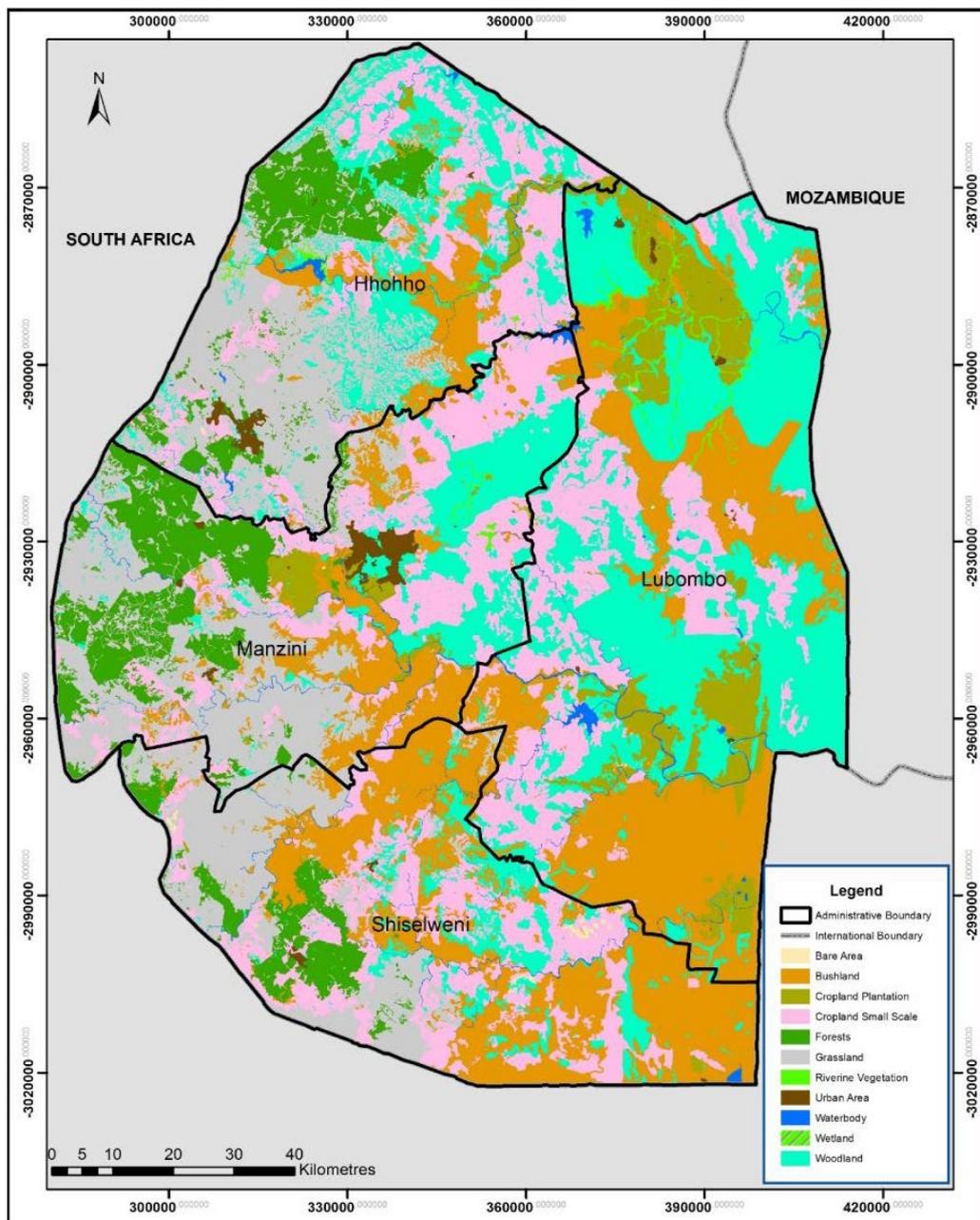


Figure 2. Eswatini land cover 2015. Source: (Muyambi, 2016).

#### **4. Classification methods in remote sensing**

Land use and / or land cover classification methods may be grouped into five categories, which can be further aggregated into three classifications methods. The five LULC classification methods are pixel-wise, sub-pixel, per-field and object-based classification; soft and crisp classification; parametric, non-parametric and non-metric classification; spectral, contextual and spectral-contextual classification; and supervised, unsupervised and hybrid classification. The three LULC classification methods are classic, manual, and advanced. These have already been discussed in Section 3. In this section, special attention is given to advanced classifiers, as applicable to even complex landscapes, and research shows that advanced image classifiers produce better results compared to classic classifiers (Huang *et al.*, 2002; Rogan *et al.*, 2003).

The need to provide LULC classification even in heterogeneous landscapes and the desire to improve classification accuracy output from remotely sensed data has resulted in the development of advanced classifiers. Based on literature (Lu & Weng, 2007; Nath *et al.*, 2014, Prasad *et al.*, 2015), this review has grouped these advanced classifiers into six categories namely 1) pixel-based algorithms, 2) subpixel algorithms, 3) per-field algorithms, 4) contextual based approaches, 5) knowledge-based algorithms, and 6) combinative approaches of multi classifiers. Examples of advanced pixel-based classifiers include non-parametric classifiers such as Support Vector Machines (SVM) and Random Forest (RF). These classifiers, unlike parametric classifiers, do not assume that the data set has a normal distribution, and they have the capacity to incorporate non-spectral data into a classification procedure (Maxwell *et al.*, 2018).

Subpixel classifiers were developed for providing a more suitable representation and accurate estimation of land features, which pixel based approaches cannot efficiently handle because of the mixed pixel challenge (Kamavisdar, Saluja & Agrawal, 2019). Per-field classifiers, unlike the per-pixel approach, which group each pixel into a specific category, use land parcels as individual units using vector data (referred to as fields). This approach addresses the problem of environmental heterogeneity (Lu & Weng, 2007). Contextual-based approaches have been designed to address the intra-class spectral variation challenge. As such, this approach improves classification results by making use of spatial information from neighbouring pixels (Lu & Weng, 2007). Knowledge-based classifiers group land cover types by considering auxiliary data, such as slope, aspect, DEMs, soil data, as well as housing and population density. The process involves developing rule sets with specific binding thresholds to determine the class of a particular land cover type (Lu & Weng, 2007). Combinative approaches of multi-classifiers are based on the premise that different classifiers have their own strengths and limitations, and studies have confirmed that the combination of different approaches or classifiers can contribute to the quality and accuracy of land cover classification (Phiri & Morgenroth, 2017). When this approach is used, it is important to develop suitable rules for combining the classification results obtained through different classifiers. Such rules include production rules, majority voting, a sum rule, and stacked regression methods (Lu & Weng, 2007).

In addition to using advanced classifiers, research indicates that specific approaches are used by different researchers in the remote sensing community to improve classification accuracy. This review established six approaches for improving classification accuracy. These are the use of textures, fusion of multi sensor or multi resolution data, use of multi-temporal data, image transforms, fine spatial resolution data, and hyper-spectral data (Lu & Weng, 2007; Prasad *et al.*, 2015). Use of texture refers to the consideration of the placement and spatial arrangement of recurrence of tones, which essentially describes how pixels vary in a neighbourhood (Jensen, 2009). For instance, texture metrics improve classification accuracy since they mitigate spectral confusion where there are spectrally similar classes (Carleer & Wolff, 2006). Fusion of multi sensor or multi resolution data in remote sensing is the process of integrating imagery with different bands or different resolutions to produce one image containing more detailed information than each of the original sources (Zhang, 2020). There are indications that this procedure enhances classification accuracy (Hedhli *et al.*, 2017). Multi-temporal data refers to data that have been captured at different time intervals. Research indicates that the use of high temporal resolution data result in improved classification accuracy, particularly where vegetation classification is required (Zhang, 2020). Image transforms such as Principal Component Analysis (PCA), minimum noise fraction, and others are important techniques for feature extraction, reducing dimensionality of datasets, and improving classification accuracy, especially with high resolution datasets (Salah, 2017). Fine spatial resolution data such as QuickBird provide an opportunity for extracting more detailed information on different LULC features because it reduces the mixed-pixel problem. However, the analyst should ensure that challenges associated with fine spatial resolution such as shadows caused by tall building, topography and trees are well handled. Hyperspectral data is imagery with multiple bands. Such imagery have a potential of improving classification accuracy, especially where numerous bands have an effect in discriminating the classes of interest (Lu & Weng, 2007).

Research also indicates that there are specific techniques applied to enhance classification accuracy of remotely sensed data. These are the use of ancillary data, stratification, post classification processing and the use of multisource data (Salah, 2017). Examples of ancillary data include topography, soil, road, and census data. However, caution has to be taken when identifying the variable that is most effective in separating land-cover classes (Peddle & Ferguson, 2002). Stratification may be useful in improving classification accuracy. For instance, census data can be used to create different strata (Prasad *et al.*, 2015), and this may be done as a pre-classification step, during classification, and as a post-classification procedure (Lu & Weng, 2007). The post-classification process is another technique that can be applied to enhance classification accuracy. For instance, Prasad *et al.* (2015) used housing density data for improving their initial classification output. Lastly, the use of multisource data also assist in improving classification accuracy, and it requires different classification approaches such as knowledge based or fuzzy contextual classification (Lu & Weng, 2007). Multisource data refers to the involvement of data from different sources such as combining digital elevation models, soil, spectral data, texture data and existing GIS-based maps from different sources (Prasad *et al.*, 2015). Table 2 provides a summary of advanced

classifiers, and these have been grouped into the six categories that have been explained above. Specific examples of advanced classifiers are provided as well as the frequency they appear in the reviewed articles and their references where applicable. In addition, the table provides categories of approaches for improving classification accuracy, the frequency at which they appear in the reviewed articles, the data used for improving classification accuracy and references where applicable. Table 2 illustrates that only two advanced classifiers and two approaches for improving classification accuracy have been applied in the reviewed Eswatini remote sensing and GIS reviewed articles.

Table 2. Categorization of classification methods and examples of advanced classifiers for each method together with approaches for improving classification accuracy and the frequency at which each classifier (Column 3) and approach (Column 6) appear in the reviewed articles.

Classification method Category	Advanced classifier	Freq (class.)	Ref	Improving classification accuracy	Freq (appr.)	Improving classification accuracy	Ref
Pixel-based algorithms	Support Vector Machines	0	-	Use of textures	0	-	-
	Random Forest	1	Cohen <i>et al.</i> (2013)				
	Multiple Endmember Spectral Mixture Analysis	0	-				
Subpixel algorithms	Fuzzy Classifier-Visual Attention Feature	0	-	Fusion of multi sensor or multi resolution data	0	-	-
	Expert knowledge	0	-				
	Decision rule	0	-				
	Parcel based classification	0	-				
Per-field algorithms	Object based classification	3	(Dlamini <i>et al.</i> , 2015; Franke <i>et al.</i> , 2015 & Muyambi, 2016)	Use of multi temporal data	3	MODIS, RapidEye and WorldView-2 imagery	(Dlamini <i>et al.</i> , 2015; Dlamini, 2014 & Franke <i>et al.</i> , 2015)
Contextual based approaches	Iterative Context Forest	0	-	Image transforms	0	-	-
	Extraction and Classification of Homogeneous Objects	0	-				
Knowledge-based algorithms	Rule-Based Classification	0	-	Fine spatial resolution data	3	MODIS, RapidEye and WorldView-2 imagery	(Dlamini <i>et al.</i> , 2015; Dlamini, 2014 & Franke <i>et al.</i> , 2015)
	Knowledge-Based Classification	0	-				
Combinative approaches of multi classifiers	MLC, ISODATA and DT	0	-	Hyper-spectral data	0	-	-

Classification method Category	Advanced classifier	Freq (class.)	Ref	Improving classification accuracy	Freq (appr.)	Improving classification accuracy	Ref
	Artificial Neural Network and Expert Knowledge	0	-				

## 5. Discussion

Since there are only eight thematic areas that were identified in the reviewed articles, this article suggests that future research should investigate, using remote sensing and GIS, the unexplored topics. In addition, The United Nations (2017) promote the application of remote sensing in producing data for monitoring and supporting the implementation of SDGs. As such, in addition to the use of remote sensing and GIS in enhancing the production of SDGs related information, potential themes for investigation include geological mapping and identification of mineral surface deposits, mapping of soil types, human settlement mapping, soil moisture mapping (Harris, 1998), and climate change (Yang, Fu, Chen, & Xu, 2013).

From the examples of some of the advanced remote sensing classifiers shown in Table 2, only two were used in the reviewed articles. These are random forest (Cohen *et al.*, 2013), which fall under advanced per-pixel category, and object-based classification (Dlamini *et al.*, 2015; Franke *et al.*, 2015; Muyambi, 2016), which falls in the group of per-field algorithms. Advanced classifiers from the remaining classification method categories, such as sub-pixel algorithms, contextual-based approaches, knowledge-based algorithms, and combinative approaches of multi classifiers categories have not been identified in any reviewed articles. These can be explored in future research.

This review has established that out of the six suggested approaches for improving classification accuracy discussed in this article, only two of these were applied (the use of multi-temporal, and the use of fine spatial resolution data). The multi-temporal approach was illustrated through the use of WorldView-2 imagery with a temporal resolution of 1.1 day and RapidEye imagery, 1 day temporal resolution (Dlamini *et al.*, 2015; Franke *et al.*, 2015), and MODIS data with a 2 days temporal resolution (Dlamini, 2014). The use of fine spatial resolution data was demonstrated using RapidEye imagery, 5m spatial resolution, and the use of WorldView-2 imagery, 2m spatial resolution (Dlamini *et al.*, 2015; Franke *et al.*, 2015). Other approaches for improving accuracy classification discussed in this review including the use of textures, fusion of multi sensor or multi resolution data, image transforms, and hyper-spectral data have not been identified in the reviewed articles.

Among the techniques for improving classification accuracy discussed, three were implemented in the reviewed articles. These are the use of ancillary data, post-classification procedure and the use of multisource data. Cohen *et al.* (2013) used ancillary data including rainfall, temperature, elevation, and other data sets. Franke *et al.* (2015) used land cover map, wetlands, population density, malaria incidence and other data sets to improve accuracy classification in a study for malaria control, while Dlamini (2011b) included 13 ancillary datasets (such as altitude, slope angle, slope aspect, mean

annual rainfall, mean annual temperature, relative humidity) that enhanced classification in a study for fire risk mapping. Franke *et al.* (2015) computed the NDVI as a post-classification procedure to improve classification accuracy. On the use of multisource data, Franke *et al.* (2015) included, RapidEye satellites imagery, Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER), GeoEye-1, and IKONOS-2, rainfall estimates, DEMS, surface temperature, and emissivity datasets in the study on Earth observation in support of malaria control and epidemiology. Still on the use of multisource data, Dlamini, *et al.* (2015) used RapidEye satellites imagery, land surface, temperature and emissivity, rainfall estimates, and DEM datasets. However, the stratification technique for improving classification accuracy, one of the suggested techniques for improving classification accuracy, has not been applied in any of the reviewed articles.

The review further shows that some authors were able to demonstrate that different LULC classification approaches employed have different strengths and weaknesses. Referring to the strengths of the BN model, Dlamini (2011a) noted its cost effectiveness and capability to use incomplete datasets. He also observed that it is able to separate spectral signatures for individual plant species (Dlamini, 2014). Researchers that used manual digitisation, (Khalili, 2007; Dlamini & Mabaso, 2011), rated the manual method as the most accurate compared to the other methods. Inaccuracies in the various LULC classifications outputs were a result of the medium spatial resolution of Landsat ETM+ imagery (Manyatsi & Ntshangase, 2008) as well as the general atmospheric effect associated with satellite images, and limited availability of NDVI data (Mkhabela & Mashinini, 2005). The inability of the BN model to separate spectral signatures for roads and rocks from those of roofing materials for building (Dlamini (2011a) also caused poor LULC classification.

Several authors provided information on the validation of their LULC classification outputs. Khalili (2007) used a different data source as ground truth data for water levels for the Incomati River Basin (including Maguga Dam). In validating the LULC classification outputs, various authors (Manyatsi & Ntshangase, 2008; Dlamini, 2011a; Dlamini, 2011b; Dlamini, *et al.*, 2015; Franke *et al.*, 2015; Muyambi, 2016; Dlamini, 2017) provided either the overall accuracy and Kappa coefficient values or the kappa coefficient values only. However, not all authors provided such measures, a trend already noted by Costa *et al.* (2018). Furthermore, in addition to these measures of accuracy, Olofsson *et al.* (2013) argue that computing standard errors or confidence intervals for error-adjusted area estimates where land cover and / or land cover change has been mapped should also be included, since this quantifies the uncertainty attributable to sampling variability, which should be taken into account by users of the final classification map. Olofsson *et al.* (2013) further cite researchers such as Card (1982) and Stehman and Foody (2009), who have published methods and formulas for accuracy estimates and the standard errors for area estimation. Figure 2 is a typical LULC map extracted from one of the reviewed articles (Muyambi, 2016). Olofsson *et al.* (2013) argue that such maps should be presented together with accuracy assessment quantifiers including standard errors or confidence intervals for error-adjusted area estimates. Notably, in all the reviewed articles none of the researchers provided error-adjusted area estimates as part of their accuracy assessment reports. Nevertheless, some of the authors for the reviewed articles made recommendations for future studies.

Dlamini (2017) and Mkhabela, & Mashinini (2005) suggested that additional data such as DEMs, rainfall, temperature, and solar radiation should be included in future studies to enhance the accuracy of LULC classification. Lastly, Dlamini (2014) recommended that findings from his study that classified invasive alien plants could be applied to broader applications in remote sensing.

The remote sensing community has explored and continues to explore different types of remotely sensed images in working toward providing improved LULC classification results. Remote sensing images that have been explored for improving LULC classification include Radar remotely sensed imagery, fused imagery, hyperspectral imagery, and Very High-Resolution imagery (VHR). Optical remotely sensed imagery is unable to capture usable images during adverse weather conditions or at night. Furthermore, low resolution optical imagery exhibits the mixed pixel problem, and the similarities of spectral reflectance on landscape associated with optical images features are problematic (Muthukumarasamy *et al.*, 2019). In comparison, Synthetic Aperture Radar (SAR) imagery captures imagery based on the geometry instead of the reflectance of the target features, overcoming some of these issues inherent to optical imagery (Muthukumarasamy *et al.*, 2019). Furthermore, Krishna *et al.* (2018) argue that hyperspectral remote sensing is a solution to the problem of mixed pixels and spectral similarity associated with optically derived imagery, due to the numerous bands of hyperspectral data that provide spectral information per pixel, allowing for the discrimination of feature classes, yielding improved LULC classification accuracy. However, this imagery comes with high dimensionality and huge volumes of data resulting in the Hughes phenomenon (Christovam *et al.*, 2019). In addition, hyperspectral imagery is relatively difficult to process compared to multispectral imagery, demanding bigger storage capacity (Zhang & Sriharan, 2005). Regardless, such imagery can yield improved accuracy relating to LULC classification.

Krishna *et al.* (2018) further indicate that the development of VHR remotely sensed imagery enables the extraction of detailed level LULC information, yielding improved classification accuracy. Improved results have also been observed in the use of fused imagery. For instance, Zhang *et al.* (2020), argue that the advantages of imagery produced through fused optical and SAR images is that specific features not clearly detected on passive sensor imagery may instead be relatively observable and delineated on microwave imagery and *vice versa*. This is because of the complementary characteristics of the different sensors involved, yielding a sharpened and improved geometrically corrected imagery (Amarsaikhana *et al.*, 2010).

In addition to extracting LULC information from various types of remotely sensed imagery, researchers have applied diverse techniques for producing LULC maps that have improved accuracies. These techniques include applying object-based classification instead of pixel based, utilizing non-parametric classifiers, and machine learning ensemble classifiers. In a study conducted by Ai *et al.* (2020), the researchers applied object-based classification, a method that considers contextual information. The researchers noted that object-based classification produced better-quality maps compared to traditional pixel-based classification, while Robertson *et al.* (2011) state that object based methods are increasingly applied in LULC classification because of their superiority over pixel-based methods. However, object-based classification is often associated with image segmentation

(over- and under-segmentation). Where under-segmentation has occurred, the resultant image objects cover more than one class, causing classification errors. On the other hand, over-segmentation yields misrepresentations of the real earth object (Liu & Xia, 2010). Regardless, object-based classification yields improved classification compared to pixel-based methods.

Non-parametric classifiers (RF or SVM), also produce improved classification compared to traditional classifiers such as Maximum Likelihood, Minimum Distance, and others (Breiman, 1996). Furthermore, machine-learning ensemble, a technique that combines different machine learning classifiers such as RF and SVM, is also being increasingly utilised because of its superiority over single base classifiers. For instance, Vasilakos *et al.* (2020) compared classification results from SVM, RF, K-Nearest Neighbour (KNN), and Artificial Neural Networks (ANN), and concluded that in cases where no classifier clearly performed better than others, the ensemble approach was the best alternative.

The types of remote sensing images and techniques discussed above undoubtedly contribute to increased LULC classification accuracy and LULC work completed for Eswatini would improve through the application of such imagery and techniques. Furthermore, Eswatini researchers can adopt the highlighted techniques on local data to produce novel LULC classification results based on Eswatini context. While the types of images and applied techniques referred to have their limitations, Eswatini researchers can adopt such for future studies and explore means of mitigating their weaknesses.

Based on the sources of remote sensing data mentioned by different authors in the reviewed articles, there is a need for the remote sensing and GIS community in Eswatini to prepare an EO data hub. Preparations for emerging EO data initiatives such as DEAfrica and other big data initiatives that promote the production of useful local, regional, and global information are critical for future research purposes. The main aim behind DEAfrica is to assist potential but disadvantaged EO data users – those that lack the capacity, infrastructure, and appropriate internet bandwidth to access and subsequently process EO data (United Nations, 2017). The United Nations (2017) also noted that where expertise to handle EO data exists, the data are limited to a small number of users, subsequently limiting the use of EO data. This situation has necessitated the need to provide EO data at ARD stage, through initiatives such as Digital Earth Australia (Dhu *et al.*, 2017), DEAfrica (Agrawal, 2019), and others. Even with such initiatives in place, several EO data users may still lack reliable Internet connection to access EO ARD. To mitigate this challenge, once EO ARD become available for Eswatini, it is recommended that the data should be downloaded through automated systems to big-capacity local servers, such as those available at the National Data Development Center (NDDC) located at the Surveyor General's Department, where all interested users may freely access the data. Different government departments, researchers and other private consultants may thus benefit from this EO data hub. Furthermore, EO can also be adopted by the Ministry of Education and Training where EO data and applications can form part of the secondary school curriculum. This can assist Eswatini in taking advantage of the Fourth Industrial Revolution, which is characterized by big data and data analytics.

This review notes that among the four reviewed articles published in 2015 and onward, no LULC study was done to explicitly provide information on different SDGs nor their indicators. Paganini (2018) states that using EO data for SDGs information is useful in producing timely statistical reports, reduction of survey frequencies, and provision of data at more explicit geographical levels. Specific SDGs that require the use of remote sensing include SDG 2-Hunger and Food security, SDG 6-Water and sanitation, SDG 11-Cities, SDG 13-Combating climate changes, SDG 14-Marine and coastal ecosystems, and SDG 15-Terrestrial ecosystems (United Nations, 2017). Friedl (2016) notes that out of the 17 SDGs, 14 have indicators that need information from EO data, and such information can be derived through LULC mapping. Specific SDGs indicators that can directly benefit from LULC mapping using EO data include, but are not limited to, SDG 2, indicator 2.4.1 *Proportion of agricultural area under productive and sustainable agriculture*; SDG 6, indicator 6.6.1 *Change in the extent of water-related ecosystems over time*; SDG 11, indicator 11.3.1 *Ratio of land consumption rate to population growth rate*; and SDG 15, indicator 15.2.1 *Forest cover under sustainable forest management*. In future, Eswatini researchers should take advantage of already established international EO initiatives and combine these with other data sets in the production of information required by national development programmes and global frameworks, such as the SDGs. For instance, the Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) is a global initiative that conducts monthly reports on four main crop conditions in main production areas and potential countries with food insecurity (Anderson *et al.*, 2017). These reports utilise satellite, *in-situ*, and ancillary data. Furthermore, the University of Maryland (USA), which is part of the global forest watch initiative of World Resources, has developed an EO-based methodology that informs SDGs indicators 15.1.1 and 15.2.1. Peru has adopted this methodology for official reporting (Anderson *et al.*, 2017). Other studies on the adoption of EO data in support of SDGs include evaluating the fraction of the population with convenient access to public transport (Moller, 2016), and determining the number of households with access to basic services in Mexico (Ocampo, 2016).

Like in any country, different sectors or departments working on SDGs in Eswatini can thus benefit from LULC mapping using EO data. With a specific focus on Eswatini, SDG 2 can be supported by information management systems for effective planning (Ministry of Economic Planning and Development, 2019), achievable using LULC mapping and EO data. Eswatini aims to achieve the reduction of Malaria (SDG 3), something that can be done through remote sensing as demonstrated by Cohen *et al.* (2013), Dlamini, *et al.* (2015), and Franke *et al.* (2015). Monitoring of water resources, including wetland areas in support of SDG 6, can further be achieved using remote sensing approaches, including those of LULC mapping. With reference to SDG 6, an area of support identified is sanitation and hygiene mapping (Ministry of Economic Planning and Development, 2019), which can be supported by EO data derived from remote sensing. As such, LULC studies can explicitly contribute to the achievement of the SDGs and associated indicators for Eswatini. Furthermore, the above indicators and goals are a responsibility of different sectors that can clearly benefit from the use of EO data in support of SDGs indicators in Eswatini. The proposed EO ARD hub at the NDCC can be used to assist in the realisation of such goals.

## **6. Future directions**

Based on results derived from this review, LULC exercises should use emerging high spatial satellite images, such as Sentinel and PlanetScope for future research. The use of Radar remotely sensed imagery and the fusion of radar and optical imagery is also encouraged since literature indicates that these imagery types and data fusion approach enhance LULC classification accuracy.

Researchers are further encouraged to provide, where possible, weaknesses and strengths for any LULC classification methods or techniques applied in their research to assist future researchers to minimise those weaknesses. This includes the inclusion of computation of standard errors or confidence intervals for error-adjusted area estimates as part of accuracy assessment reporting. The adaptation of some of the advanced image classifiers such as Support Vector Machines, Multiple Endmember Spectral Mixture Analysis, Knowledge-Based Classification, and Combinative Approaches of Multi Classifiers are also recommended for future studies.

Once EO ARD becomes available for Eswatini, automated systems that will download the data into big-capacity local servers, such as those available at the National Data Development Center (NDDC) located at the Surveyor General's Department, are recommended to facilitate free and easy access to EO data. EO related topics are recommended to the Ministry of Education and Training where EO data and applications can form part of the secondary school curriculum. This will assist Eswatini to take advantage of the Fourth Industrial Revolution, which is characterised by big data and data analytics.

Lastly, based on the findings, this review, recommends undertaking of future studies on geological mapping and identification of mineral surface deposits, mapping of soil types, human settlement mapping, soil moisture mapping, climate change, and SDGs related mapping. LULC-focused research articles should explicitly indicate their applicability to the achievement of SDGs and their indicators, in support of Eswatini's Vision 2022 of the National Development Strategy (NDS), the Strategy for Sustainable and Inclusive Growth 2030 (SSDIG), as well as Africa's Agenda 2063.

## **7. Conclusion**

This paper assesses current knowledge on the use of remote sensing and GIS in LULC monitoring and classification in Eswatini. It establishes that the reviewed articles cover eight thematic areas namely 1) water resources, 2) land degradation, 3) forestry, 4) urban expansion, 5) crop production, 6) wildfire detection, 7) disease surveillance, and 8) general mapping. LULC classification methods of reviewed articles can be categorised into three major groupings namely manual, classic, and advanced methods. Where provided, limitations and /or strengths of each specific classification approach are captured. Special attention was given to the use of advanced remote sensing classifiers. Based on literature, some advanced remote sensing image classification algorithms are provided (grouped into six categories). Notably, most of these advanced image classification algorithms were not applied in the reviewed articles. Furthermore, this paper ascertains that few classification

approaches to improve classification accuracy, as suggested by recent remote sensing classification reviews, were applied in the reviewed articles. However, most (three out of four) of the classification techniques for improving classification accuracy suggested by literature were applied.

Finally, none of the reviewed articles, even those published from 2015 onward, explicitly aim to achieve an SDG or any indicator. However, remote sensing and EO data have the potential to greatly contribute to the realisation of the SDGs (Friedl, 2016; United Nations, 2017; Paganini, 2018; Walter, 2020). This must be seen in light with Eswatini's commitment to achieving the SDGs, in particular the priority SDGs (1-4, 6-8, 13, 16, 17) (Ministry of Economic Planning and Development, 2019).

In conclusion, this review recommends: 1) the inclusion of higher resolution imagery for mapping purposes, 2) the adaptation of strengths and weaknesses for any image classification technique employed in future publications, 3) the use of more varied approaches and techniques for improving classification accuracy and area estimates, 4) inclusion of standard errors or confidence intervals for error-adjusted area estimates as part of accuracy assessment reporting, 5) the application of advanced image classifiers, and 6) the application of Earth Observation (EO) Analysis Ready Data (ARD) in the production of information for the support of the SDGs.

## **8. Acknowledgements**

The authors would like to thank support from the Department of Geography, Geoinformatics & Meteorology at the University of Pretoria.

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