

https://dspace.org/

# Remote sensing based land use land cover classificationfor th Heuningness Catchment Cape Agulhas South Africa

**D Cloete; Cletah Shoko; T Dube; S Clarke**

PERGAMON-ELSEVIER SCIENCE LTD
https://hdl.handle.net/10539/41767
WOS

Downloaded from a DSpace repository. https://dspace.org/

Physics and Chemistry of the Earth 134 (2024) 103559

Contents lists available at ScienceDirect

Physics and Chemistry of the Earth

journal homepage: www.elsevier.com/locate/pce

# Remote sensing-based land use land cover classification for the Heuningnes Catchment, Cape Agulhas, South Africa

Danielle N. Cloete [a], Cletah Shoko [b], Timothy Dube [a,*], Sumaya Clarke [a]

[a] Institute for Water Studies, Faculty of Natural Sciences, University of the Western Cape, Cape Town, South Africa
[b] School of Geography, Archaeology and Environmental Studies, University of Witwatersrand, Johannesburg, South Africa

ARTICLE INFO

*Keywords:*
Land management
Machine-learning techniques
Sentinel-2

ABSTRACT

The primary objective of this study was to evaluate the effectiveness of Sentinel 2 and machine-learning technique for classifying seasonal land use land cover (LULC) changes on an annual basis, in the Heuningnes Catchment in Cape Agulhas, South Africa. The study focused on July 2017, October 2017, March 2018, and July 2018, representing both dry and wet seasons within the Catchment. The study also assessed the rainfall and temperature variations and how they link with these short-term changes in LULC. The classification results revealed a consistent increase in the extent of bare rock and soil cover from October 2017 to July 2018. The wet seasons of July 2017 and July 2018 exhibited the highest percentage of vegetation cover. The overall accuracy of the SVM classification ranged between 55 % and 75 %, with the wet seasons demonstrating higher overall accuracies of 75 %. The performance of SVM was evaluated using kappa statistics, which indicated a moderate to substantial level of agreement ranging from 0.43 to 0.69. By employing machine-learning techniques and satellite data, this study contributes to a better understanding of LULC patterns and their implications for water security, sustainable development goals, and community livelihoods in the Heuningnes Catchment of Cape Agulhas, South Africa.

## 1. Introduction

Different land use land cover (LULC) types have varying effects on earth-atmospheric processes (Horne et al., 2017). For example, urbanization, characterized by the extensive development of impervious surfaces like buildings, roads, and concrete areas, directly impacts water quality by introducing harmful materials that become incorporated into surface runoff, thereby contributing to water quality degradation (Cheng et al., 2022). On the other hand, agricultural activities also have a major influence on surface water quality, due to the extensive use of fertilizers and chemicals, which become major pollutants, (Cheng et al., 2022).

In addition, LULC changes also influence land degradation. For example, the changes from grasslands to bare promote soil loss through erosion, thereby leading to the deterioration of soil quality. Similarly, soil erosion results in river sedimentation, thereby reducing the capacity of the rivers to hold water. This affect water availability. The impacts of LULC changes on surface water quality have been extensively studied over the years (Cheng et al., 2022; Namugize et al., 2018a, 2018b; Ighalo et al., 2021; Park and Lee, 2020). Different land use and cover types have varying effect on water quality, due to local topographical and climatic variations. For example, Cheng et al. (2022) provide a detailed review of the relationship between varying land use land cover on water quality. Overall, the review noted that land use change affects various ecological preprocess, surface run-off, infiltration which in turn affect water quality. In a recent study, Baltodano et al. (2022) reported relationship between urban expansion for the Katari River Basin in the Bolivian Andes and chlorophyl and turbidity, for Lake Titicaca in South America, using remote sensing, field-based water quality assessment and water indices. In another study, Gorgoglione et al. (2020) assessed the relationship between LULC and water quality in the Santa Lucía catchment of Uruguay, in South America. The findings indicated a strong correlation between total phosphorus concentration and agriculture-land, high corelation between nitrogen and urban-land use, as well as inverse correlation between total phosphorus concentration and forest-land use.

The application of remote sensing techniques for LULC monitoring and change detection remains a critical issue (Yuh et al., 2023). Remotely sensed data allows for the extraction of high-resolution, multispectral information covering large inaccessible areas in real-time, making the process more cost-effective and time efficient (Yuh

* Corresponding author.
*E-mail address:* dube.timoth@gmail.com (T. Dube).

https://doi.org/10.1016/j.pce.2024.103559
Received 27 June 2023; Received in revised form 27 October 2023; Accepted 9 January 2024
Available online 1 February 2024
1474-7065/© 2024 Elsevier Ltd. All rights reserved.

et al., 2023; Mhanna et al., 2023). These techniques enable the mapping of land cover changes and provide insights into their influence on various earth-atmospheric processes (Butt et al., 2015). Moreover, this information is crucial for developing strategies for spatial planning, utilization, and conservation of vital land resources to accommodate the exponential growth of human populations and address increasing land degradation. Traditional approaches remain time-consuming, expensive, and lacked updated information on the dynamics of various LULC patterns (Phiri et al., 2020; Yuh et al., 2023). On the other hand, advancements in remote sensing technologies, such as the launch of Sentinel-2 in 2015, have revolutionized LULC monitoring. Sentinel-2, with its multispectral capabilities, high spatial and temporal resolution, and the availability of timely and free access data over large-scale areas, has significantly enhanced the monitoring of land use land cover (Phiri et al., 2020).

In addition, the use of advanced machine learning techniques is gaining popularity in image classification using remotely sensed data for LULC change analysis ((Yuh et al., 2023; Talukdar et al., 2020). For example, Random forests (RF) and support vector machine (SVM), have shown great potential in LULC detection and mapping over time (Jamali 2021; Yuh et al., 2023; Phiri et al., 2020). For example, Jamali (2020) proved the potential of RF and SVM with deep learning techniques and Landsat 8 in mapping land cover types in the Shiraz city of Iran for the 18$^{th}$ of August 2022. Findings reported that all machine learning performed well with accuracies above 98 % and the use of deep learning was reliable when Landsat 8 was used at 15m spatial resolution, compared to 30m. Similarly, Jamali (2021) used Landsat 7 Enhanced Thematic Mapper (ETM) and Landsat 8, to compare K-nearest Neighbour (KNN), SVM, Artificial Neural Network (ANN) and RF in detecting LULC changes for November 2000 and November 2020, in Cameroon. All the machine learning produced accuracies above 80 %.

Although LULC mapping is has been conducted using remote sensing, the seasonal changes at catchment scale have received limited attention. Thus, most LULC change focuses on longer time such as 20 years (*e.g.,* Yuh et al., 2023, Jamali, 2021). This has not been possible due to the use of medium spatial resolution sensor, such as Landsat (*e.g.,* Mhanna et al., 2023; Obeidat et al., 2019), as well as low spatial resolution sensors, such as MODIS (*e.g.,* García-Mora et al., 2012; Mhanna et al., 2023) and AVHRR. García-Mora et al. (2012) provide a detailed review of application of MODIS for LULC mapping, including its limitations. These datasets have been reported to fail to detect LULC changes within short times, such as on annual or seasonal basis. However, the availability of Sentinel 2 and advanced machine classification techniques allows for a better detection and mapping of LULC changes at short intervals. In this regard, this study evaluated the effectiveness of Sentinel 2 multispectral remote sensing in mapping and detecting changes in LULC within the Heuningnes catchment in South Africa. In addition, the study assessed the rainfall and temperature variations during the period of study to see if there are any links with LULC changes.

## 2. Materials and methods

### 2.1. Study area

The study was conducted in the Heuningnes catchment, located in the Overberg District of the Western Cape Province, South Africa (Fig. 1). The catchment encompasses an area of approximately 1,401 km$^2$, including towns such as Bredasdorp, Napier, and Elim. Within the Heuningnes catchment, there are sub-catchments formed by the Droe, Kars, Poort, and Nuwejaars Rivers (Clark et al., 2015). The Nuwejaars River eventually flows into the Soetendalsvlei, which is 3 km wide and 8 km long (Mkunyana et al., 2019). The Heuningnes River, on the other hand, feeds into the Heuningnes River estuary, which extends over 19 km and encompasses 1,475 ha of open water along the South Coast (Estuarine and Plan, 2019). Two tributaries, the Kars River and the Nuwejaars River, join the river estuary. The topography of the catchment is described as mountainous in the upper reaches and gradually becomes flatter as it reaches the lower-lying areas near the coast. The sub-catchments within the Heuningnes catchment exhibit a mix of steep,

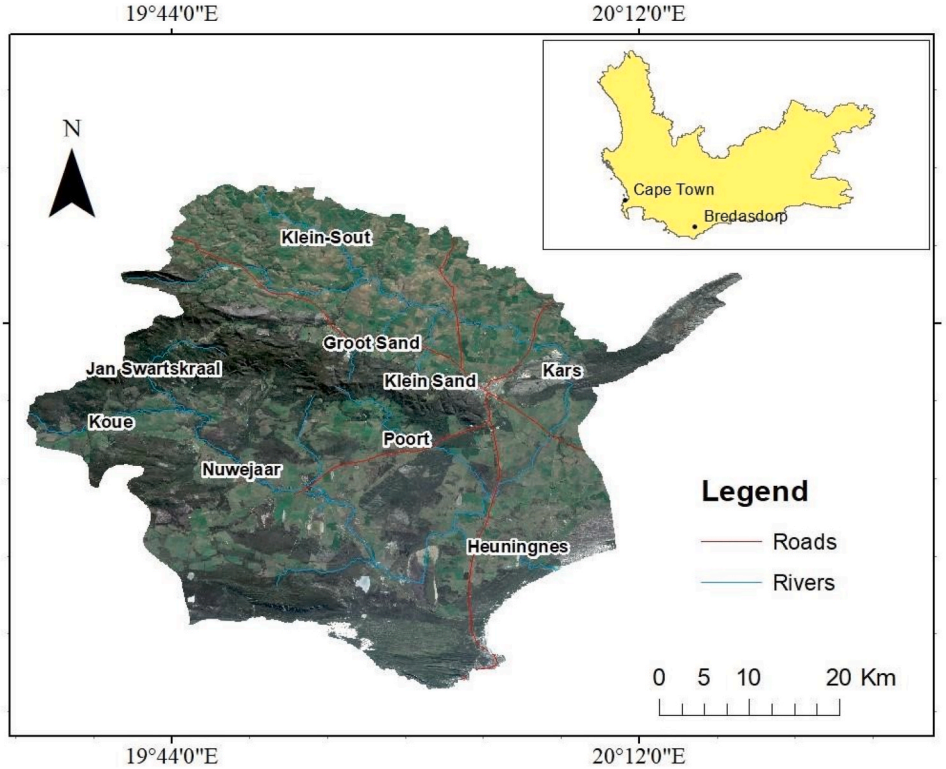



**Fig. 1.** Location of the heuningnes catchment, in Cape Agulhas, South Africa.

flat, and undulating terrain. The geology of the region consists of shales and sandstones from the Table Mountain Group. The soil characteristics shallow, medium, and moderate sandy clay loams (Clark et al., 2015). The catchment experiences a Mediterranean climate and receives an average annual rainfall of about 450 mm along the coast and 650 mm inland along the foothills. Maximum temperatures reach 27 °C in January, while minimum temperatures occur in July and August, dropping to 8 °C.

### 2.2. Satellite data acquisition

Sentinel-2 images were used to assess the land use land cover in the Heuningnes catchment, Cape Agulhas, South Africa. Images were obtained from the USGS earth explorer website (https://www.usgs.gov), and represented the period between July 2017 and July 2018, as well as October 2017 and March 2018, covering the wet and dry periods, respectively. Images were selected with a 10 % less cloud coverage. Table 1 displays Sentinel-2 band number, description, wavelength unit and resolution.

### 2.3. Climate data

Climate data were acquired from the Institute of Water Studies (IWS) to observe rainfall and temperature variation across the Heuningnes catchment. LULC Rainfall and temperature have been reported to influence LULC changes (*e.g.,* Mngube et al., 2020). In this regard, the study used the data to compare how it varies in relation to LULC changes.

### 2.4. Image pre-processing and classification

These images were pre-processed in Quantum GIS, for atmospheric correction by applying the dark object subtraction (DOS1) correction tool, which considers and corrects shaded objects, and is an essential step in obtaining true colour of inland water bodies (Bi et al., 2018; Rumora et al., 2020). Atmospheric correction is vital as it ensures accuracy in classification results. Additionally, image segmentation was applied as pre-processing step for the preparation of the image classification. The segment means shift algorithm groups pixels of a similar spectral and spatial characteristic, to reduce noise effects, because of overlapping pixels causing inaccuracies within the final classification result. Furthermore, segmentation is the process of using similar smaller units together to produce larger regions, where different land cover classes can be discerned. Further processing was done in a GIS environment, where bands 5, 6, 7, 8a, 11 and 12 were resampled from a 20m resolution to a 10m resolution. The resampled bands were mosaicked resulting in a single complete image of the study area.

For image classifications, five different land use classes were observed namely: surface waterbodies and streams; vegetation collective including indigenous, grasslands, invasive plants, and agricultural land; bare rock and soil; urban and other, which includes hill shade.

**Table 1**
Spatial and spectral properties of Sentinel 2 satellite data.

| Band number | Band description | Wavelength (nm) | Spatial Resolution (m) |
|---|---|---|---|
| **2** | **Blue** | **490** | **10** |
| **3** | Green | 560 | 10 |
| **4** | Red | 665 | 10 |
| **5** | Red edge | 705 | 20 |
| **6** | Red edge | 740 | 20 |
| **7** | Red edge | 783 | 20 |
| **8** | NIR | 842 | 10 |
| **8a** | Red edge | 865 | 20 |
| **11** | SWIR | 1610 | 20 |
| **12** | SWIR | 2190 | 20 |

NIR: Near Infrared, SWIR: Shortwave Infrared.

Classifications was achieved by applying the supervised classification method, Support Vector Machine (SVM). As stated by (Rudrapal, 2015), SVM can function regardless of having a small training dataset, it is less prone to noise and continues to produce accurate results. For preparation of SVM, training samples were prepared by creating polygon signatures where a class is assigned to pixels representing the various land use land cover classes.

### 2.5. Accuracy assessments

Accuracy assessments was done to evaluate the accuracy of image classifications. Datasets used were acquired through digitization in Google Earth Pro. A total of 350 points were created in Google Earth Pro, with 70 points per class. An error matrix was created, to demonstrate the classified pixels against the reference pixels. These reference points were compared to the classified image to see whether there is correspondence between them. The accuracy assessments measurements used were the overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and Kappa coefficient (Kc). The producer accuracy refers to the correctly classified pixels for each class, in relation to the total reference points created for each class and indicates; whereas user accuracy represents the correctly classified pixels proportionate to validated points for each class (Tselka et al., 2023). The overall accuracy refers to the number of correctly classified pixels proportionate to the incorrectly classified pixels, whereas the kappa statistic represents the overall agreement of the classification technique (Olofsson et al., 2013; Rwanga and Ndambuki, 2017; Zhen et al., 2013). Accuracy assessment equations are presented in Table 2.

Fig. 2 provides a detailed summary of the analysis method.

## 3. Results

### 3.1. Classification accuracies

Table 3 displays accuracy assessment results of the image classification using Sentinel 2 and SVM, for July 2017 to July 2018. The highest overall accuracy was obtained in July 2017 and July 2018 with 75 %. The producer accuracies ranged between 46 % and 97 % and user accuracies ranged between 52 % and 96 %, for the wet season. For the dry seasons, October 2017 and March 2018, the overall accuracy ranges between 55 % and 66 %, with kappa coefficients of 0.43 and 0.58 respectively. The different LULC classes had producer accuracies, ranging between 0 % for vegetation in October 2017, and 100 % for other classes, whereas the user accuracies ranged between 40 % for urban areas and 96 % for other LULC.

### 3.2. Mapping land use land cover changes

Fig. 3 illustrates LULC classification for the wet seasons of July 2017

**Table 2**
Accuracy assessment metrics used in the study (adopted from Tselka et al., 2023).

| Equation number | Index | Symbol | Equation |
|---|---|---|---|
| (1) | Overall accuracy | OA | $\frac{1}{N}\sum_{i=1}^{r} n_{ii}$ |
| (2) | Producers accuracy | PA | $\frac{n_{ii}}{n_{icol}}$ |
| (3) | Users accuracy | UA | $\frac{n_{ii}}{n_{irow}}$ |
| (4) | Kappa index | $K_c$ | $N\sum_{i=1}^{r} n_{ii} - \sum_{i=1}^{r} \frac{n_{icol} n_{irow}}{N^2} - \sum_{i=1}^{r} n_{icol} n_{irow}$ |

$n_{ii}$: number of pixels correctly classified in a category; $N$: total number of pixels in the confusion matrix; $r$: the number of rows; and $n_{icol}$ and $n_{irow}$ are the column (reference data) and row (predicted classes) total.

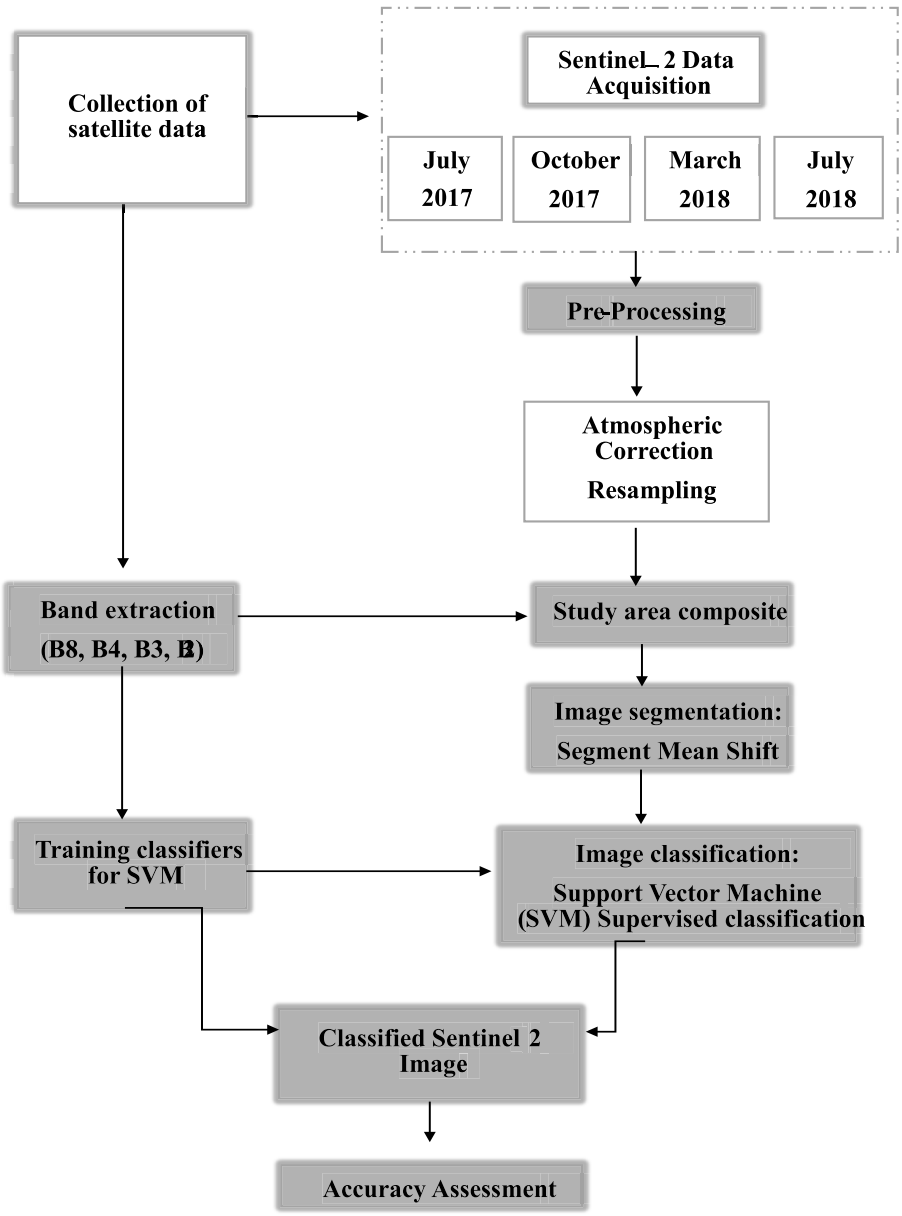



**Fig. 2.** Flow chart illustrating the process for image classification of a Sentinel – 2 image.

**Table 3**
Accuracy assessment results for the study period.

| Class | July 2017 | | October 2017 | | March 2018 | | July 2018 | |
|---|---|---|---|---|---|---|---|---|
| | PA | UA | PA | UA | PA | UA | PA | UA |
| Water | 79 | 96 | 76 | 96 | 76 | 88 | 77 | 93 |
| Vegetation | 96 | 69 | 0 | 69 | 33 | 64 | 96 | 78 |
| Other | 97 | 91 | 100 | 61 | 93 | 93 | 91 | 96 |
| Bare rock & soil | 57 | 62 | 19 | 62 | 53 | 71 | 49 | 61 |
| Urban | 46 | 57 | 79 | 45 | 76 | 40 | 61 | 52 |
| OA | 75 % | | 55 % | | 66 % | | 75 % | |
| Kc | 69 % | | 43 % | | 58 % | | 69 % | |

and July 2018 and for the dry seasons, October 2017, and March 2018. Fig. 4 further highlights the area coverage for the different LULC types, within the catchment. Vegetation was the dominant land cover class, with a total of 77 % coverage in July 2017. October 2017 holds the lowest vegetation cover of 33 %. For 2018, March had the highest water coverage of 12 %, and October 2017, the lowest water coverage with only 1 %. Urban and other, has a 29 % and 35 % coverage respectively, and was recorded as the period with the highest urban and other land cover. These land cover types are predominantly along the western part of the catchment, and along the coast, for October 2017. The other land cover type is predominantly present within the mountain range area, at the centre of the catchment, as most of the other land cover type consists of hill shade effects. In March 2018 and July 2018, bare rock and soil has increased from 2 % in October 2017, to 17 % in March 2018 and then a further increased to 18 % in July 2018.

### 3.3. Climate variations

Climate data received from the Institute of Water Studies (IWS) to observe rainfall and temperature variation across the Heuningnes catchment, see Fig. 5. The highest average rainfall was recorded as 10.43 mm within Tierfontein in 2017, and the lowest average rainfall was recorded as 4.46 mm within Napier in 2018. In 2018, Spanjaardskloof recorded the highest maximum temperature of 24.42 °C and in 2017, Moddervlei recorded the lowest minimum temperature of 9.98 °C.

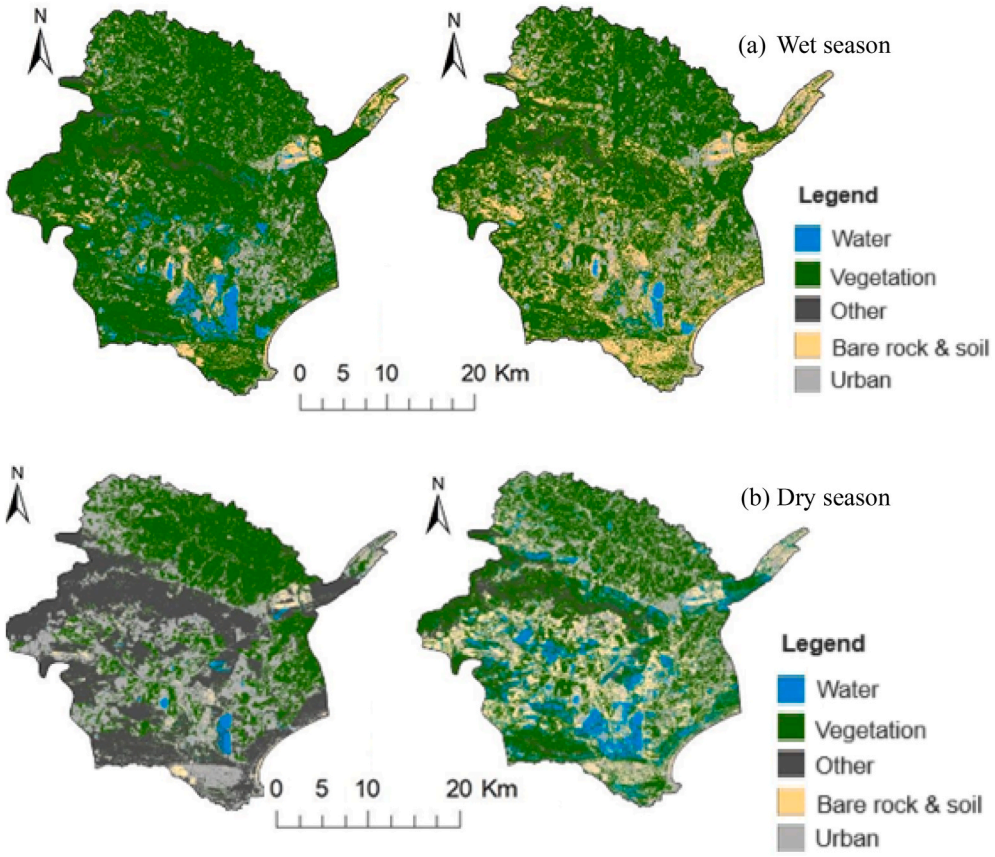



**Fig. 3.** Classified images with support vector machine during the study period.

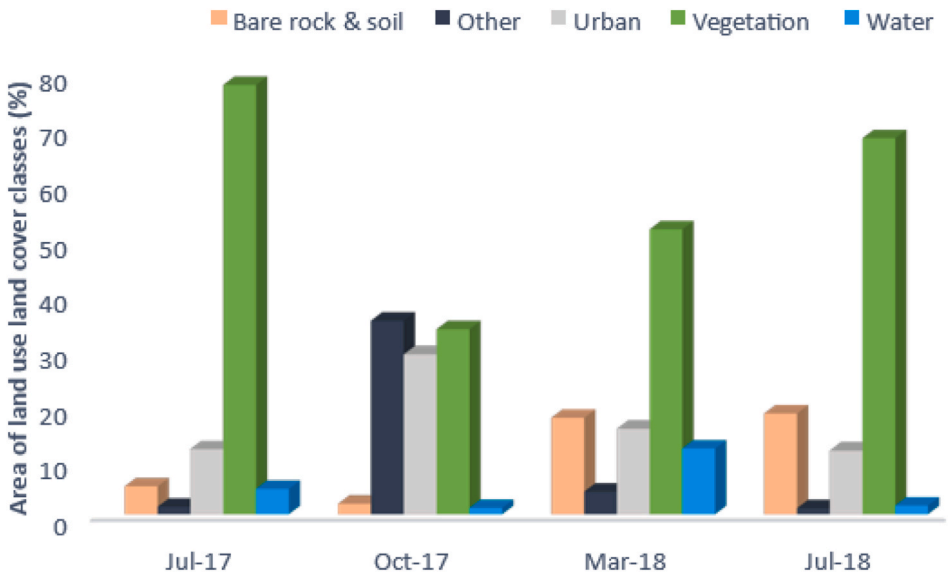



**Fig. 4.** The area of the different LULC classes, between July 2017 and July 2018.

## 4. Discussion

The primary objective of this study was to determine seasonal land use land cover changes within the Heuningnes Catchment in Cape Agulhas, South Africa. The analysis was conducted during both the wet season (July 2017 and July 2018) and the dry season (October 2017 and March 2018). The results revealed that the wet seasons exhibited the highest percentage of vegetation cover. This could be expected, as the climatic conditions, such as rainfall and temperature during the wet season promote vegetation regrowth, health and expansion. The study by.

The spatial distribution maps have shown that vegetation class was the most dominant across the catchment covering approximately 77 % of the study area in July 2017, which is the wet season, whereas the lowest areal coverage of vegetation was detected in October 2017, covering only 33 % of the study area. The vegetation class comprise both

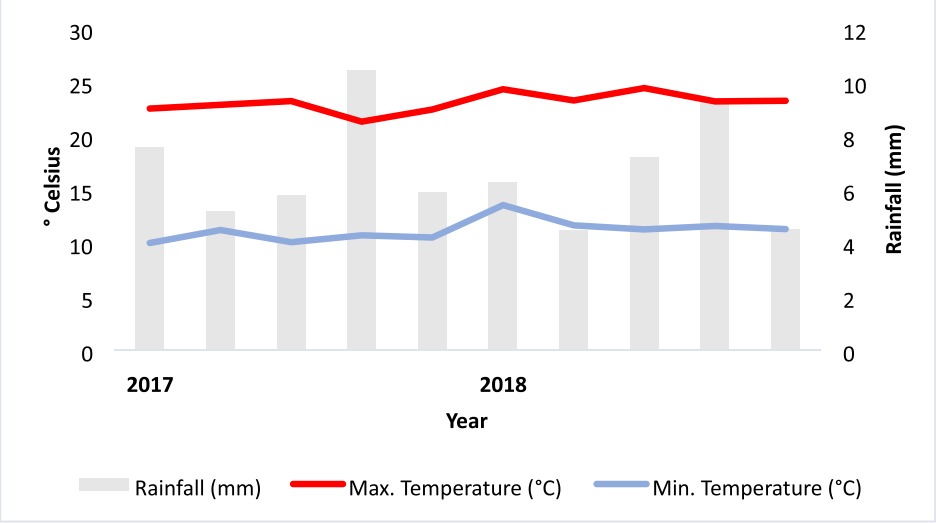



**Fig. 5.** Climate variations for 2017 and 2018 across the study catchment.

agricultural and natural vegetation. Previous studies have reported different vegetation classes within the catchment including plantations, invasive species and farms (*e.g.,* Mtengwana et al., 2020; Shoko et al., 2020; Mtengwana et al., 2021). In this regard, the changes in vegetation greenness and farming activities between the wet and dry seasons results in a reduction in the area covered by vegetation. For example, natural vegetation might shed their leaves, and farms cleared, thereby appearing bare or classified as other. It was observed that water bodies are quite limited within the study area, only covering up to 12 %.

For the wet seasons, July 2017 and July 2018, the overall accuracy is 75 %, with a kappa coefficient of 0.69. According to (Rwanga and Ndambuki, 2017), this kappa value indicates a substantial level of agreement, within the SVM classification algorithm used. For the dry seasons, October 2017 and March 2018, the overall accuracy ranges between 55 % and 66 %, with kappa coefficients of 0.43 and 0.58 respectively, indicating moderate level agreement (Rwanga and Ndambuki, 2017). Therefore, the classification during the dry period resulted in lower accuracies compared to the wet season. Classification results during the dry season can be influenced by various factors. One common error observed in the classification results was the occurrence of mixed pixels, particularly between waterbodies and vegetation cover, which was prominent in the Voelvlei and Soetendalsvlei areas. To address this issue, an object-based classification technique, such as image segmentation, was applied. Image segmentation involves aggregating spectrally similar objects into specific classes, helping to correct the error of mixed pixels (Y. Chen et al., 2018). Also, the spatial resolution of the satellite used also result in mixed pixel problems (Foody, 2008).

The classification results for October 2017 indicated an overestimation of urban areas and hill shade, with 100 % producer's accuracy, while no pixels were classified as vegetation, resulting in a user's accuracy of 69 %. In March 2018, waterbodies within the catchment appeared to be overclassified. The use of support vector machine (SVM) for land cover mapping proved to be more suitable compared to other classification algorithms such as maximum likelihood classification. SVM does not assume normal distribution of data and can accommodate a wider range of values, allowing for better representation of land cover classes. Moreover, SVM achieves accurate results even with smaller training sets (Kang et al., 2018). The overall classification accuracy using SVM ranged between 55 % and 75 %, with kappa coefficients ranging between 43 % and 69 % for the period from July 2017 to July 2018. However, it is important to note that the overclassification error observed could be attributed to the image segmentation technique employed, as the algorithm may result in over-segmentation with low spatial resolution images and under-segmentation with high-resolution images (Y. Chen et al., 2018; Liu and Xia, 2010).

The use of Sentinel 2 also proves its potential in detecting LULC on an annual basis. This allows the detection of seasonal, intra-annual, annual changes in LULC. This provides basis for future studies to focus at local scale on a seasonal basis. Previous studies have also provided the potential of Sentinel 2 to identify, detecting and mapping various land use land cover, and specific vegetation species, within the present catchment (Chiloane et al., 2023; Mtengwana et al., 2020, 2021; Shoko et al., 2020), as well as beyond (Mishra et al., 2020; Akyürek et al., 2018). In these studies2, Sentinel proved more beneficial in detecting LULC patterns. One of the key benefits of Sentinel 2 is the accessibility of data, particularly for developing countries, due to the economic advantages of the Sentinel-2 mission. Sentinel-2's red-edge band 5 is useful for mapping various LULC. The availability of high-resolution and timely data from Sentinel-2 enables the monitoring of dynamic environmental changes over large areas (Astola et al., 2019; Phiri et al., 2020).

### 4.1. *Implications of the study on land and water resources management*

The application of a suitable image classification algorithm for land use land cover analysis in the Heuningnes Catchment has significant implications for water security, the achievement of Sustainable Development Goals (SDGs), and community livelihoods. Accurate land cover mapping provides valuable information on the distribution and extent of vegetation, waterbodies, and urban areas, which are crucial components for assessing water resources and their availability for human needs, agriculture, and ecosystem health. Water security, as a fundamental aspect of sustainable development, relies on effective management and conservation of water resources. By accurately mapping land cover and detecting changes over time, decision-makers can assess the impact of land use practices, such as irrigation and urban expansion, on water availability and quality. This information enables the formulation and implementation of targeted strategies for water resource management, ensuring sustainable water use, reducing water stress, and improving resilience to water-related challenges. Furthermore, the findings of the study have direct relevance to several SDGs, including Goal 6 (Clean Water and Sanitation), and Goal 15 (Life on Land). Accurate land cover mapping supports the monitoring and evaluation of progress towards these goals by providing data on the status of water resources, urbanization patterns, and ecosystem integrity. It allows policymakers to identify areas at risk of land degradation, prioritize conservation efforts,

and implement measures to enhance community livelihoods and ecosystem services.

The integration of land cover information with water security, SDGs, and community livelihoods is essential for informed decision-making and sustainable development planning. The identification of appropriate image classification algorithms, such as Support Vector Machine, and the utilization of satellite data, such as Sentinel-2, contribute to improved land cover mapping accuracy, enabling a comprehensive understanding of the landscape and its implications for water resources, SDGs, and community well-being. By promoting effective land management practices and supporting the achievement of water-related targets within the SDGs, this research ultimately aims to enhance water security, foster sustainable development, and improve the livelihoods of local communities.

## 5. Conclusion

In conclusion, this study demonstrated the successful application of Sentinel-2 data for land use land cover mapping in the Heuningnes Catchment, Cape Agulhas, South Africa, during the period of July 2017 to July 2018. The classification accuracies ranged from 55 % to 75 %, and the kappa coefficients ranged from 43 % to 69 %, using support vector machine (SVM) algorithm. This technology offers valuable insights into the spatial patterns and trends of land use, allowing for better monitoring and management of natural resources in the Heuningnes Catchment and similar regions. However, there were a few limitations observed, such as mixed pixels between waterbodies and vegetation cover, as well as over-classification of hill shade and urban cover, the overall results highlight the potential of Sentinel-2 for retrieving high-resolution and timely information on the dynamic changes in land cover. Therefore, further research should be conducted to address and improve the misclassification between waterbodies, hillshade, and vegetation cover. Additionally, incorporating ancillary data, such as field measurements, could enhance the accuracy of land use land cover mapping. Furthermore, the application of Sentinel-2 data should be integrated into land management and planning strategies in the Heuningnes Catchment and other similar areas. This will enable policymakers and stakeholders to make informed decisions regarding land use, conservation efforts, and sustainable development. Regular monitoring using Sentinel-2 can provide valuable information on the impact of land cover changes on water resources, ecosystems, and biodiversity, facilitating the implementation of appropriate management practices and policies. By harnessing the capabilities of remote sensing technology, we can gain a comprehensive understanding of the changing landscape and work towards more sustainable and environmentally conscious land management practices.

## Declaration of competing interest

No conflict of interest to be declared.

## Data availability

Data will be made available on request.

## References


Akyürek, D., Koç, Ö., Akbaba, E.M., Sunar, F., 2018. "Land use/land cover change detection using multi–temporal satellite dataset: a case study in Istanbul New Airport." the International Archives of the Photogrammetry. Remote Sensing and Spatial Information Sciences 42, 17–22.

Astola, H., Häme, T., Sirro, L., Molinier, M., Kilpi, J., 2019. Comparison of Sentinel-2 and Landsat 8 imagery for forest variable prediction in boreal region. Rem. Sens. Environ. 223 (December 2018), 257–273. https://doi.org/10.1016/j.rse.2019.01.019.

Baltodano, A., Agramont, A., Reusen, I., van Griensven, A., 2022. Land cover change and water quality: how remote sensing can help understand driver–impact relations in the Lake Titicaca Basin. Water 14 (7), 1021.

Bi, S., Li, Y., Wang, Q., Lyu, H., Liu, G., Zheng, Z., Du, C., Mu, M., Xu, J., Lei, S., & Miao, S. (2018). Inland water Atmospheric Correction based on Turbidity Classification using OLCI and SLSTR synergistic observations. Rem. Sens., 10(7). https://doi.org/10.3390/rs10071002.

Butt, A., Shabbir, R., Ahmad, S.S., Aziz, N., 2015. Land use change mapping and analysis using Remote Sensing and GIS: a case study of Simly watershed, Islamabad, Pakistan. Egyptian Journal of Remote Sensing and Space Science 18 (2), 251–259. https://doi.org/10.1016/j.ejrs.2015.07.003.

Chen, Y., Zhou, Y., Ge, Y., An, R., Chen, Y., 2018. Enhancing land cover mapping through integration of pixel-based and object-based classifications from remotely sensed imagery. Rem. Sens. 10 (1) https://doi.org/10.3390/rs10010077.

Cheng, C., Zhang, F., Shi, J., Kung, H.-T., 2022. What is the relationship between land use and surface water quality? A review and prospects from remote sensing perspective. Environ. Sci. Pollut. Control Ser. 56887–56907. https://doi.org/10.1007/s11356-022-21348-x.

Chiloane, C., Dube, T., Shoko, C., 2023. Multispectral remote sensing of potential groundwater dependent vegetation in the greater Floristic region of the Western Cape, South Africa. S. Afr. Geogr. J. 1–19.

Clark, B.M., van Niekerk, L., Turpie, J., Taljaard, S., Adams, J., Cowie, M., A, B., Lamberth, S., 2015. Determination of the ecological water requirements for the klein estuary. September 199. https://doi.org/10.13140/RG.2.2.28830.46401.

Estuarine, H., Plan, M., 2019. Heuningnes River Estuarine Management Plan.

Foody, G., 2008. Harshness in image classification accuracy assessment. Int. J. Rem. Sens. 29 (11), 3137–3158. https://doi.org/10.1080/01431160701442120.

García-Mora, T.J., Mas, J.F., Hinkley, E.A., 2012. Land cover mapping applications with MODIS: a literature review. International Journal of Digital Earth 5 (1), 63–87.

Gorgoglione, A., Gregorio, J., Rios, A., Alonso, J., Chreties, C., Fossati, M., 2020. Influence of land use/land cover on surface-water quality of Santa Lucìa river, Uruguay. Sustainability 12 (11), 4692.

Horne, A.C., Angus Webb, J., O'Donnell, E., Arthington, A.H., McClain, M., Bond, N., Acreman, M., Hart, B., Stewardson, M.J., Richter, B., Poff, N.L.R., 2017. Research priorities to improve future environmental water outcomes. Front. Environ. Sci. 5 (DEC), 1–11. https://doi.org/10.3389/fenvs.2017.00089.

Ighalo, J.O., Adeniyi, A.G., Adeniran, J.A., Ogunniyi, S., 2021. A systematic literature analysis of the nature and regional distribution of water pollution sources in Nigeria. J. Clean. Prod. 283 (xxxx), 124566 https://doi.org/10.1016/j.jclepro.2020.124566.

Jamali, A., 2021. Land use land cover mapping using advanced machine learning classifiers. Ekológia 40 (3), 286–300.

Jamali, A., 2020. Land use land cover mapping using advanced machine learning classifiers: a case study of Shiraz city, Iran. Earth Science Informatics 13 (4), 1015–1030.

Kang, J., Zhang, H., Yang, H., Zhang, L., 2018. Support vector machine classification of crop lands using sentinel-2 imagery. In: 2018 7th International Conference on AgroGeoinformatics, *Agro-Geoinformatics*, pp. 1–6. https://doi.org/10.1109/AgroGeoinformatics.2018.8476101. *2018*.

Liu, D., Xia, F., 2010. Assessing object-based classification: advantages and limitations. Remote Sensing Letters 1 (4), 187–194. https://doi.org/10.1080/01431161003743173.

Mhanna, S., Halloran, L.J., Zwahlen, F., Asaad, A.H., Brunner, P., 2023. Using machine learning and remote sensing to track land use/land cover changes due to armed conflict. Sci. Total Environ. 898, 165600.

Mishra, P.K., Rai, A., Rai, S.C., 2020. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. The Egyptian Journal of Remote Sensing and Space Science 23 (2), 133–143.

Mngube, F.N., Kapiyo, R., Aboum, P., Anyona, D., Dida, G.O., 2020. Subtle impacts of temperature and rainfall patterns on land cover change overtime and future projections in the Mara River Basin, Kenya. Open J. Soil Sci. 10 (9), 327.

Mtengwana, B., Dube, T., Mkunyana, Y.P., Mazvimavi, D., 2020. Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants in a water-limited catchment, South Africa. Afr. J. Ecol. 58 (4), 709–718.

Mtengwana, B., Dube, T., Mudereri, B.T., Shoko, C., 2021. Modeling the geographic spread and proliferation of invasive alien plants (IAPs) into new ecosystems using multi-source data and multiple predictive models in the Heuningnes catchment, South Africa. GIScience Remote Sens. 58 (4), 483–500.

Namugize, J.N., Jewitt, G., Graham, M., 2018a. Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. Phys. Chem. Earth 105, 247–264. https://doi.org/10.1016/j.pce.2018.03.013. November 2017.

Namugize, J.N., Jewitt, G., Graham, M., 2018b. Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. Phys. Chem. Earth 105 (March), 247–264. https://doi.org/10.1016/j.pce.2018.03.013.

Obeidat, M., Awawdeh, M., Lababneh, A., 2019. Assessment of land use/land cover change and its environmental impacts using remote sensing and GIS techniques, Yarmouk River Basin, north Jordan. Arabian J. Geosci. 12 (22) https://doi.org/10.1007/s12517-019-4905-z.

Olofsson, P., Foody, G.M., Stehman, S.V., Woodcock, C.E., 2013. Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation. Rem. Sens. Environ. 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031.

Park, S.R., Lee, S.W., 2020. Spatially varying and scale-dependent relationships of land use types with stream water quality. Int. J. Environ. Res. Publ. Health 17 (5). https://doi.org/10.3390/ijerph17051673.

Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V.R., Murayama, Y., Ranagalage, M., 2020. Remote sensing sentinel-2 data for land cover/use mapping : a review. Rem. Sens. 2291 (12), 14.

Rudrapal, D., 2015. Land Cover Classification using Support Vector Machine 4 (9), 584–588.

Rumora, L., Miler, M., Medak, D., 2020. Impact of various atmospheric corrections on sentinel-2 land cover classification accuracy using machine learning classifiers. ISPRS Int. J. Geo-Inf. 9 (4) https://doi.org/10.3390/ijgi9040277.

Rwanga, S.S., Ndambuki, J.M., 2017. Accuracy assessment of land use/land cover classification using remote sensing and GIS. Int. J. Geosci. 8 (4), 611–622. https://doi.org/10.4236/ijg.2017.84033.

Shoko, C., Mutanga, O., Dube, T., 2020. Remotely sensed characterization of Acacia longifolia invasive plants in the Cape Floristic region of the Western Cape, South Africa. J. Appl. Remote Sens. 14 (4), 044511-044511.

Talukdar, S., Singha, P., Mahato, S., Shahfahad Pal, S., Liou, Y.A., Rahman, A., 2020. Land-use land-cover classification by machine learning classifiers for satellite observations-A review. Rem. Sens. 12 (7) https://doi.org/10.3390/rs12071135.

Tselka, I., Detsikas, S.E., Petropoulos, G.P., Demertzi, I.I., 2023. Google Earth Engine and machine learning classifiers for obtaining burnt area cartography: a case study from a Mediterranean setting. In: Geoinformatics for Geosciences. Elsevier, pp. 131–148.

Yuh, Y.G., Tracz, W., Matthews, H.D., Turner, S.E., 2023. Application of machine learning approaches for land cover monitoring in northern Cameroon. Ecol. Inf. 74, 101955.

Zhen, Z., Quackenbush, L.J., Stehman, S.V., Zhang, L., 2013. Impact of training and validation sample selection on classification accuracy and accuracy assessment when using reference polygons in object-based classification. Int. J. Rem. Sens. 34 (19), 6914–6930. https://doi.org/10.1080/01431161.2013.810822.