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MAPPING OF LAND USE / LAND COVER OF KLERKSDORP–ORKNEY–STILFONTEIN–HARTEBEESTFONTEIN (KOSH) REGION FOR THE YEARS 2020 AND 2019 USING SENTINEL-2 DATA

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The article presents mapping of current land use / land cover and of year 2019 of Klerksdorp–Orkney–Stilfontein–Hartebeestfontein (KOSH) region using Sentinel-2 data. This study made use of VNIR bands of Sentinel-2 acquired on 10 March 2020, 16 March 2019 and National Land Cover (NLC) dataset of year 2018 to investigate how land use change and vegetation alteration has occurred during 2018 to 2020. The Level 1 Sentinel-2 data were pre-processed to obtain ground reflectance using Sen2Cor algorithm. The classification system of NLC 2018 was used for identifying the training sites for 56 classes present. Further processing to produce intended classes and post processing of classification products were performed using Geomatica Object Analyst. The analysis involved image segmentation, attribute calculation for geometrical parameters, mean, standard deviation and 10 vegetation indices of pixels covered in segments of VNIR bands, training site selection, classification and post classification analysis. Though attempts were made to classify the images with training sites and different attributes, the best classification result was obtained with standard deviation of 4 VNIR bands and 10 vegetation indices. For classifying March 2019 image, the batch classification algorithm was applied using training model file generated for classification of March 2020 data. The percentage of total area covered by five major classes for the years 2020 and 2019 respectively are: grasslands - 49.32% & 42.14%; temporary crops (rainfed) - 32.90% & 32.92%; open woodland – 4.00% & 3.03%; mine waste (tailings) and resource dumps – 1.96% &2.46%; residential formal (grass) – 1.53% & 1.46%.

Keywords: *remote sensing, Sentinel-2, KOSH, land use / land cover dynamics, Object Analyst, classification.*

Introduction

Knowledge of land cover and land use change is necessary in order to model the earth system and its environments (for example by studying aspects such as hydrological processes and climate change) and for many purposes related to land and natural resource management. The study of land cover change is quite important because of its impacts on local climate, hydrology, radiation balance, and the diversity and abundance of terrestrial species (Boriah et al., 2008). Most (80%) of the land cover in South Africa is natural or semi-natural, and monitoring and projecting changes in land cover is vital for proper management and development of its geographical areas and sustainable utilisation of the natural resources. Mining and agricultural practices are major human activities on the land in South Africa. The change of land cover due to mining and associated development in the area (changes in land use / land cover due to human activities that are linked to mining) has resulted in significant changes in climate and the environment (for example changes in the catchment hydrology resulting in increased surface runoff in certain areas and associated pollution and also depletion of surface water resources due to reduction of natural infiltration and ground water recharge).

South Africa has a mining history of more than 100 years. Today the South African mining industry still is a key sector to the economy with a contribution of 8% to the national GDP, even with the substantial decline of the gold mining in the Witwatersrand basin, as new mineral deposit types are being developed and exploited. However, the remnants of mining still exist today in the form of large tailings sites and underground shafts throughout the major mining areas in Gauteng, the North West and Free-State provinces, near the densely populated cities of the Gauteng Metropolitan Region. Even this post-mining landscape is very dynamic. Old tailings dam sites are being reprocessed, as new technologies become available, or rising commodity prices favour the extraction of leftover value. The problems that may be attributed to such a dynamic mining and post-mining landscape are for example the generation of acid mine drainage, metal transport in surface water and groundwater, e.g., iron precipitation in water bodies, major subsidence and migration of tailings material to the neighbouring settlements. These may dramatically affect the existing natural cover, land use practices and the lives of the people in such a mining area, where the former settlements of the mineworkers have grown into these large economically thriving urban centres, which attracts people from rural parts of South Africa. The land-use in these population centres, e.g. for recreation, farming, and housing, conflicts with the future, current and former usage of the land by the mineral resource industry. The above listed problems and conflict faced in the country due to changes in land use practices / land cover severely affects the environment in complex ways, leading to complex situations that impact the ecological security for sustainable development/generation.

Freely available remote sensing datasets made available through optical satellites such as Advanced Space-borne Thermal Emission and Reflection (ASTER) radiometer, Landsat and Sentinel-2 are being widely used in land cover studies and monitoring as they aid in discriminating various land covers and land uses. This study aimed to conduct environmental monitoring and assessment of the current (year 2020) land use / land cover and one year ago (year 2019) of Klerksdorp–Orkney–Stilfontein–Hartebeestfontein or KOSH using geospatial technologies and remote sensing, using optical data from Sentinel-2 satellite. This research intended to make use of existing satellite-based land-cover products, recent satellite data to investigate how land use change and vegetation disturbances has altered during 2018 to 2020.

Presented here are the results obtained from different remote sensing data processing & analyses conducted on Sentinel-2 data covering the Klerksdorp–Orkney–Stilfontein–Hartebeestfontein (KOSH) region acquired in March 2020 and March 2019 using different tools available in SNAP and Geomatica software (using Object Analyst module) and their usefulness to aid in understanding the current land use / land cover classes and their dynamics.

Area of research and its characteristics

The area chosen initially for the environmental monitoring is the Klerksdorp–Orkney–Stilfontein–Hartebeestfontein (KOSH) region in the Northwest Province of South Africa, covering an area of 2755 km^2 and falling within the Vaal River catchment (fig. 1). The KOSH area is located approximately 160 km southwest of Johannesburg. The Vaal River flows through the south-eastern part of the KOSH region. The majority of the KOSH area has a sandy loam soil texture with an undulating relief, whereas the relief of the region south of Orkney is flat (Midgley, Pitman and Middleton, 1994). The KOSH region forms part of the Witwatersrand gold mining region, including the Far East, Central Rand, Western and Far West basins and the Free State gold mines, and which is at serious risk from acid mine drainage (Mail&Guardian, 2014).

Gold mining operations by a number of different gold mining companies have been undertaken in the KOSH area since 1950s (SAFLII, 2013). Gold mining entails the construction of shafts, underground tunnels and the excavation of rocks to access gold-bearing ore. Many years of gold mining have resulted in the underground interconnection of all the mines in the KOSH area. The labyrinth of interconnecting tunnels, shafts, mined-out areas and natural fissures have created a pathway through which the underground water flows from the aquifers into the shallower mines and shafts and from there into the deeper areas. It is an undisputed fact that mining of gold in the KOSH area over the years has contributed to the drainage of underground water into the mines. Thus, mining companies are spending huge amounts of money to pump water out of their mines. The area has a number of sinkholes in the vicinity of Buffelsfontein's Eastern Shaft that have developed as a result of the lowering of the water table following dewatering (Pulles et al., 2005).

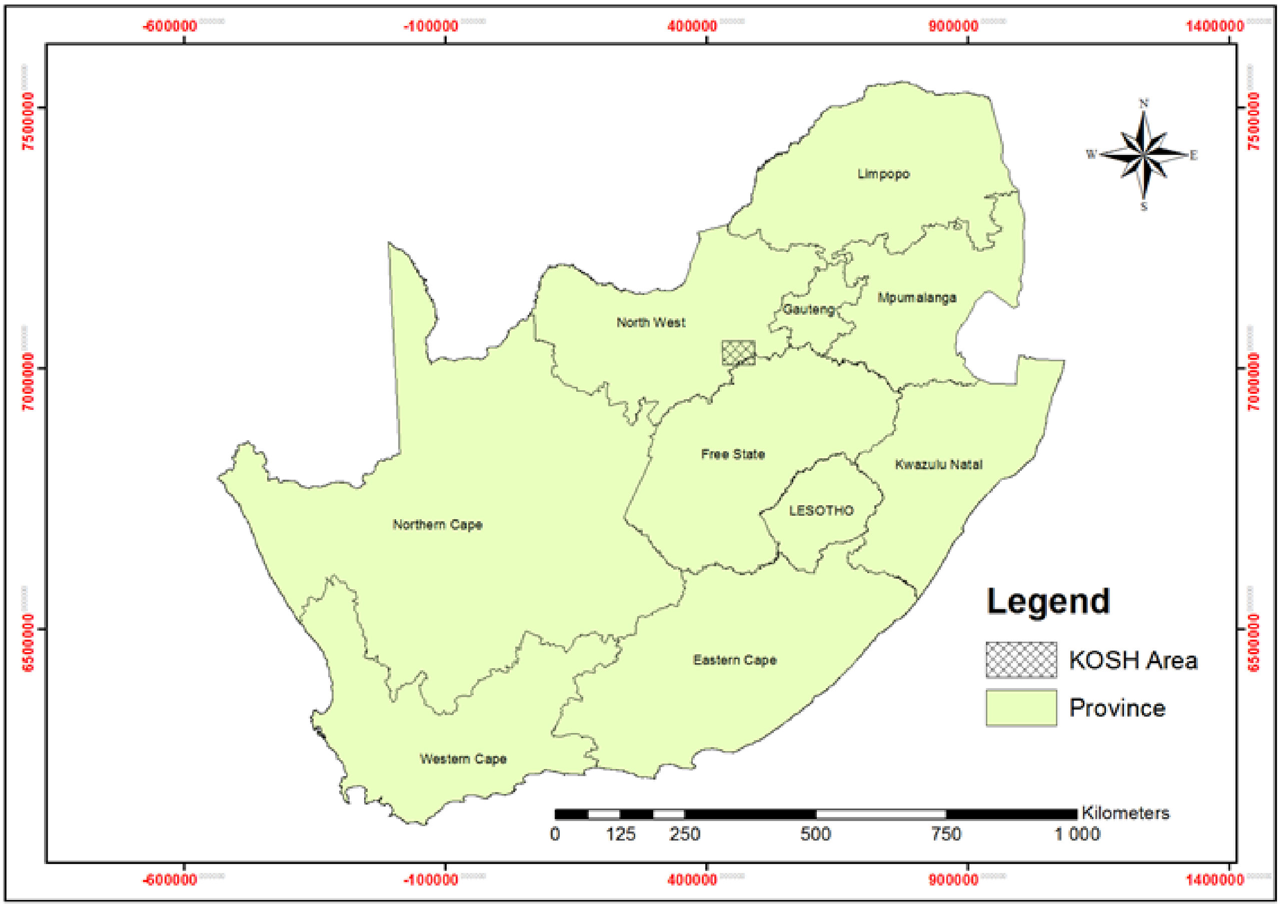


Fig. 1. Locality map of the KOSH area

Geological background of study area

The KOSH area is underlain mainly by an intercalated assemblage of sedimentary and extrusive rocks, porous unconsolidated and consolidated sedimentary strata, acid and intermediate intrusive rocks and basic/mafic lavas (such as dolomite, gold-bearing conglomerates, Black Reef quartzite, Ventersdorp lavas and dykes) and has shallow aquifers containing uncontaminated water relatively close to the surface (Midgley et al., 1994).

Materials and methods of research

Data and software used for remote sensing analyses

The satellite data used in this study comprised the Sentinel-2 satellite image having 13 optical image bands spanning from the Visible and Near Infra-Red (VNIR) and Short Wave Infrared (SWIR) spectral range having resolutions of 10m, 20 and 60 respectively. Multi Spectral Instrument (MSI) of Sentinel-2 measures the Earth's reflected radiance in 13 spectral bands from VNIR to SWIR. Sentinel-2 data acquired on 13 spectral bands in the VNIR and SWIR regions has the following resolutions for its different bands:

- four bands at 10 m: Band 2, Band 3, Band 4, and Band 8.
- six bands at 20 m: Band 5, Band 6, Band 7, Band 8a, Band 11, and Band 12
- three bands at 60 m: Band 1, Band 9, and Band 10.

Recent scenes of Sentinel-2 data covering the study area of KOSH region were searched in the Copernicus Scientific Data Hub (https://scihub.copernicus.eu/dhus/#/home) and two suitable cloud free images for the end of summer period (acquired on 10 March 2020 and 16 March 2019) were identified and downloaded them.

Software used for the analyses

The software used in this study are the following: the Sentinel Application Platform, known as SNAP Toolbox, developed by the European Space Agency (ESA), PCI Geomatica with its add on module Object Analyst, ArcGIS and Google Earth Pro. SNAP stands for "SeNtinels Application Platform" and it is a fully free and open-source toolbox platform that supports processing of raster imagery from ESA, Copernicus Sentinel 1/2/3, and many third party satellite missions (ESA-STEP, 2018). Object Analyst is an add-on package for PCI Geomatica software that provides tools for segmentation, classification, and feature extraction.

Product type of downloaded Sentinel-2 data

The downloaded Sentinel-2 data is a Level-1C product composed of 100 x 100 km^2 tiles comprising 13 bands (ortho-images) in a UTM projection. Per-pixel radiometric measurements of this data are provided in Top Of Atmosphere (TOA) reflectance along with the parameters to transform them into radiances. Level-1C products are resampled with a constant Ground Sampling Distance (GSD) or resolutions of 10, 20 and 60 m depending on the native resolution of the different spectral bands. As the Level-1C Sentinel -2 has already undergone radiometric and geometric correction, the main pre-processing required for this data is atmospheric correction to produce ground surface reflectance.

Initial data processing using SNAP software

The downloaded Sentinel-2 data was imported in SNAP software and processed for atmospheric correction using Sen2Cor software plugin installed in it. Sen2Cor is a processor for Sentinel-2 Level 2A product generation and formatting; it performs the atmospheric-, terrain and cirrus correction of TOA Level 1C input data. This step converted the Level-1C product type (having top of the atmosphere reflectance) to Level-2A data having surface reflectance. The Level 2 VNIR bands were saved in tiff file format. The extent of coverage of the pre-processed VNIR scene acquired on 10 March 2020 is shown in Figure 2. Later, this data set was subsetted for the area of interest covering the KOSH region using its geo-coordinate bounds (Figure 3). Similarly, the Sentinel-2 scene acquired on 16 March 2019 was processed to Level 2 and subsetted for the area of KOSH region (Figure 4). Figure 3 shows the satellite view of the KOSH region as seen through Sentinel-2 on 10 March in RGB: Band 4-Band 3-Band 2. Figure 4 shows the same area as seen through VNIR bands in RGB: Band 4- Band 3-Band 2 of the same satellite acquired on 16th March 2019.

Other dataset used

Other datasets used in this study are the National Land Cover (NLC) 2018 dataset covering KOSH having 20 m resolution derived from Sentinel-2 data of year 2017-2018 and Google Earth Pro Images of different years (mainly years 2018, 2019 and 2020). Figure 5 shows National Land Cover (NLC) 2018 data extracted for the KOSH region and the legend for this map is shown in Figure 6. There are 56 land cover types present in the subset of NLC 2018 covering the KOSH region. The original legend of the dataset has 73 land cover classes. The description of these land cover classes is given in Thompson (2019).

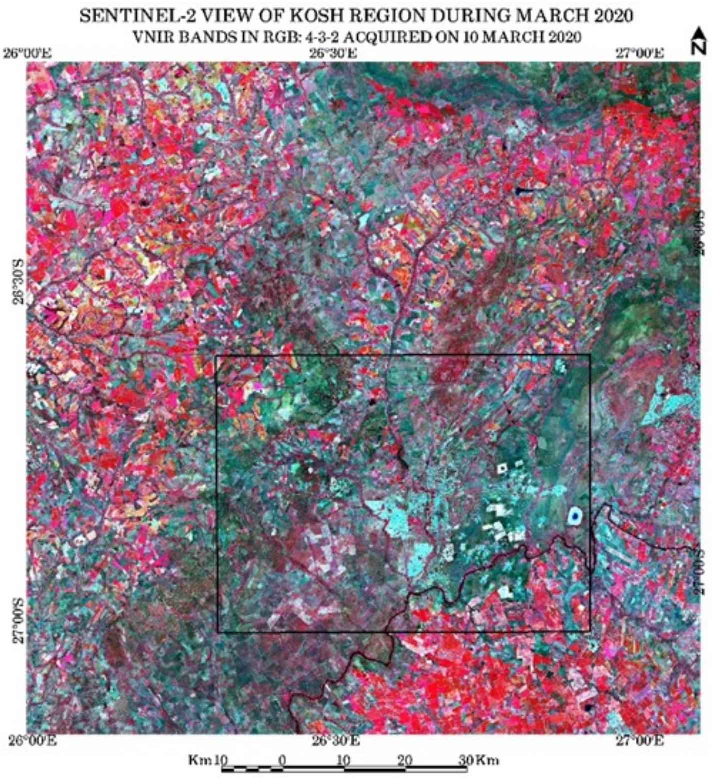


Fig. 2. The extent of full scene of Sentinel-2 imagery (VNIR bands in RGB: B4-B3-B2) acquired on 10 March 2020 overlaid with a polygon covering the extent of KOSH region

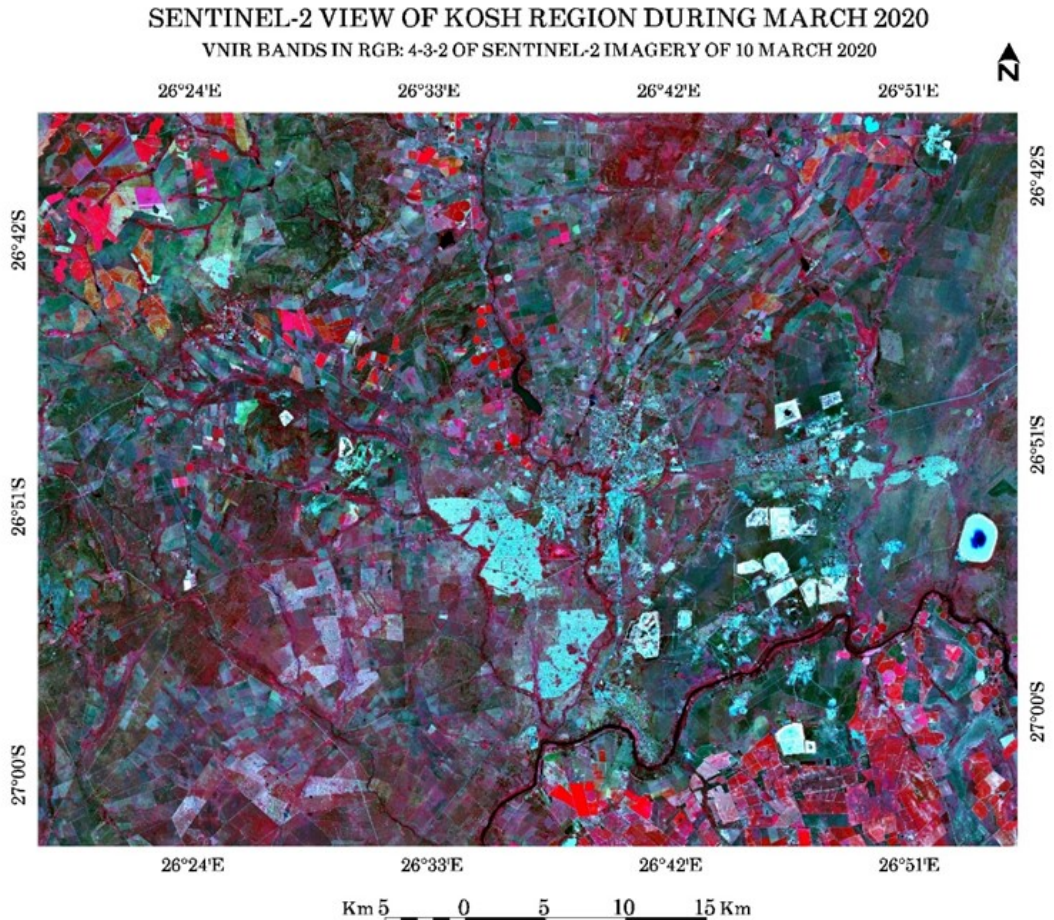


Fig. 3. Subset of Sentinel-2 imagery (VNIR bands in RGB: B4-B3-B2) acquired on 10 March 2020 covering the extent of KOSH region.

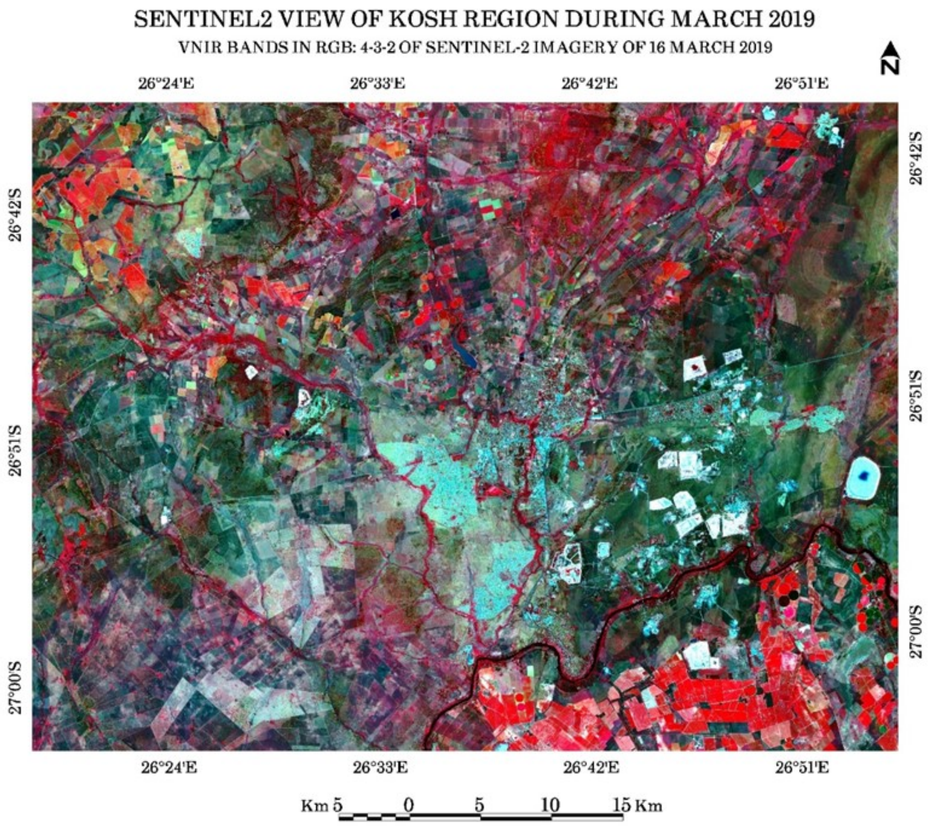


Fig. 4. Subset of Sentinel-2 imagery (VNIR bands in RGB: B4-B3-B2) acquired on 16 March 2019 covering the extent of KOSH region

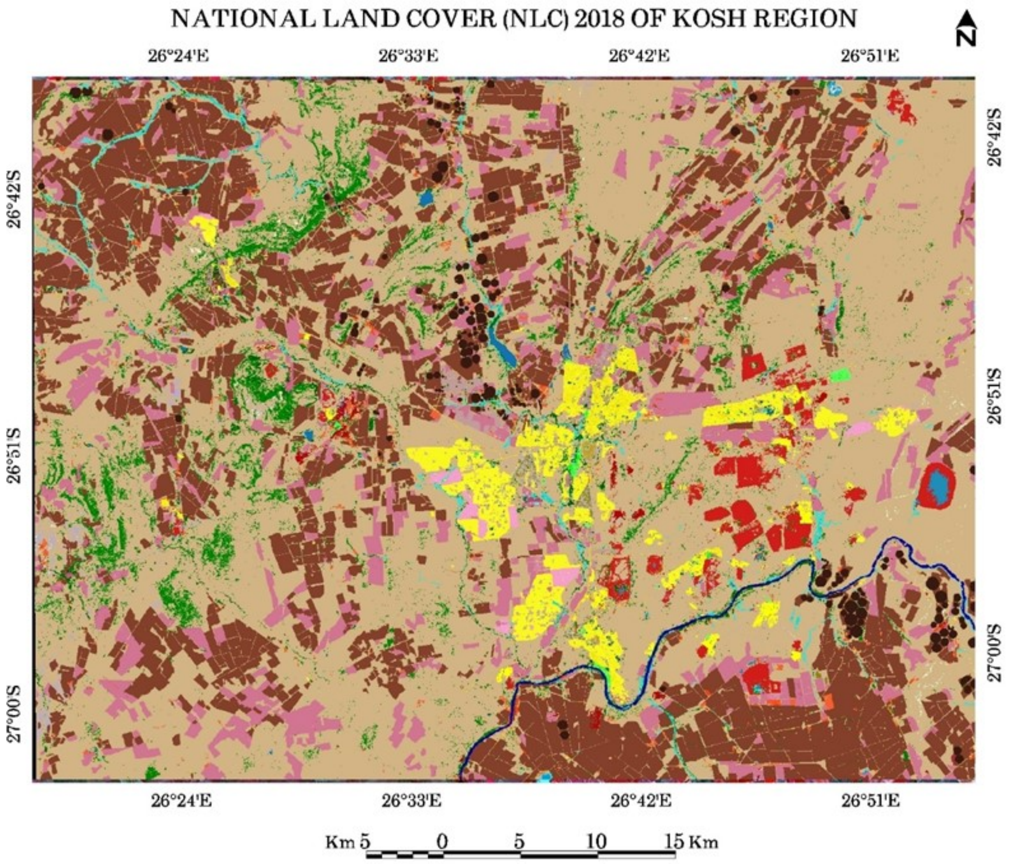


Fig. 5. The National Land Cover (NLC) 2018 dataset covering the extent of KOSH region

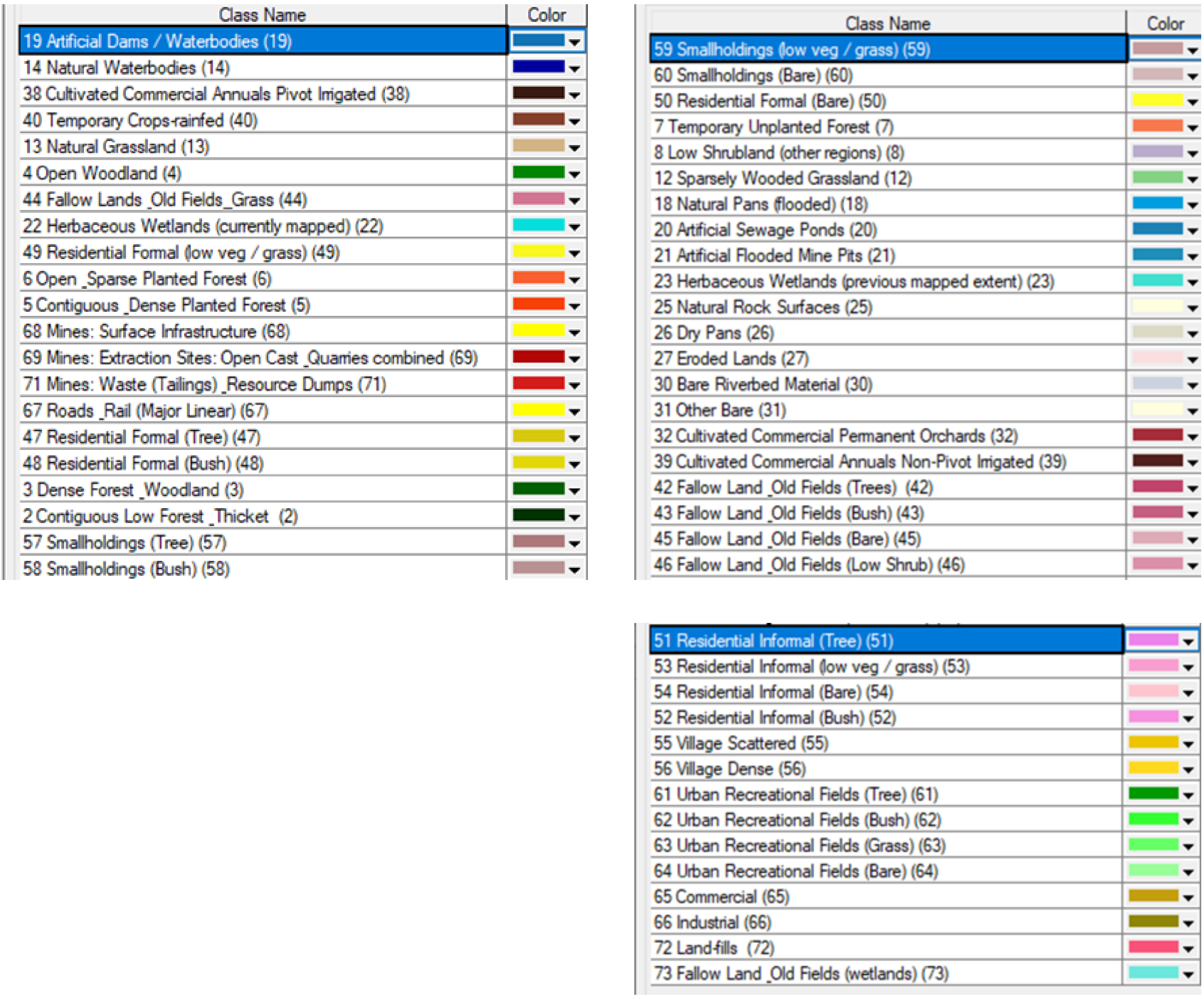


Fig. 6. Legend of the National Land Cover (NLC) 2018 dataset covering the KOSH region

A visual examination of the VNIR bands of Sentinel-2 data acquired on 10 March 2020 (Figure 3) with 2018 NLC data (Figure 5) reveals that there is some change in the extent of some land covers (e.g. change of grassland to agricultural use) during the last two years.

Image analysis for land use / land cover classification using Geomatica Object Analyst

A simple process flow for object-based image analysis (OBIA) is using Geomatica Object Analyst involves pre-processing of image, image segmentation, classification and post classification analysis. As the pre-processing and subsetting were already made using SNAP, the remaining steps of image segmentation classification and post classification analysis were carried out in Geomatica software using Object Analyst add on module. The first attempt made was to map land covers for the KOSH region using Sentinel-2 data acquired on 10 March 2020 based on the classification system followed in the National Land Cover (NLC) dataset of 2018 (after identifying 56 classes present in the subset of NLC 2018 for KOSH) using the Trial License of Geomatica Object Analyst module and Sentinel-2 data. The main steps to be followed in the workflow of image classification using Geomatica Object Analyst are the following: loading and examining input data, segmentation of the input data into a vector layer for training site generation and image classification, attribute calculation for image classification, training site editing, selection of classification method: whether supervised or unsupervised (supervised classification involves selection of the identified training sites) and post classification editing.

Segmentation is the process of extracting discrete regions of image objects from an image. The segmentation involves creating a vector layer showing boundaries of various objects present in the area of interest with specified bands of the imagery. The parameter values to be entered for the segmentation are scale, shape and compactness. The attribute calculation involves calculation of geometrical parameters (compactness, elongation, circularity and rectangularity), calculation of mean and standard deviation of the pixels beneath an object from the selected bands and calculation of vegetation indices attributes (e.g. NDVI, Leaf Area Index etc.). The vegetation indices that can be calculated using Object Analyst are shown in table 5.

Table **1**

Descriptions of each Vegetation Index that can be calculated using Geomatica Object Analyst.

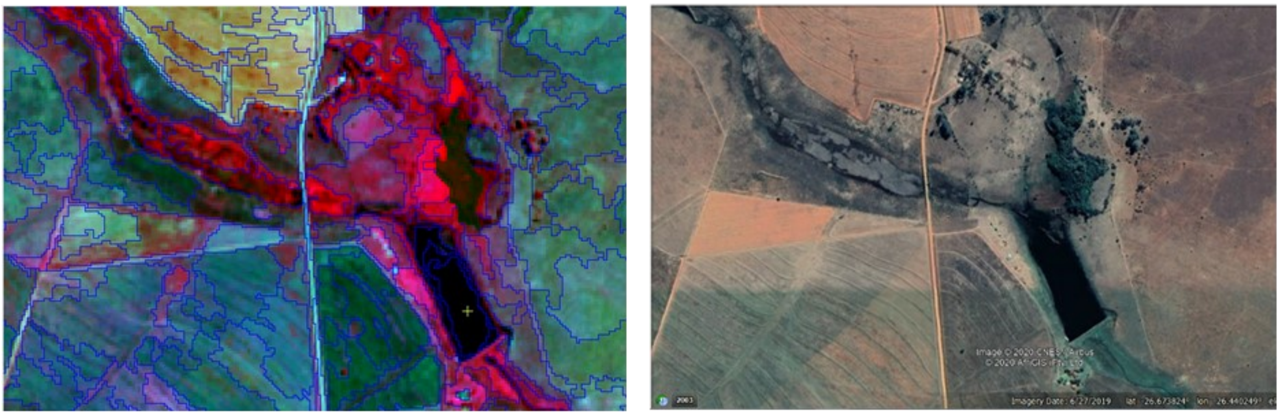
Attribute	**Short name**	**Description**
Green/Red Vegetation Index	GRVI	GRVI = (Green − Red) ÷ (Green + Red)
Greenness Index	GI	GI = ((2.0 × Green) − (Red + Blue)) ÷ ((2.0 × Green) + Red + Blue)
Vegetation Difference Index	VDI	VDI = NIR − Red
Ratio Vegetation Index	RVI	RVI = NIR ÷ Red
Normalized Difference Vegetation	NDVI	NDVI = (NIR − Red) ÷ (NIR + Red)
Transformed Difference Vegetation Index	TDVI	TDVI = (NIR − Red) ÷ (NIR + Red) + .5
Soil Adjusted Vegetation Index	SAVI	SAVI = ((NIR − Red) ÷ (NIR + Red + L)) × (1 + L) The L-value is based on the amount of green vegetative cover. L is a default of 0.5, which means, generally, areas of moderate green vegetative cover.
Modified Soil Adjusted Vegetation Index	MSAVI2	MSAVI2 = (0.5) × (2(NIR + 1) − √((2 × NIR + 1) − 8(NIR − Red)))
Global Environmental Monitoring Index	GEMI	GEMI = eta × (1 − 0.25 × eta) − ((Red − 0.125) ÷ (1 − Red)) Where eta = (2 × (NIR − Red) + 1.5 × NIR + 0.5 × Red) ÷ (NIR + Red + 0.5)
Leaf Area Index	LAI	LAI = (3.618 × EVI) − 0.118 Where EVI (Enhanced Vegetation Index) = 2.5 × (NIR − Red) ÷ (1 + NIR + (6 × Red) − (7.5 × Blue)

Source: PCI-Geomatics (2017).

The task of identifying training sites involves viewing of the image and interpreting the features present in it and giving proper names for the intended classes from the segmented vector layer.

The existing NLC 2018 data of KOSH region has 56 land cover classes. While generating training sites, the description of each such present land cover class was read to identify the corresponding classes from the image. Other useful data like existing Google Earth Pro imagery of different dates (since year 2014 and until May 2020) and NLC 2018 were also viewed while identifying the land cover types and assigning class names to the training site polygons. An example view of training site identification from zoomed segmented vector layer and zoomed view of Google Earth image for certain land cover classes are shown in Figure 7. Efforts were made to zoom into the image for different distant locations and identify at least 20 to 30 training sites for each class for an accurate classification of the image. Some land cover classes like landfill, bare river bed material and informal settlement (having trees or bush) have only limited numbers in the area of study for training site; the only available such sites (sometimes only single site is present) were marked as training sites. While examining the NLC 2018 data covering the KOSH region for training site identification, numerous errors were observed in this classified product. A few example errors observed are the following types:

- Class 61 Urban Recreational Fields (Grass) is classified as Class 3: Dense woodland (Fig. 8 and Fig. 9).
- Agricultural crop land classified as Class 3: Dense woodland (Fig. 10 and Fig. 11).



(a). Zoomed view of segmented polygons. (b). Google Earth Pro view (27 June 2019).

Figure 7. Zoomed view of segmented polygons from Object Analyst overlaid with Sentinel-2 image of 10 March 2020 (a); Google Earth image of 27 June 2019 for marking training sites (b)

The study area was thoroughly examined in Google Earth Pro along with side by side displaying of the satellite image and the existing NLC 2018 dataset. In order to improve the classification accuracy, more typical patches classes were identified from the segmented vector as training sites. Any errors seen in the identification of land cover classes of the previously identified training sites were also edited in this step. The corresponding display colours of the classes of NLC 2018 in RGB were identified and assigned those colours to each class identified as training site. The assigned colours for different land use / land cover classes and the total number of training sites identified for the supervised classification using Geomatica Object Analyst for the 56 land cover classes present in the KOSH region based on the classes seen in the NLC 2018 dataset is shown in figure 12 to figure 14.

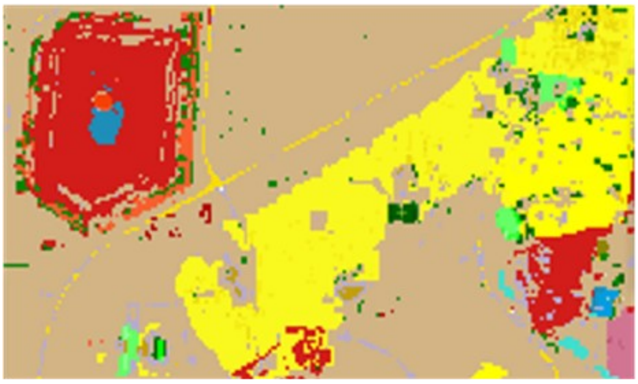


Fig. 8. Class 61: Urban Recreational Fields with grass (green patch) classified as Class 3: Dense forest & woodland in NLC 2018

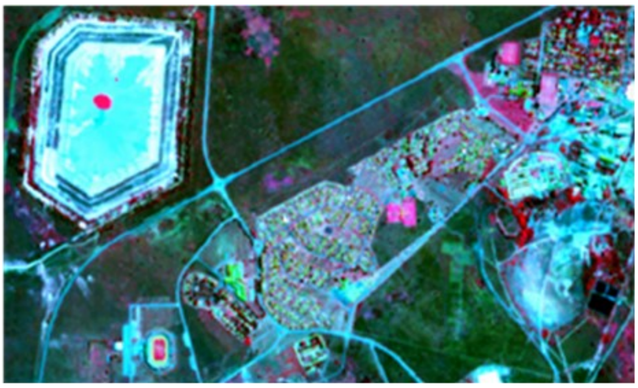


Fig. 9. View of 10 March 2020 Sentinel-2 image confirming errors seen in NLC 2018 (grassy recreation area classified as woodland)

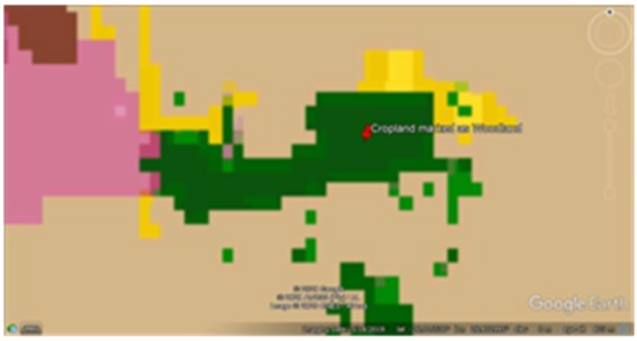


Fig. 10. Error of agricultural crop land classified as Class 3: Dense woodland in NLC 2018 data covering KOSH region

Fig. 11. Google Earth Pro image confirming errors observed in the classes of NLC 2018 (agricultural field area classified as woodland)

Class Name	Color	Training Count
19 Artificial Dams / Waterbodies (19)		66
14 Natural Waterbodies (14)		90
38 Cultivated Commercial Annuals Pivot Irrigated (38)		588
40 Temporary Crops-rainfed (40)		2717
13 Natural Grassland (13)		1905
4 Open Woodland (4)		319
44 Fallow Lands _Old Fields_Grass (44)		773
22 Herbaceous Wetlands (currently mapped) (22)		64
49 Residential Formal (low veg / grass) (49)		372
6 Open _Sparse Planted Forest (6)		50
5 Contiguous _Dense Planted Forest (5)		56
68 Mines: Surface Infrastructure (68)		76
69 Mines: Extraction Sites: Open Cast _Quarries combined (69)		136
71 Mines: Waste (Tailings) _Resource Dumps (71)		1639
67 Roads _Rail (Major Linear) (67)		166
47 Residential Formal (Tree) (47)		183
48 Residential Formal (Bush) (48)		60
3 Dense Forest _Woodland (3)		160
2 Contiguous Low Forest _Thicket (2)		46
57 Smallholdings (Tree) (57)		57
58 Smallholdings (Bush) (58)		45

Fig. 12. Part one of total training sites identified for the KOSH region using Object Analyst for the classification of 3 March 2020 Sentinel-2 image

Class Name	Color	Training Count
59 Smallholdings (low veg / grass) (59)		48
60 Smallholdings (Bare) (60)		18
50 Residential Formal (Bare) (50)		559
7 Temporary Unplanted Forest (7)		10
8 Low Shrubland (other regions) (8)		180
12 Sparsely Wooded Grassland (12)		148
18 Natural Pans (flooded) (18)		9
20 Artificial Sewage Ponds (20)		11
21 Artificial Flooded Mine Pits (21)		7
23 Herbaceous Wetlands (previous mapped extent) (23)		95
25 Natural Rock Surfaces (25)		52
26 Dry Pans (26)		10
27 Eroded Lands (27)		10
30 Bare Riverbed Material (30)		5
31 Other Bare (31)		58
32 Cultivated Commercial Permanent Orchards (32)		8
39 Cultivated Commercial Annuals Non-Pivot Irrigated (39)		306
42 Fallow Land _Old Fields (Trees) (42)		61
43 Fallow Land _Old Fields (Bush) (43)		83
45 Fallow Land _Old Fields (Bare) (45)		47
46 Fallow Land _Old Fields (Low Shrub) (46)		66

Fig. 13. Part two of total training sites identified for the KOSH region using Object Analyst for the classification of 3 March 2020 Sentinel-2 image

Class Name	Color	Training Count
51 Residential Informal (Tree) (51)		8
53 Residential Informal (low veg / grass) (53)		54
54 Residential Informal (Bare) (54)		46
52 Residential Informal (Bush) (52)		1
55 Village Scattered (55)		6
56 Village Dense (56)		15
61 Urban Recreational Fields (Tree) (61)		44
62 Urban Recreational Fields (Bush) (62)		23
63 Urban Recreational Fields (Grass) (63)		165
64 Urban Recreational Fields (Bare) (64)		18
65 Commercial (65)		331
66 Industrial (66)		409
72 Land-fills (72)		1
73 Fallow Land _Old Fields (wetlands) (73)		24

Fig. 14. Part three of total training sites identified for the KOSH region using Object Analyst for the classification of 3 March 2020 Sentinel-2 image

Figure 15 shows the spatial distribution and the extent of identified training sites for the 56 classes present in the KOSH region.

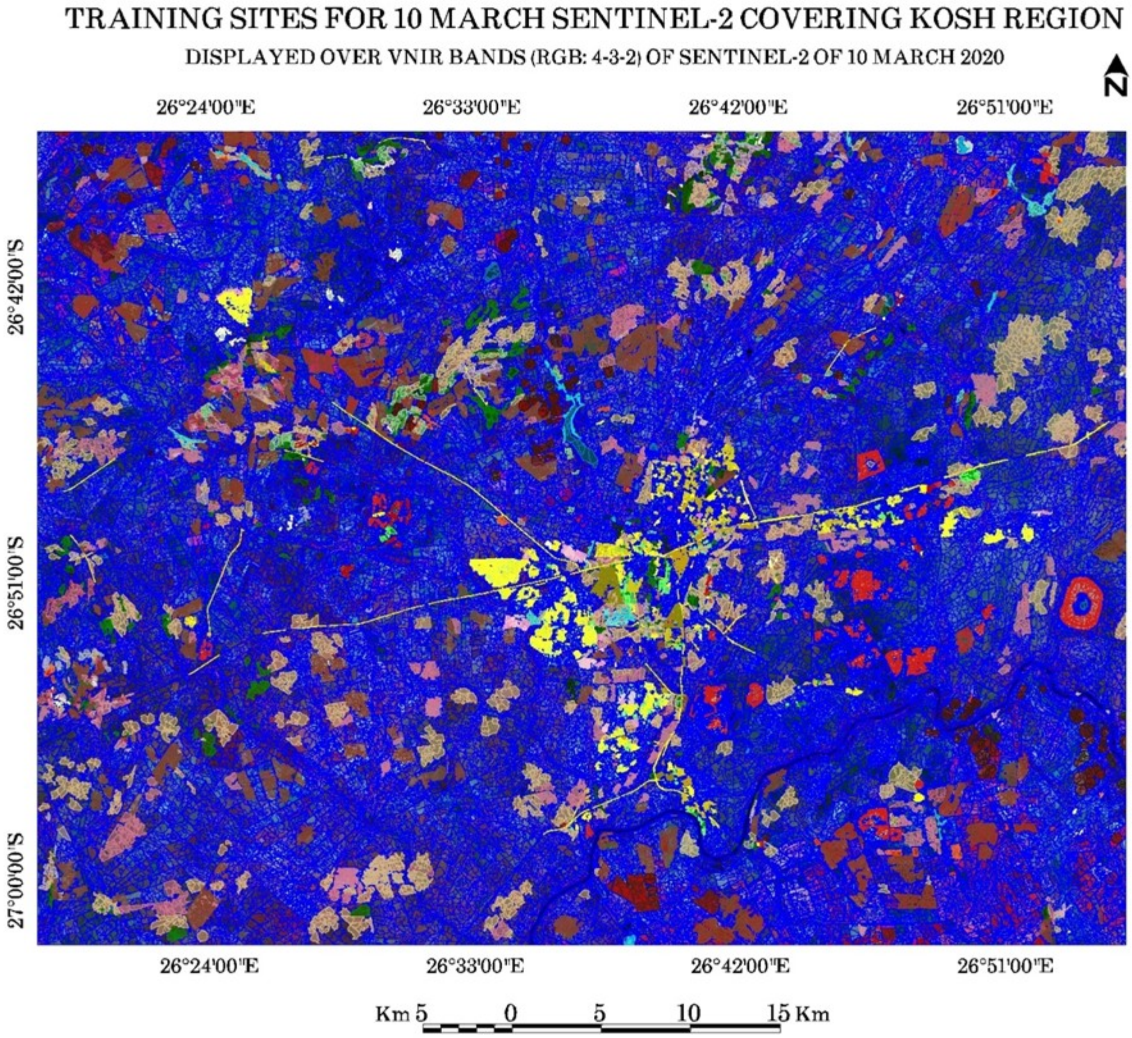


Fig. 15. Spatial distribution of training sites identified from the segmentation vector for the 3 March 2020 Sentinel-2 image covering KOSH region (overlaid with Sentinel-2 imagery)

Results and discussion

Many attempts of making supervised classification results were made in Object Analyst with different input options such as mean of four bands and NDVI, standard deviation and mean of four bands with all 10 available vegetation indices, standard deviation of 4 bands and all 10 vegetation indices, standard deviation of 4 bands, 10 vegetation indices and three geometric parameters (circularity, elongation and rectangularity) and standard deviation of 4 bands, 10 vegetation indices, elongation and circularity and finally with the inputs of standard deviation of 4 bands and 10 vegetation indices and elongation. The classification result obtained for the inputs of mean of four bands and NDVI from 10 March 2020 is shown in figure 16. Though this result showed better results for most of the areas including the urban part, some areas in the east and north-east were misclassified as residential patches with grassland cover wherein the real land use / land cover is cover is natural only grassland. Hence this result is not good to consider for a comparison with 2018 data. A better result of classification obtained for the year 2020 was with the attribute combination of standard deviation of 4 bands, and 10 vegetation indices (fig. 17).

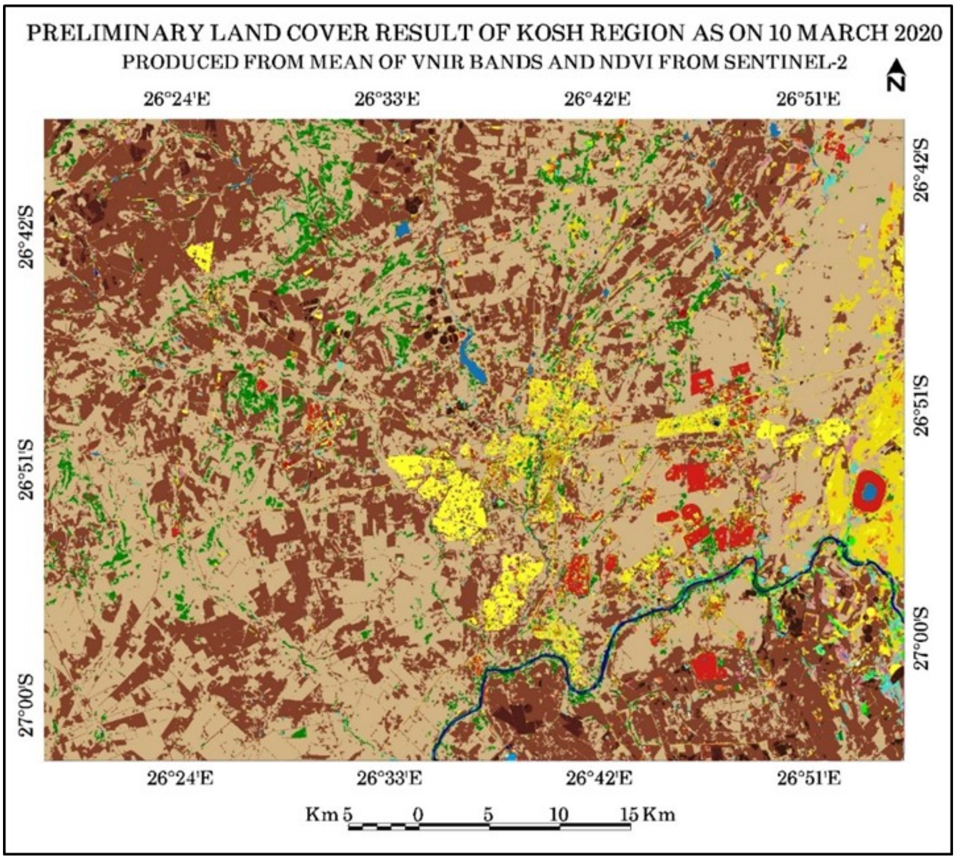


Fig. 16. Preliminary classification result obtained for 10 March 2020 with inputs of mean of 4 bands and NDVI values

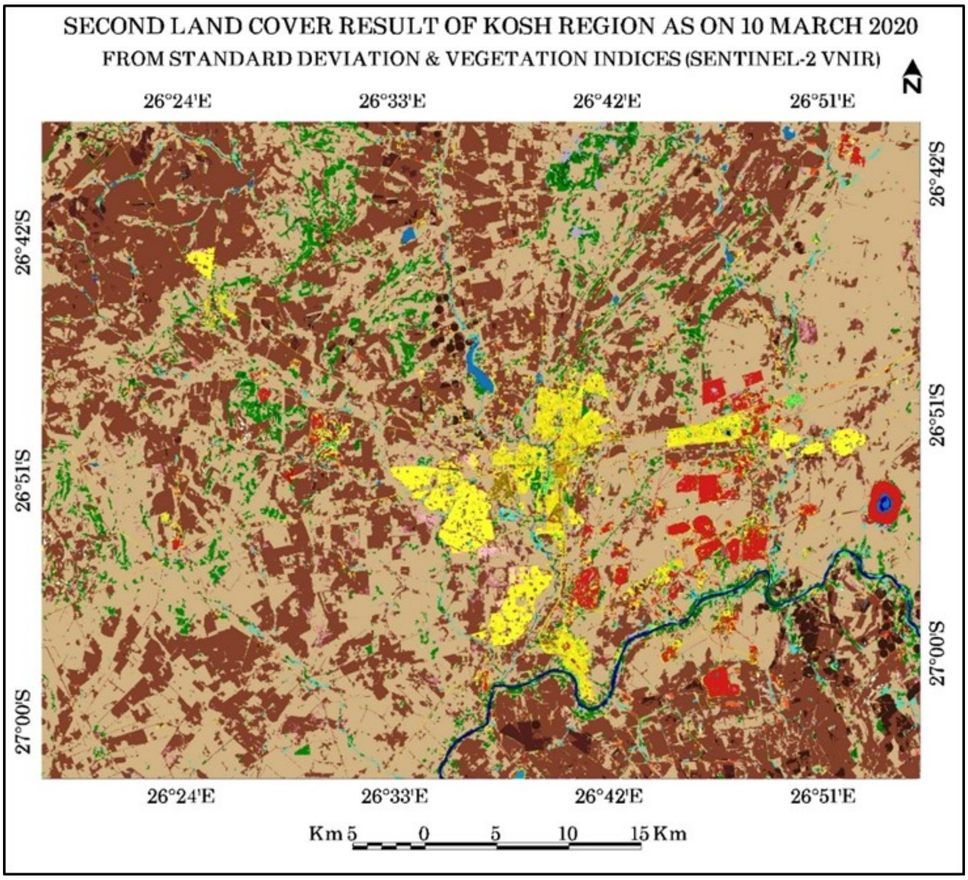


Fig. 17. Second classification result obtained for 10 March 2020 with inputs of standard deviation of 4 bands and ten vegetation indices values

On further examining this classification result by zooming into it some wrong classes or errors were noticed in the urban areas and surrounding areas of Klerksdorp. Many patches of urban residential, industrial and commercial sites were misclassified as mining dumps, some commercial areas were classified as industrial areas, and similarly some commercial and residential areas were classified as industrial areas. Due to similarities in pixel values of industrial & commercial and mining dumps, some sites in urban area were classified as these areas. More training sites were needed to distinguish such areas in the urban areas and surrounding areas of Klerksdorp. A zoomed view of urban area and surrounding areas of Klerksdorp showing such errors is shown in Figure 18. A comparison of the same area portion with the NLC 2018 data (fig. 19) reveals that the classification result is having similarity in many sites while certain areas were showing with more details than the NLC 2018 (especially in the residential, commercial and industrial areas). The major road network in this classified product is also much clearer as compared to the one seen in the NLC 2018 data. The extent of class 44 (fallow fields currently having grassland) is much less in the land use / land cover obtained for the year 2020 when compared with the 2018 NLC data.

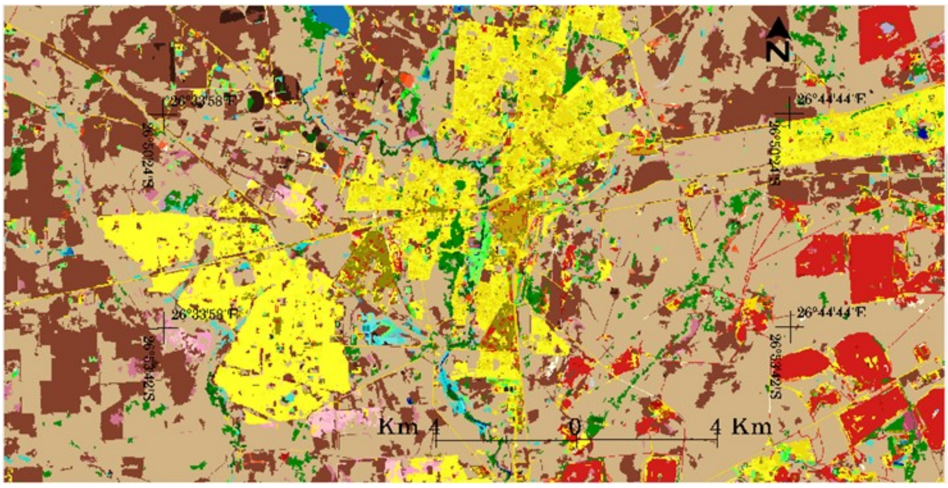


Fig. 18. Classification result of 10 March 2020 using standard deviation of 4 bands and 10 vegetation indices values showing some wrong classes in the urban areas and surrounding areas of Klerksdorp

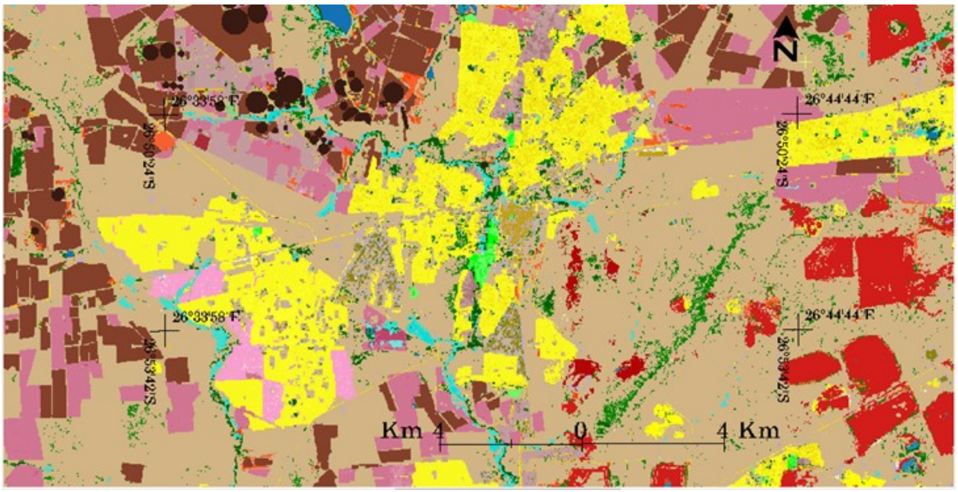


Fig. 19. Portion of NLC 2018 dataset covering urban and surrounding areas of Klerksdorp

A zoomed Sentinel-2 view of the urban and surrounding of the Klerksdorp was examined to identify and locate the misclassified segments. The misclassified patches were further selected and edited (re-assigned correct classes) after viewing those areas in the satellite image and Google Earth Pro image of the same year. A view of zoomed portion of Klerksdorp area as seen through the March 2020 satellite image, and the re-assigned (corrections made) portion of the same area are shown in Figure 20. Some areas seen around the sites of mine dumps and mine surface infrastructure and exaction sites were also misclassified as other classes mainly Class 66 Industrial, Class 50 Residential Formal (Bare) and Class 49 Residential Formal (low veg / grass) due to similarities of the attribute values. There were many such misclassified small segments and all such sites were edited. It was a very time consuming task to distinguish such areas belonging to Class 68 Mines Surface Infrastructure (having yellow colour shades) with residential areas having similar yellow colour shades. On examining the total number of classes identified from the classification product, it was noticed that only 54 classes were mapped and two land cover classes viz. Class 32 Cultivated Commercial Permanent Orchards and Class 52 Residential Informal (Bush) were not classified or missing. The patches of these classes were identified by examining the NLC 2018 data, the Google Earth Pro images and the Sentinel-2 image and such areas were located and the corresponding polygon segments were reassigned with correct class names.

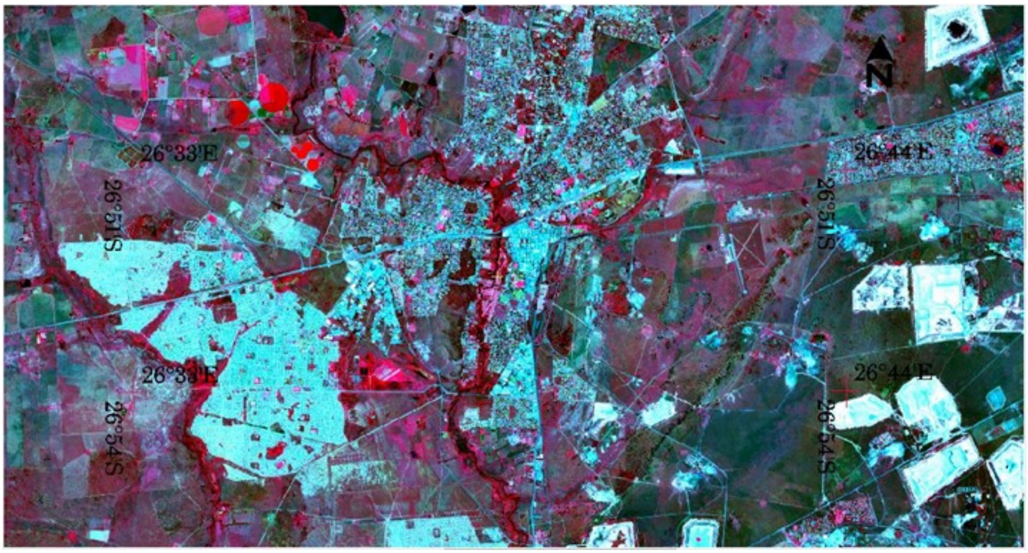


Fig. 20. A view of Klerksdorp and surrounding areas as seen through the Sentinel-2 on 10 March 2020

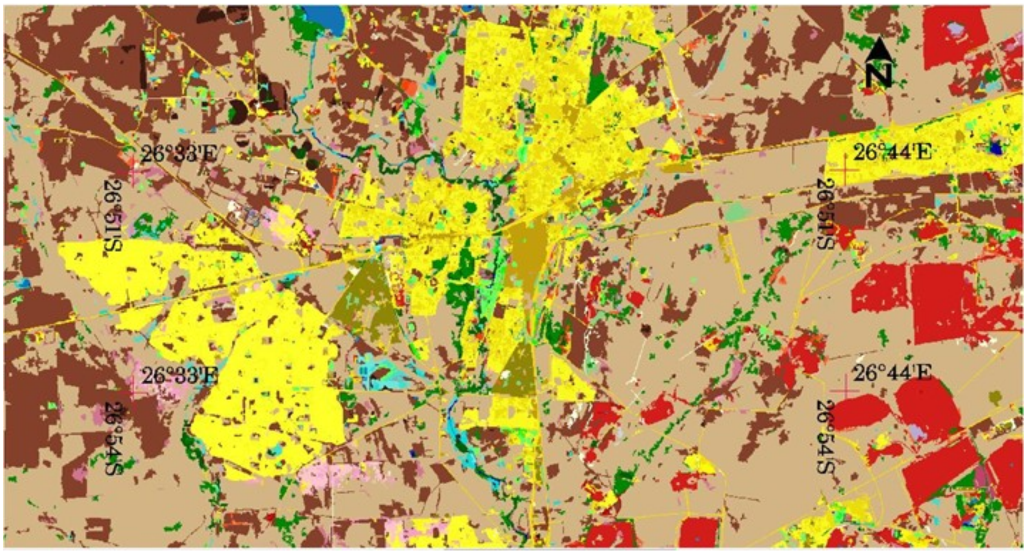


Fig. 21. A view of Klerksdorp and surrounding areas showing re-assigned (corrected) patches of land cover classification result

After doing re-assigning or editing of misclassified patches of the urban and peripheral area areas, mine dump areas, and the missing two classes, the final result of land use / land cover mapping obtained is shown in figure 22. The legend with 56 classes are shown in figure 23.

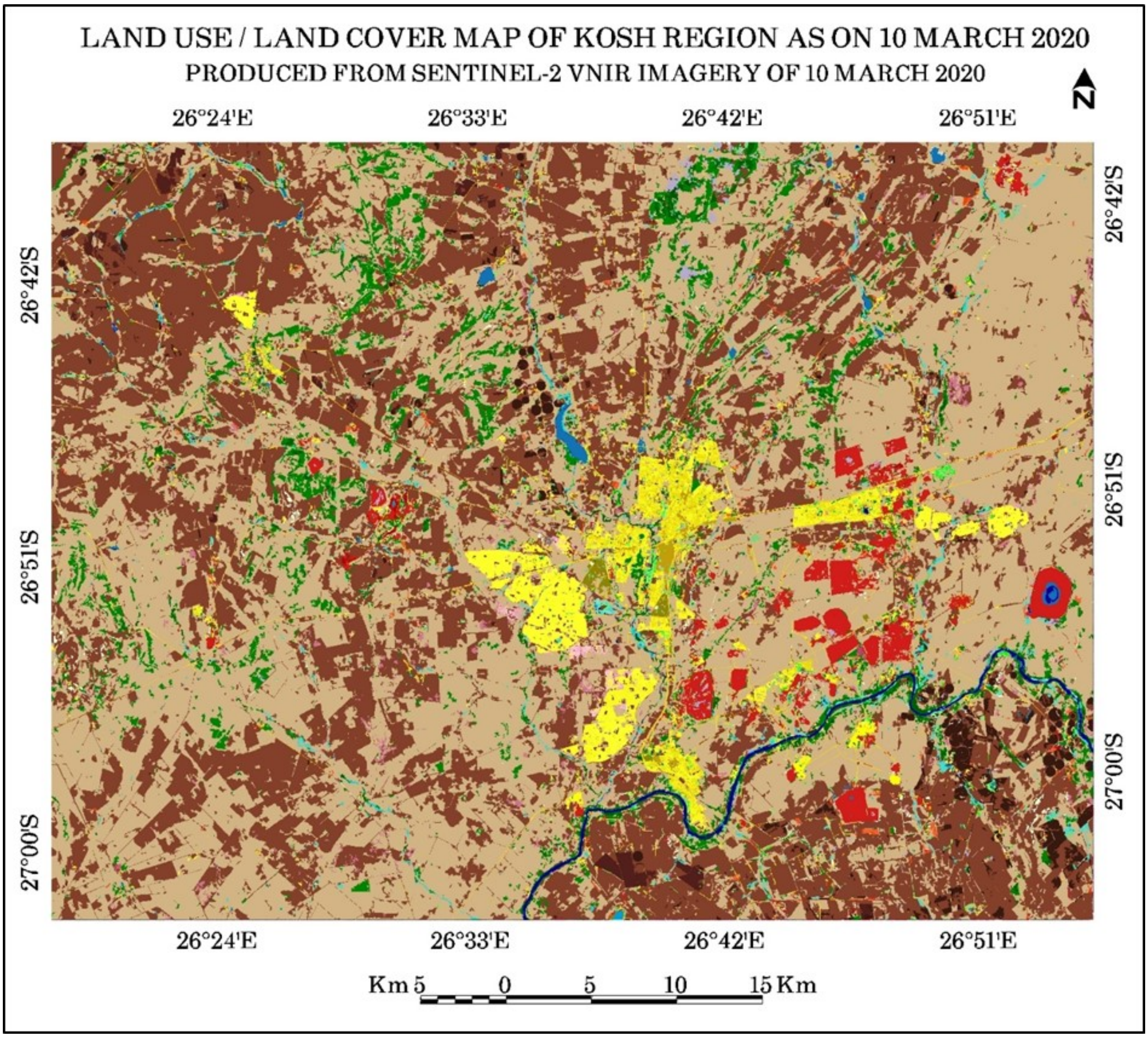


Fig. 22. Final land use / land cover map of KOSH region (after re-assigning of classes) obtained from Sentinel-2 data of 10 March 2020 with inputs of standard deviation of 4 bands and 10 vegetation indices

Comparison of land use / land cover classes for year 2020 with NLC 2018

A comparison of the final result of land use / land cover mapping for the year 2020 (fig. 22) with the NLC 2018 of KOSH region (fig. 4) reveals that land use / land cover map of year 2020 has more forest patches (open woodland patches) in the north, mining dumps and rain-fed agricultural fields whereas NLC 2018 of KOSH region has more patches of Class 44 Fallow Land & Old Fields _Grass (shown in light pink shade). The NLC 2018 is a smoothed 20 m resolution product whereas this map of 10 m is not smoothed. The number of patches of class 44 (Fallow Land & Old Fields currently with Grassland) is significantly reduced in this classification result for the year 2020. This is evident in the area figures of the major classes from the NLC 2018 showing a percentage of 7.95% for Class 44 (table 2) and area figure of 0.52% for Class 44 calculated for the land use / land cover map for the year 2020 (table 3).

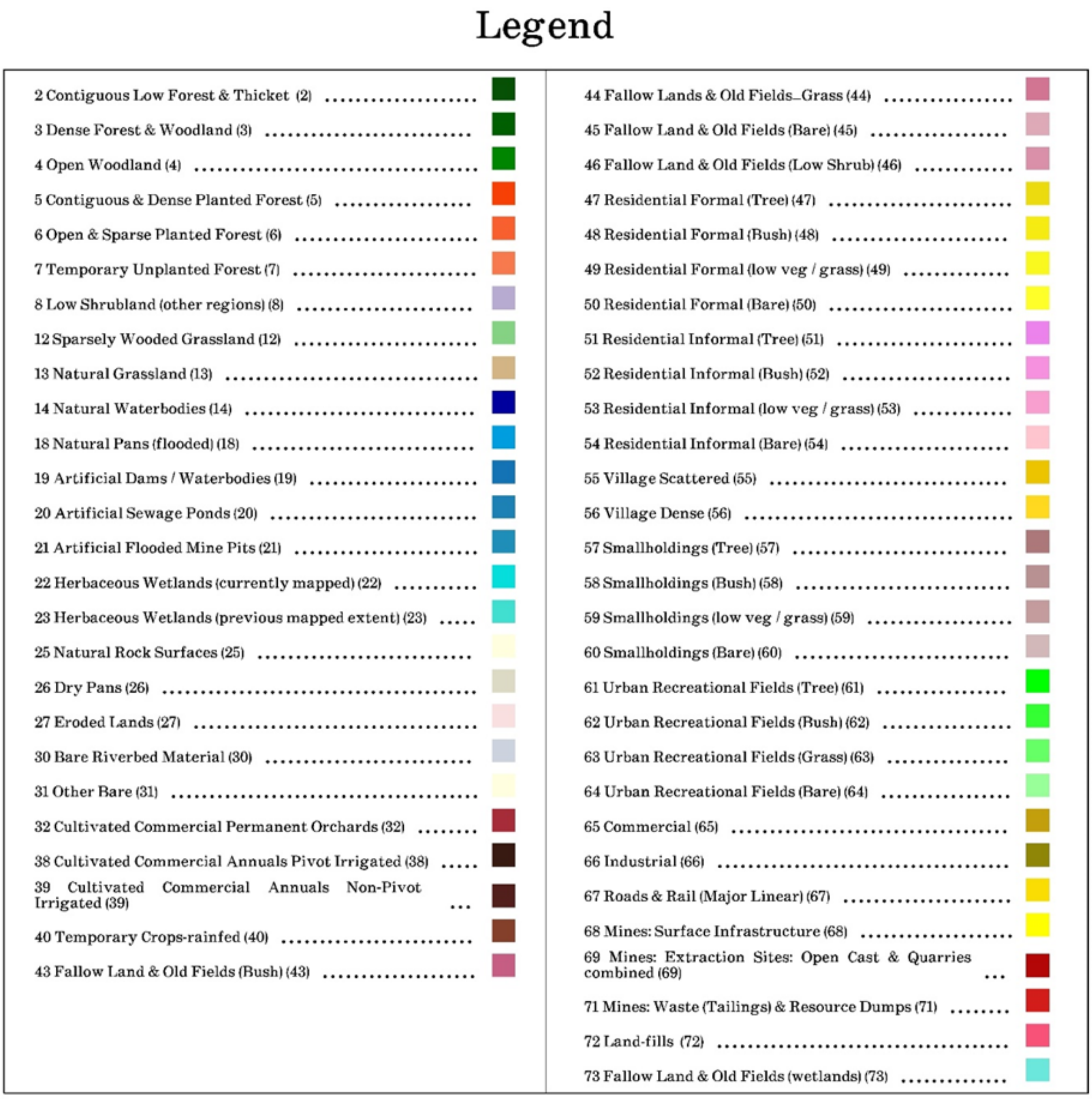


Fig. 23. Legend for the land use / land cover map of KOSH region prepared from Sentinel-2 data

Table 2

Area figures of the major classes from the NLC 2018 covering KOSH region

NLC 2018 Class	**NLC2018 Code**	**Area (square m)**	**% Area**
Natural grassland	13	1477709246	53,84%
Commercial annual crops rain-fed / dryland	40	621965313	22,66%
Fallow land & old fields (grass)	44	218126602	7,95%
Open woodland	4	99682011	3,63%
Residential formal (low veg / grass)	49	59050767	2,15%
Mine: tailings and resource dumps	71	42172445	1,54%
Commercial annual crops pivot irrigated	38	32203283	1,17%
Dense forest & woodland	3	27512798	1,00%
Low shrubland (other)	8	20322662	0,74%
Herbaceous wetlands (previously mapped)	23	18071345	0,66%
Open & sparse plantation forest	6	13731598	0,50%

Table 3

Area calculated for the different land use / land cover classes for the year 2020

1	13 Natural Grassland (13)	1 368 617 300	49,32%
2	40 Temporary Crops-rainfed (40)	913 123 000	32,90%
3	4 Open Woodland (4)	110 938 100	4,00%
4	71 Mines: Waste (Tailings) & Resource Dumps (71)	54 450 200	1,96%
5	49 Residential Formal (low veg / grass) (49)	42 396 900	1,53%
6	38 Cultivated Commercial Annuals Pivot Irrigated (38)	36 283 200	1,31%
7	50 Residential Formal (Bare) (50)	35 013 800	1,26%
8	3 Dense Forest & Woodland (3)	21 340 000	0,77%
9	47 Residential Formal (Tree) (47)	20 616 400	0,74%
10	67 Roads & Rail (Major Linear) (67)	18 490 300	0,67%
11	39 Cultivated Commercial Annuals Non-Pivot Irrigated (39)	16 359 500	0,59%
12	44 Fallow Lands & Old Fields_Grass (44)	14 376 500	0,52%
13	23 Herbaceous Wetlands (previous mapped extent) (23)	11 774 000	0,42%
14	63 Urban Recreational Fields (Grass) (63)	9 129 300	0,33%
15	14 Natural Waterbodies (14)	8 430 900	0,30%
16	19 Artificial Dams / Waterbodies (19)	8 106 500	0,29%
17	22 Herbaceous Wetlands (currently mapped) (22)	7 313 600	0,26%
18	6 Open & Sparse Planted Forest (6)	7 072 100	0,25%
19	8 Low Shrubland (other regions) (8)	7 027 900	0,25%
20	66 Industrial (66)	6 700 200	0,24%
21	65 Commercial (65)	5 197 000	0,19%
22	12 Sparsely Wooded Grassland (12)	4 952 800	0,18%
23	31 Other Bare (31)	4 687 100	0,17%
24	5 Contiguous & Dense Planted Forest (5)	4 422 100	0,16%
25	61 Urban Recreational Fields (Tree) (61)	4 218 700	0,15%
26	69 Mines: Extraction Sites: Open Cast & Quarries combined (69)	3 811 000	0,14%
27	57 Smallholdings (Tree) (57)	3 489 500	0,13%
28	68 Mines: Surface Infrastructure (68)	3 261 200	0,12%
29	53 Residential Informal (low veg / grass) (53)	3 035 500	0,11%
30	25 Natural Rock Surfaces (25)	2 887 600	0,10%
31	54 Residential Informal (Bare) (54)	2 483 800	0,09%
32	58 Smallholdings (Bush) (58)	1 632 900	0,06%
33	48 Residential Formal (Bush) (48)	1 547 300	0,06%
34	2 Contiguous Low Forest & Thicket (2)	1 517 600	0,05%
35	42 Fallow Land & Old Fields (Trees) (42)	1 453 900	0,05%
36	73 Fallow Land & Old Fields (wetlands) (73)	1 329 300	0,05%
37	20 Artificial Sewage Ponds (20)	842 300	0,03%
38	62 Urban Recreational Fields (Bush) (62)	827 000	0,03%
39	18 Natural Pans (flooded) (18)	666 300	0,02%
40	46 Fallow Land & Old Fields (Low Shrub) (46)	658 000	0,02%
41	45 Fallow Land & Old Fields (Bare) (45)	621 300	0,02%
42	26 Dry Pans (26)	462 200	0,02%
43	7 Temporary Unplanted Forest (7)	455 400	0,02%
44	30 Bare Riverbed Material (30)	451 800	0,02%
45	59 Smallholdings (low veg / grass) (59)	411 200	0,01%
46	21 Artificial Flooded Mine Pits (21)	393 900	0,01%
47	27 Eroded Lands (27)	340 700	0,01%
48	32 Cultivated Commercial Permanent Orchards (32)	291 800	0,01%
49	43 Fallow Land & Old Fields (Bush) (43)	279 600	0,01%
50	64 Urban Recreational Fields (Bare) (64)	237 900	0,01%
51	56 Village Dense (56)	233 300	0,01%
52	60 Smallholdings (Bare) (60)	186 700	0,01%
53	55 Village Scattered (55)	153 500	0,01%
54	51 Residential Informal (Tree) (51)	87 900	0,003%
55	72 Land-fills (72)	65 100	0,002%
56	52 Residential Informal (Bush) (52)	36 700	0,001%
	Sum total	**2 775 189 600**	**100,00%**

Land cover mapping of KOSH region for year 2019 using batch classification

By using the batch classification algorithm of Object Analyst, one can run classification simultaneously on a group or collection of images with similar qualities of acquisition. The classification run on an individual image (e.g. satellite image of March 2020) can be used as reference for the batch (e.g. the image of March 2019) to be processed. The batch classification applies a segmentation step, an attribute-calculation step, a Support Vector Machine (SVM)-classification step (based on the training-model file created from the first individual image classified). The training model file created with the option of having input attributes of standard deviation of VNIR bands and 10 vegetation indices was used in the batch classification. The batch classification using a previous training model file helps to reduce the analysis time by avoiding the step of identifying training sites for a similar image of a different date of acquisition. The final result of land use / land cover obtained from the batch classification step run using the Sentinel-2 image acquired on 16 March 2019 is shown in figure 24. A visual examination of the result of land use / land cover classification result (fig. 24) using the Sentinel-2 data of 16 March 2019 reveals that most of the areas of Class 13 Natural Grassland is mapped correctly.

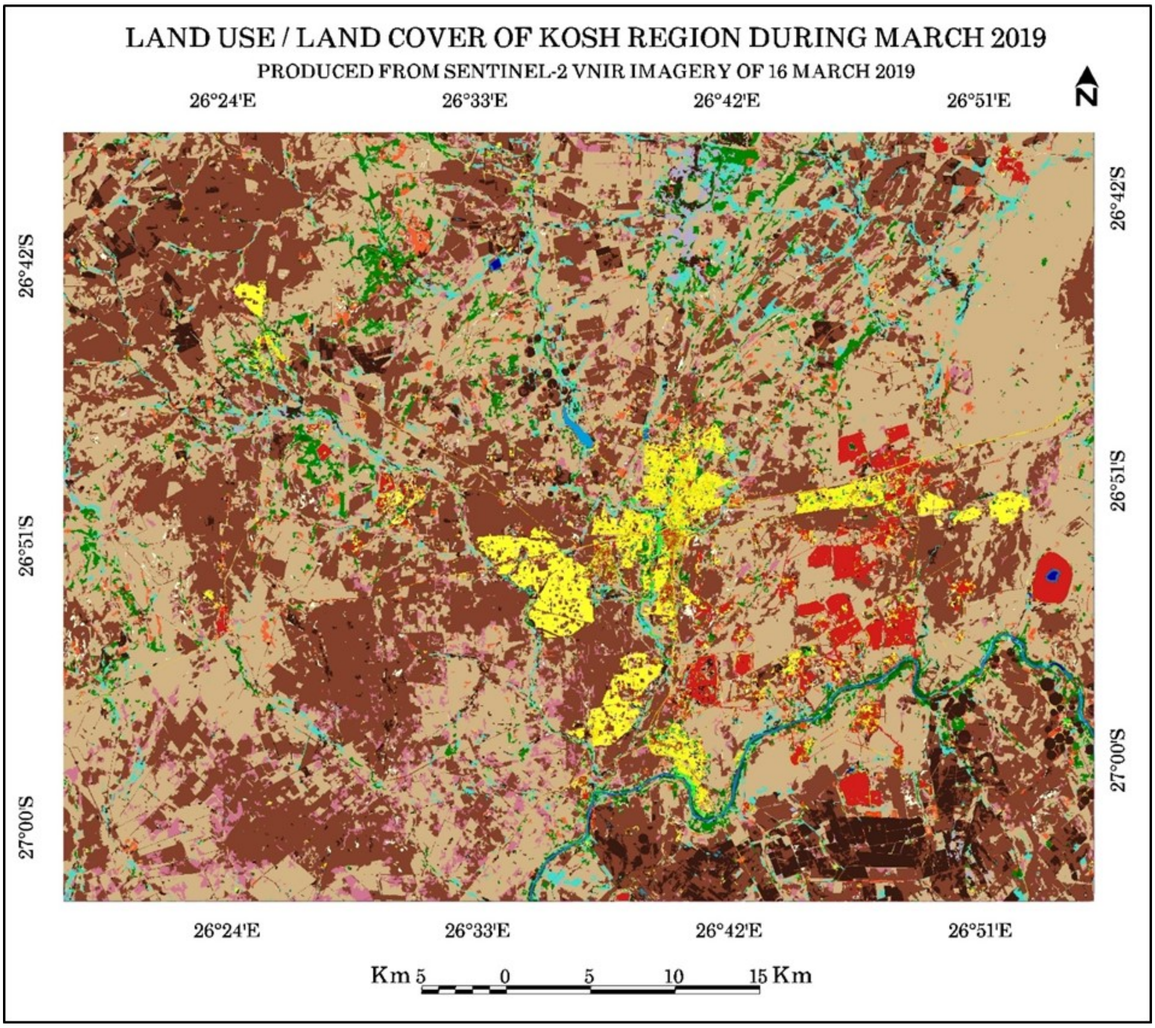
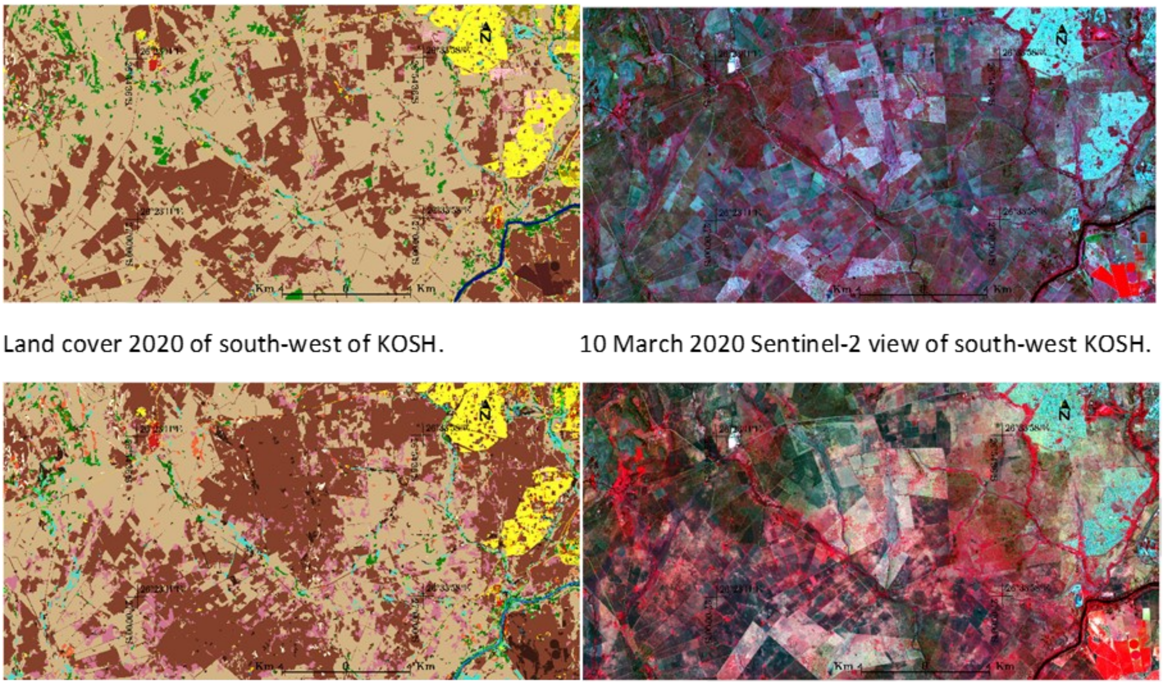


Fig. 24. Land cover classification result obtained from the Sentinel-2 image of 16 March 2019 using Batch Classification option of Object Analyst

Comparison of land covers of year 2019, year 2020 and NLC 2018

The north-eastern part of the land use / land cover map for the year (Figure 24) shows many patches of Class 23 Herbaceous Wetlands (previous mapped extent) that are actually Class 13 Natural Grassland in the land use / land cover of year 2020 and NLC 2018. The eastern part of year

2019 result shows more patches of Class 40 Temporary Crops-rainfed when compared with the result for year 2020. The south-eastern part of the result for the year 2019 shows more patches of Class 38 Cultivated Commercial Annuals Pivot Irrigated. Similarly, more patches of Class 23 Herbaceous Wetlands (previous mapped extent) are seen in the south-western region of the land use / land cover map for the year 2019. It is also found that most of the area of the Vaal River (Class 14 Natural waterbodies) seen in the south-eastern part of figure 24 is mapped as Class 20 Artificial Sewage Ponds, which is noticed as an error in the classification using batch classification. A portion of the results of land use / land cover classification for the years 2020 and 2019 showing the south-west part of KOSH region along with corresponding satellite images of years 2020 and 2019 showing the same extent is shown in figure 25.



Land cover 2020 of south-west of KOSH. 10 March 2020 Sentinel-2 view of south-west KOSH.

Land cover 2019 of south-west of KOSH. 16 March 2019 Sentinel-2 view of south-west KOSH.

Fig. 25. A portion of the results of land use / land cover classification for years 2020 and 2019 showing the south-west part of KOSH region along with corresponding satellite images of years 2020 and 2019

A close look of these figures reveals that the result for the year 2019 is distinct with more small patches of class 44 Fallow Land & Old Fields _Grass (shown in light pink shade) that are seen towards the south-west part. On comparing the satellite images of March 2019 and 2020, it can be observed that some natural grassland (Class 13) seen in the year 2019 has become agricultural fields (in south-west) and such land use dynamics changes are evident through comparison of satellite images or land cover dataset. More vegetation cover is seen in the north of 2019 image. There is some slight dissimilarities in the appearance of these two satellite images due to some difference in pixel values. Such dissimilarities observed in the satellite images of two different years (year 2019 and year 2020) will give a different result when batch classification is applied on the other image with the training sites of year 2020.

A further examination of the classification result for the year 2019 revealed that three land use / land cover classes viz. Class 2 Contiguous Low Forest & Thicket, Class 32 Cultivated Commercial Permanent Orchards and Class 52 Residential Informal (Bush) were not mapped or missing in the attribute table. The number and areal extent of the training sites for these two classes were very less (not sufficient enough) and their attributes or characteristics were not so distinct, hence they were not mapped in the batch classification. Locations of such classes have to be identified in the image and the corresponding polygon segments have to be manually re-assigned in order to show these classes in the final map. The land use / land cover map for the year 2019 requires further examination at many locations for accuracy check and subsequent editing or re-assigning of the wrong polygon segments.

The summarised area figures for the present 53 land cover classes for the year 2019 is shown in Table 4. Comparison of percentage area figures for the major land cover classes of year 2020 and 2019 show that Class 13 Natural Grassland constitutes 49.32% of the total area in the year 2020 whereas in the year 2019 the extent of this class is less (42.14% of the total area). The areal extent of the same class in NLC 2018 dataset is higher (53.84% of the total area). Class 40 Temporary crops rainfed constitutes 32.90% of total area during year 2020 whereas in year 2019 it covers nearly same extent (32.97% of total area). The same class seen in NLC 2018 covers much lesser areal extent (22.66% of total area).

Class 4 Open woodland covered 4% of the total area in the year 2020 whereas in the year 2019 it covered 3% of the total area. This class covered 3.6% of the total area in NLC 2018. The area figures of Class 4 Open woodland do not vary much in these years. Class 71 Mines: Waste (Tailings) & Resource Dumps constitute 1.96% of the total area in the year 2020. The extent of this class in the year 2019 is found to be 2.5% of the total area whereas in NLC 2018, this class is having an area of 1.5% of the total area. The higher resolution of VNIR bands at 10 m has contributed to more accurate mapping of this class. Class 44 Fallow Lands & Old Fields_Grass covered about 8% of the total area in NLC 2018 whereas in the year 2019 this class covered less area (3.3% of total area) whereas in year 2020 it decreased significantly to 0.5% of the total area. Class 49 Residential Formal (low veg / grass) had constituted 2.15% of the total area in NLC 2018 whereas in the land use / land cover map of year 2020 it covered only 1.53% of the total area. For this class during the year 2019 the calculated percentage area is 1.5% of the total area. Class 38 Cultivated Commercial Annuals Pivot Irrigated had covered 1.2% of the total area in NLC 2018 while this class has constituted 1.3% of the total area in the land use / land cover map of year 2020. For the year 2019, this class covered significantly higher percentage area of 5%. Class 3 Dense Forest & Woodland had covered 1% of the total percentage area in NLC 2018 whereas in the year 2020 the percentage of this class reduced to 0.8% of the total area. In the year 2019, the coverage of this class is still much lower (0.4% of the total area).

Conclusions

Recent Sentinel-2 satellite images acquired in March 2020 and 2019 covering the KOSH region could be classified using Geomatica Object Analyst and produced some useful land cover products to aid in land cover change detection and land use dynamics studies. The Sentinel-2 VNIR bands (10 m) are suitable for land cover mapping (for discriminating different land use / land covers including informal settlements, road network, mine dumps, urban recreation fields, different vegetation covers and agricultural practices etc.). Vegetation indices alone are not enough to differentiate urban areas (commercial/roads) and mining dumps. Use of lower resolution SWIR bands along with VNIR bands might improve the classification accuracy for urban area if a 20 m resolution output with lesser details is opted. The land cover datasets shown in this study would help in understanding the land use / land cover dynamics and also studies of environmental monitoring. This study could illustrate the usefulness of remote sensing analysis to aid in land cover mapping using freely available high resolution Sentinel-2 data. Editing of the identified training sites of year 2020 along with viewing of the features of 2019 satellite data will enhance the classification accuracy for year 2019.

Table 4

Area calculated for the different land use / land cover classes for the year 2019

Sr No.	**Land use / land cover during March 2019**	**Area (m^2)**	**% Area**
1	13 Natural Grassland (13)	1 169 347 200	42,14%
2	40 Temporary Crops-rainfed (40)	915 042 200	32,97%
3	38 Cultivated Commercial Annuals Pivot Irrigated (38)	139 129 500	5,01%
4	44 Fallow Lands & Old Fields_Grass (44)	90 974 100	3,28%
5	4 Open Woodland (4)	84 056 900	3,03%
6	71 Mines: Waste (Tailings) & Resource Dumps (71)	68 146 800	2,46%
7	23 Herbaceous Wetlands (previous mapped extent) (23)	58 082 300	2,09%
8	49 Residential Formal (low veg / grass) (49)	40 510 100	1,46%
9	6 Open & Sparse Planted Forest (6)	40 115 400	1,45%
10	50 Residential Formal (Bare) (50)	38 608 000	1,39%
11	12 Sparsely Wooded Grassland (12)	16 352 700	0,59%
12	67 Roads & Rail (Major Linear) (67)	15 578 600	0,56%
13	8 Low Shrubland (other regions) (8)	12 300 300	0,44%
14	3 Dense Forest & Woodland (3)	11 509 900	0,41%
15	25 Natural Rock Surfaces (25)	9 014 200	0,32%
16	31 Other Bare (31)	6 396 200	0,23%
17	61 Urban Recreational Fields (Tree) (61)	6 377 500	0,23%
18	47 Residential Formal (Tree) (47)	5 411 100	0,19%
19	5 Contiguous & Dense Planted Forest (5)	5 107 100	0,18%
20	66 Industrial (66)	4 439 100	0,16%
21	20 Artificial Sewage Ponds (20)	4 031 500	0,15%
22	19 Artificial Dams / Waterbodies (19)	3 718 600	0,13%
23	63 Urban Recreational Fields (Grass) (63)	3 521 000	0,13%
24	69 Mines: Extraction Sites: Open Cast & Quarries combined (69)	3 309 900	0,12%
25	30 Bare Riverbed Material (30)	2 786 500	0,10%
26	22 Herbaceous Wetlands (currently mapped) (22)	2 193 600	0,08%
27	65 Commercial (65)	2 105 400	0,08%
28	73 Fallow Land & Old Fields (wetlands) (73)	1 778 600	0,06%
29	14 Natural Waterbodies (14)	1 707 000	0,06%
30	18 Natural Pans (flooded) (18)	1 665 800	0,06%
31	7 Temporary Unplanted Forest (7)	1 619 100	0,06%
32	58 Smallholdings (Bush) (58)	1 573 100	0,06%
33	48 Residential Formal (Bush) (48)	1 409 300	0,05%
34	54 Residential Informal (Bare) (54)	1 290 600	0,05%
35	39 Cultivated Commercial Annuals Non-Pivot Irrigated (39)	848 600	0,03%
36	53 Residential Informal (low veg / grass) (53)	610 900	0,02%
37	59 Smallholdings (low veg / grass) (59)	558 000	0,02%
38	26 Dry Pans (26)	508 200	0,02%
39	2 Contiguous Low Forest & Thicket (2)	504 200	0,02%
40	57 Smallholdings (Tree) (57)	457 900	0,02%
41	27 Eroded Lands (27)	441 100	0,02%
42	68 Mines: Surface Infrastructure (68)	404 100	0,01%
43	21 Artificial Flooded Mine Pits (21)	339 200	0,01%
44	51 Residential Informal (Tree) (51)	256 600	0,01%
45	55 Village Scattered (55)	211 400	0,01%
46	62 Urban Recreational Fields (Bush) (62)	178 300	0,01%
47	64 Urban Recreational Fields (Bare) (64)	141 400	0,01%
48	45 Fallow Land & Old Fields (Bare) (45)	133 400	0,005%
49	46 Fallow Land & Old Fields (Low Shrub) (46)	132 100	0,005%
50	56 Village Dense (56)	121 900	0,004%
51	72 Land-fills (72)	91 000	0,003%
52	60 Smallholdings (Bare) (60)	30 100	0,001%
53	52 Residential Informal (Bush) (52)	12 000	0,0004%
	Sum total	**2 775 189 600**	**100,00%**

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References

1. Boriah, S. et al. Land cover change detection: A case study, in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, **2008**, pp. 857–865.
2. ESA-STEP, *ESA SNAP Toolbox surpasses 300000 downloads*, **2018**, Available at: http://step.esa.int/main/esa-snap-toolbox-surpasses-300000-downloads/ (Accessed: 10 September 2019).
3. Mail&Guardian, Former mine owners to cough up, *Mail & Guardian*, **2014**, Available at: http://mg.co.za/article/2014-01-17-00-former-mine-owners-to-cough-up.
4. Midgley, D. C., Pitman, W. V. and Middleton, B. J., *Surface water resources of South Africa 1990: Book of Maps, Volume II. Drainage Region C Vaal - Report 298/2.2/94,* **1994**.
5. PCI-Geomatics, Object Analyst: Technical Specifiations, *PCI Geomatics*, **2017**, p. 11. Available at: https://www.pcigeomatics.com/pdf/geomatica/techspecs/2017/Object-Analyst.pdf.
6. Pulles, W., Banister, S. and Van Biljon, M., *Development of appropriate procedures toward sand after closure of underground gold mines from a water management perspective: Report No.1215/1/05*, **2005**, Available at: http://www.wrc.org.za/Lists/Knowledge Hub Items/Attachments/7697/1215-1-05_EXECUTIVE SUMMARY.pdf.
7. SAFLII, Judgment of Case No: 971/12 from the Supreme Court of Appeal of South Africa, *SOUTHERN AFRICAN LEGAL INFORMATION INSTITUTE (SAFLII)*, **2013**, Available at: http://www.saflii.org/za/cases/ZASCA/2013/206.pdf.
8. Thompson, M., *South African National Land-Cover 2018 Report & Accuracy Assessment*, **2019**.