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Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants in a water-limited catchment, South Africa

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Abstract

Invasive Alien Plants (IAPs) pose major threats to biodiversity, ecosystem functioning and services. The availability of moderate resolution satellite data (e.g. Sentinel-2 Multispectral Instrument and Landsat-8 Operational Land Imager) offers an opportunity to map and monitor the occurrence and spatial distribution of IAPs. The use of two multispectral remote sensing data sets to map and monitor IAPs in the Heuningnes Catchment, South Africa, was therefore investigated using the maximum likelihood classification algorithm. It was possible to identify areas infested with IAPs using remote sensing data. Specifically, IAPs were mapped with a higher overall accuracy of 71%, using Sentinel-2 MSI as compared to using Landsat 8 OLI, which produced 63% accuracy. However, both sensors showed similar patterns in the spatial distribution of IAPs within the hillslopes and riparian zones of the catchment. This work demonstrates the utility of the two multispectral data sets in mapping and monitoring the occurrence and distribution of IAPs, which contributes to improved ecological modelling and thus to improved management of invasions and biodiversity in the catchment.

Résumé

Les plantes étrangères envahissantes constituent une grave menace pour la biodiversité, le fonctionnement et les services de l'écosystème. La disponibilité de données satellite à résolution moyenne (ex. : Sentinel-2 Multispectral Instrument et Landsat 8 Operational Land Imager) offre l'opportunité de cartographier et de contrôler l'apparition et la répartition spatiale des plantes étrangères envahissantes. L'utilisation de deux ensembles de données multispectrales obtenues par télédétection pour cartographier et contrôler les plantes étrangères envahissantes sur le bassin versant d'Heuningnes, en Afrique du Sud, a fait l'objet d'une étude en utilisant l'algorithme classification de vraisemblance maximale. L'identification des zones envahies par les plantes étrangères envahissantes a été rendue possible à l'aide de données obtenues par télédétection. Les plantes étrangères envahissantes ont notamment été cartographiées avec une précision d'ensemble plus élevée de 71,03% à l'aide de Sentinel 2 MSI, en comparaison avec l'utilisation de Landsat 8, qui a permis d'atteindre une précision de 62,95%. Cependant, les deux sondes ont montré des tendances similaires dans la répartition spatiale des plantes étrangères envahissantes sur les flancs des collines et dans les zones riveraines du bassin versant. Ce travail démontre l'utilité de deux ensembles de données multispectrales dans la cartographie et le contrôle de l'apparition et de la répartition des plantes étrangères envahissantes, ce qui contribue à l'amélioration de la modélisation écologique et donc de la gestion des invasions et de la biodiversité dans le bassin versant.

KEYWORDS

agroecosystems, catchment scale, fynbos-dominated ecosystems, satellite data, water scarcity

1 | INTRODUCTION

The spreading of invasive alien species is a global problem. A review by Turbelin, Malamud, and Francis (2017) established that in terms of the number of occurrences of alien species, the USA, New Zealand, Australia and South Africa were the leading countries. However, small island states such as the Reunion, French Polynesia and Fiji were highly affected with number of alien species ranging from 914 to 6,890 species per 100,000 km^2. Alien species outcompete and cause a decline of the number of indigenous species. Terrestrial alien plants also increase the frequency and intensity of fires (Pyšek et al., 2012; Van Wilgen & Richardson, 2012). Initially, Invasive Alien Plants (IAPs) were introduced in different countries for economic development and to curb environmental problems. For example, *Prosopis* was introduced in Sudan to curb desertification. In South Africa, they were introduced during the 19th century for the supply of timber (e.g. *Eucalyptus*, *Pines*), fodder (e.g. *Acacias*, *Prosopis*) and stabilisation of dunes (*Acacia*). However, these species have become problematic and expand at unprecedented rates. For example, in South Africa, the condensed area covered by the different IAPs is currently equivalent to 8% of the country's total land area and 16% of the Western Cape Province (Le Maitre, Versfeld, & Chapman, 2000).

South Africa is predominantly semi-arid to arid, with an average annual rainfall of approximately 464 mm/year of which 8% forms surface run-off. Mountainous areas, which cover 8% of South Africa's land area, generate over 50% of the surface run-off and are considered to be strategic water source areas for the whole country (Nel, Colvin, Le Maitre, Smith, & Haines, 2013). However, the spread of IAPs into these mountainous areas is a major threat to the availability of water resources. Le Maitre et al. (2000) estimated that the presence of alien invasive plants causes 7% decrease in the available water due to the increase in transpiration losses. The most problematic IAPs in South Africa are the *Australian Acacia*, *Eucalyptus* and *Pinus* genera (Chamier, Schachtschneider, Le Maitre, Ashton, & Van Wilgen, 2012; Dzikiti, Schachtschneider, Naiken, Gush, & Le Maitre, 2013; Dzikiti, Schachtschneider, Naiken, Gush, Moses, et al., 2013; Meijninger & Jarmain, 2014). Studies done in the Cape Agulhas showed that IAPs were consuming water equivalent to the long-term average run-off (Mazvimavi, 2018; Mkunyana, Mazvimavi, Dzikiti, & Ntshidi, 2018). Due to the considerable adverse effects of IAPs on water resources, the South African government launched the Working for Water Programme in 1996, focusing on clearing IAPs (Le Maitre et al., 2000). Landowners such as those in the Cape Agulhas are also involved in clearing programmes. The effectiveness of clearing programmes depends on knowledge about the spatial distribution of IAPs. This requires routine monitoring since the spatial distribution of IAPs often rapidly increases over a year in some locations. National surveys of the spatial distribution have been undertaken, for example, the Southern African Plant Invaders Atlas (Henderson, 1998; Versfeld, Le Maitre, & Chapman, 1998), National Invasive Alien Plant Survey (Kotzé, Beukes, Van den Berg, & Newby, 2010). However, such surveys undertaken after a lengthy period, for example 10 years, do not provide information necessary for implementing effective clearing on an annual basis. The availability of remote sensing data offers the opportunity to monitor the changes in the spatial distribution of IAPs on an annual basis and thus assist in identifying areas to be targeted for routine clearing.

Data from Landsat 8 OLI (LT8), which has a spatial resolution of 30 m and a 16-day revisit time, and Sentinel-2 MSI (S2), with the spatial resolution of 10–20 m on selected bands and a 5-day revisit time, offer an opportunity to establish the spatial distribution of IAPs at time intervals suitable for developing routine clearing programmes. A study by Dube, Mutanga, Sibanda, Bangamwabo, and Shoko (2017a,b) showed that the spatial distribution of IAPs could be established using Landsat 7 data. The study presented in this paper, thus, has the objective of evaluating the feasibility of determining the spatial distribution of IAPs in the Heuningnes Catchment, South Africa, using LT8 and S2. The study used data sets from the two satellites in order to identify which data source would be more appropriate for accurately mapping the distribution of IAPs.

2 | MATERIALS AND METHODS

2.1 | Study area description

The National Invasive Alien Plant Survey done by Kotzé et al. (2010) and work by Le Maitre et al. (2000) showed that the Cape Agulhas area of the Western Cape Province of South Africa had the greatest proportion of over 60% of the land area being affected by IAPs.

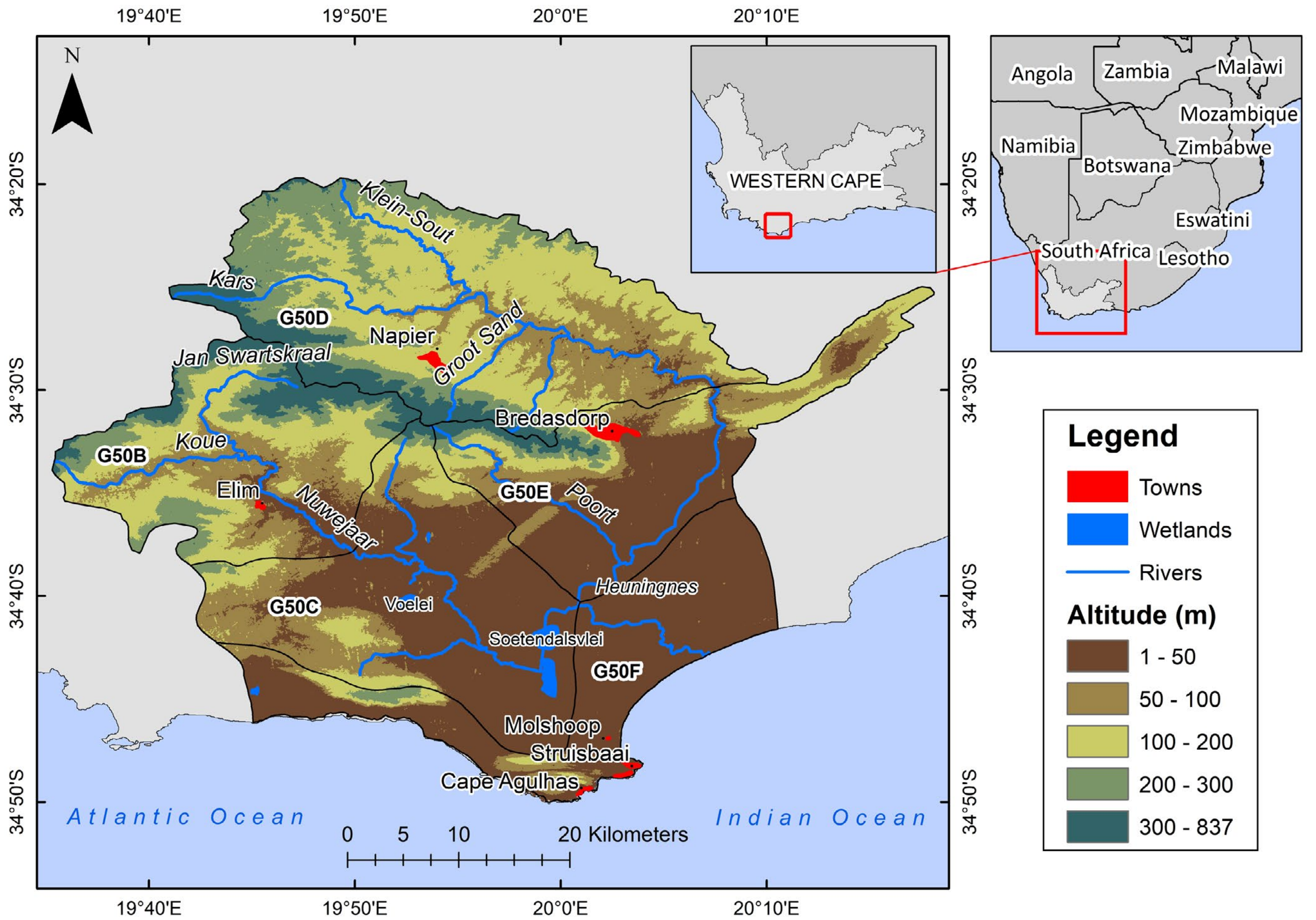

FIGURE 1 Location of the Heuningnes catchment situated in Western Cape Province, South Africa [Colour figure can be viewed at wileyonlinelibrary.com]

The Heuningnes Catchment, with a catchment area of 1,401 km^2, is located at the southernmost tip of Africa and is one of the severely affected catchments (Figure 1). Landowners in this catchment formed a forum to coordinate and implement clearing of IAPs on a continuous basis. Previous studies in this catchment found that IAPs occurred along riparian zones and hillslopes and were rapidly spreading (Mazvimavi, 2018; Mkunyana, et al., 2018). Both the Working for Water Programme and landowners require information about changes on an annual basis of areas with IAPs, in order to identify areas to be targeted for clearing. Due to this demand for information about the spatial distribution of IAPs, the Heuningnes Catchment was selected for the study presented in this paper. *Eucalyptus*, *Pinus* and *Acacia* (*Acacia longifolia*, *A. cyclops* and *A. saligna*) are the dominant species in the Heuningnes Catchment (Nowell, 2011).

The Heuningnes Catchment has an altitude varying from 100 to 700 m above sea level, on the north-western part of the catchment, while the south-western area has mostly coastal lowlands at <60 m (Figure 1). Pans and wide floodplains dominate on the south-western part. The Soetendalsvlei, which is about 3 km wide and 8 km long, is the largest lake in the catchment. Other lakes are the Voevlei (4 km by 1.7 km), Soutpan (1.3 km by 1.9 km), Longpan (1 km by 0.5 km) and Roundepan (0.6 km by 0.4 km). The Soetendalsvlei drains into the Heuningnes River that joins the Indian Ocean. The average rainfall varies from 400 mm/year in the lowlands to 675 mm/year in the mountains, which form the headwaters. Most of the rainfall occurs during winter, May–August. Average temperatures range from 10°C in winter to 28°C in summer, while the annual average A-pan evaporation rate is 1,445 mm/year.

The Heuningnes catchment is part of the Cape Floristic Region (CFR) rich in biodiversity (Fourie, De Wit, & Van der Merwe, 2013). The *sclerophyllous* shrub, fynbos, is the main indigenous vegetation, with species belonging to *Proteaceae*, *Ericaceae* and *Restionaceae* families (Mucina & Rutherford, 2006). The major land uses are dryland crop cultivation (wheat, barley, canola), livestock production (cattle and sheep), vineyards and growing of indigenous flowers (Mazvimavi, 2018; Mkunyana et al., 2018).

2.2 | Field data collection

This study required groundtruth data on the occurrence of IAPs in order to assist in the classification and validation of land cover types from satellite images. Therefore, the groundtruth data was collected during August 2018, which coincided with flowering period of most IAPs in the catchment. A plot size of 30 m × 30 m was used to collect GPS locational data on individual species within the plot. This was

FIGURE 2 Co-occurrence of IAPs [Colour figure can be viewed at wileyonlinelibrary.com]

solely informed by other works in literature that have compared the two satellite sensors, in vegetation mapping or other-related types of works (Abdullah, Skidmore, Darvishzadeh, & Heurich, 2019; Clark, 2017; Forkuor, Dimobe, Serme, & Tondoh, 2018). Species locations were recorded using the eTrex 10 Garmin GPS, with an error margin of 3.65 m (Garmin, 2019). Three hundred and sixty-five ground truth points representing different land cover types were identified and recorded. The minimum distance between the GPS points was at least 100 meters, to avoid over sampling. The observed vegetation classes included cultivated lands, natural shrubs, fynbos and alien shrubs and invasive tree species namely *Acacia longifolia*, *A. saligna*,

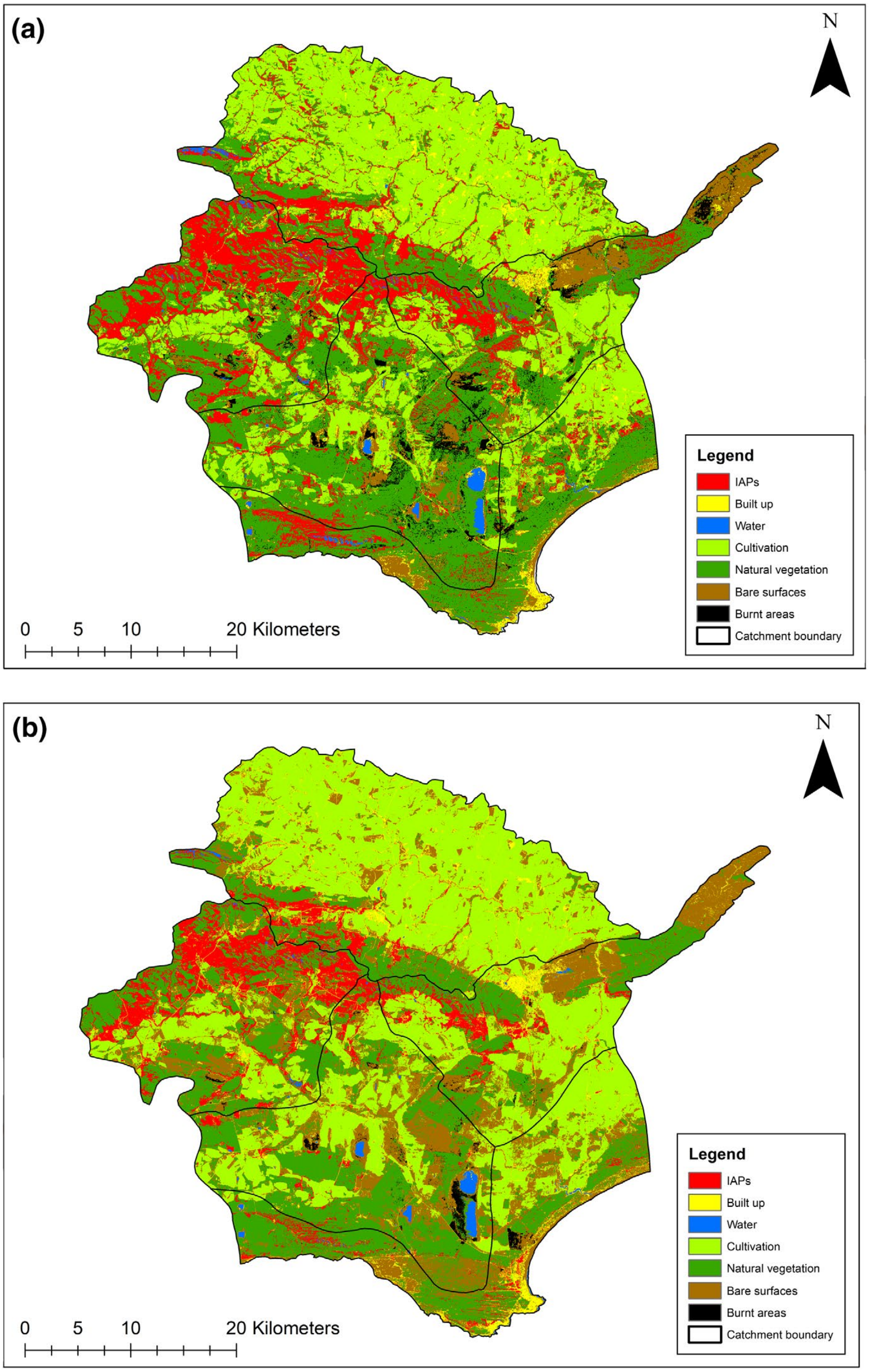

FIGURE 3 Landsat 8 (a) and Sentinel-2 (b) classified images showing discrimination of IAPs from other land cover classes [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Error matrix results for Landsat 8 OLI and Sentinel-2 image classification.

	IAPs	Built up	Water	Cultivation	Natural vegetation	Bare surfaces	Burnt areas	Total	UA (%)
L8									
IAPs	**31**	8	0	1	13	2	0	55	56
Built up	0	**21**	0	1	4	5	0	31	68
Water	5	4	**31**	2	6	7	0	55	56
Cultivation	2	1	1	**51**	11	0	0	66	77
Natural vegetation	6	5	0	5	**34**	8	1	59	58
Bare surfaces	4	7	0	4	5	**44**	0	64	69
Burnt areas	0	3	0	0	10	2	**14**	29	48
Total	48	49	32	64	83	68	15	359	
PA (%)	65	43	97	80	41	65	93		
Overall accuracy (%)	62.95								
S2									
IAPs	**37**	11	0	2	1	4	0	55	67
Built up	1	**26**	0	0	0	5	0	32	81
Water	2	7	**35**	1	1	5	0	51	69
Cultivation	1	9	0	**56**	1	4	0	71	79
Natural vegetation	0	5	0	1	**30**	15	1	52	58
Bare surfaces	0	4	1	8	1	**55**	0	69	80
Burnt areas	0	1	0	0	2	10	**16**	29	55
Total	41	63	36	68	36	98	17	359	
PA (%)	90	41	97	82	83	56	94		
Overall accuracy (%)	71.03								

Bold values indicating the number of correctly classified classes.

A. cyclops, *Eucalyptus*, *Hakea* and *Pines*. Figure 2 shows photographs of co-occuring typical IAPs occurring within the Heuningnes catchment.

2.3 | Satellite data acquisition

Landsat images were obtained from the online USGS earth observation database (http:/earthexplorer.usgs.gov). The Sentinel-2 MSI was obtained from the European Space Agency Copernicus hub. Three image scenes with minimal cloud cover (T34HCG, T34HDG and T34HCH) of S2 Level-1C products, covering the study area, were acquired for the 24th of August 2018. The LT8 scene (Path 174/Row 84) that fitted the entire study area and with minimal cloud cover was obtained for 18 July 2018. The selected images for both satellites had a cloud cover of <2%. The preferences of cloud free images resulted in a 5-week difference between images obtained from the two satellites.

2.4 | Image processing and classification

The atmospheric correction for both LT8 and S2 images was done, using the Dark Object Subtraction 1 (DOS1) (Chavez, 1988). The S2 images contained radiometric and geometric corrections, which include orthorectification and spatial registration (SUHET, 2015). Further, images from both S2 and LT8 were then re-projected to the Universal Transverse Mercator (UTM) 34 South based on the World Geodetic System (WGS) 84 Spheroid. In S2, the 20 m vegetation red-edge bands (5, 6, 7 and 8a) were resampled, using the nearest neighbour technique (Baboo & Devi, 2010) to match the 10 m spatial resolution of the visible (VIS) spectrum bands (band 2–4) and the near-infrared (NIR) band 8. The image scenes were further mosaicked to form a single image scene, covering the entire catchment. The mean mosaicking operation was applied where images overlapped. We assumed that since the image scenes were taken on the same day, the averaging of the mean would have a minimal to no difference. For the LT8 data, only bands 1–7, which constitute the coastal, visible and near-infrared regions, were used. Image band composites were generated, using the common geographic information systems tools. The study area was then extracted from the mosaicked and layer stacked image scenes prior to the classification of IAPs.

The surveyed ground truth points were overlaid on the composite image, to create training samples and signature files for image classification. The image classification process made use of raw spectral bands, to identify different land cover classes, in order to discriminate IAPs from other land cover types. The supervised maximum

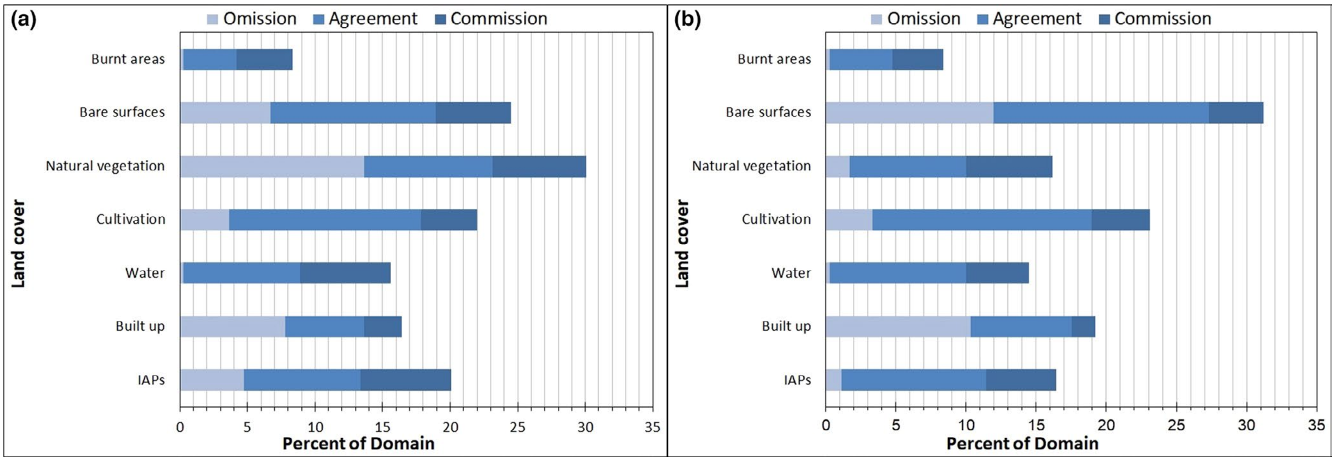

FIGURE 4 Allocation of agreements and disagreements for (a) Landsat 8 and (b) Sentinel-2 [Colour figure can be viewed at wileyonlinelibrary.com]

likelihood classification was used (Sisodia, Tiwari, & Kumar, 2014). The following metrics were used to assess the accuracy of image classification: overall accuracy, user and producer accuracy, errors of commission and the errors of omission (Coluzzi, Imbrenda, Lanfredi, & Simoniello, 2018). The allocation of agreements and disagreements was determined following Pontius and Millones (2011). The McNemar test was performed to determine whether there were any statistical differences between the two classified images. However, the class areas detected were not reflective of the true estimated size based on the actual acquired accuracies because each land cover type is subjected to accuracy errors. Therefore, the areal extent was further analysed, by considering accuracies and errors of each class, using the user's accuracy, to ascertain the reliability of the model. It is recommended that estimation of the areas invaded should be quantified based on the reference data as it provides the best assessment of ground conditions (Olofsson et al., 2014). The areas covered by IAPs were thus estimated from the classified images. The areal extents of IAPs were assessed, by considering accuracies and errors of each class, using the user's accuracy, to assess the reliability of classification results. The correlation analysis of the areas covered by different land cover types estimated from S2 and LT8 was undertaken.

3 | RESULTS

3.1 | Comparison of satellite-derived IAPs distribution at catchment scale

A visual comparison of classification done from the S2 and LT8 images showed similar spatial distribution of IAPs, within the catchment (Figure 3). IAPs occurred mostly on the hillslopes and riparian zones. As expected, the occurrence of IAPs was limited in areas dominated by crop cultivation, such as the northern part of the catchment. Landowners are obviously likely to clear any woody plant emerging in cropped lands. The IAPs were widespread on the hillslopes of the Koue Mountains, on the north-western part, and Bredasdorp Mountains on the central part. The distribution of areas affected by the IAPs tended to be widespread and patchy, particularly on the southern part on LT8, when compared to the S2 mapping results (Figure 3).

3.2 | Classification accuracy assessments

The classification of LT8 image had an overall accuracy of 63% whereas 71% was observed for the S2 image. The S2 had better user's accuracy (UA) (67%) and producer's accuracy (PA) (90%), while these were 56% and 65%, respectively, for the LT8 image (Table 1). The natural vegetation class was mapped, with a negligible difference in the UA between the two satellites, 58% for both the S2 and LT8. However, the PA for the natural vegetation was 83% for the S2 and 41% for LT8.

When considering the accuracy differences in class detection within the same satellite, the LT8 similarly represented IAPs and the natural vegetation with a negligible difference in UA (1.27%), but with better PA than natural vegetation due to high omission error (Table 1). Using the S2, the UA and PA for IAPs were both greater than that of the natural vegetation, with differences of 9.58% and 6.91%, respectively. Overall, the results showed that the S2 performed better than the LT8, when comparing the capability of detecting and mapping both IAPs and natural vegetation.

The allocation of agreements for the IAPs was higher than the allocation disagreement measures (i.e. commission and omission) for both the S2 and LT8 classified images (Figure 4a,b). However, the allocation of agreements for the S2 image (Figure 4b) was generally higher when compared to those of the LT8 (Figure 4b), for all the land cover types. Overall, the classification of the S2 image had lower disagreements than that of the LT8, across the land cover types. Classification of LT8 had an overall disagreement of 37%, while this was 29% for the S2. The omission for the natural vegetation mapped from the LT8 was very high, at 14% when compared to the 2% for the S2. This could explain the low PA for the natural vegetation in

TABLE 2 Areal estimates of land cover types for Landsat 8 and Sentinel-2 based on classification results in hectares and percentages

	Area (hectares)							
	Detected		Accurately detected		Not detected		Overestimation	
	LT8	S2	LT8	S2	LT8	S2	LT8	S2
IAPs	31,424	17,945	17,712	12,072	13,712	5,873	11,129	1,751
Built up	5,703	9,867	3,863	8,017	1,840	1,850	3,259	5,795
Water	1,534	1,216	865	835	669	382	48	34
Cultivation	66,197	76,367	51,152	60,233	15,045	16,134	13,446	13,476
Natural vegetation	70,503	49,191	40,629	28,379	29,874	20,812	41,622	8,198
Bare surfaces	13,301	37,810	9,144	30,138	4,156	7,672	4,694	16,590
Burnt areas	4,898	1,169	2,365	645	2,534	524	327	69
Total	193,561	193,565	125,730	140,319	67,831	53,245	74,526	45,913
IAPs area (%)	16	9	14	9	20	11	15	4
Accurately Detected (user's accuracy), Not Detected (omission error), Overestimated (commission error)								
Correlation	0.86		0.87		0.91		0.26	

the LT8 image classification results. The classification of the LT8 had a greater quantity and allocation disagreement (19%) when compared to that of the S2 (15%). The results showed that the S2 was slightly better than the LT8, at detecting and discriminating the IAPs. However, the McNemar statistical test results showed that the performance between the two sensors was not significantly different (p-value = 0.5254).

3.3 | Estimation of the spatial coverage of IAPs as detected by LT8 and S2

The area covered by the IAPs based on the classification of the LT8 image was approximately 22% of the catchment area (~31,424 hectares), while the estimated based on the S2 was 13% (~17,945 hectares). Table 2 further showed that the accurately detected area for IAPs was approximately 17,712 hectares (13%) and 12,072 hectares (9%) by the LT8 and S2, respectively. LT8 showed a major difference between the total detected and the accurately detected area, while S2 still retained the 9% cover for the IAPs. It can also further be observed that the area occupied by the IAPs as derived from theLT8 was greatly overestimated when compared to that of the S2. However, the correlation test between the derived areas generated from the two satellites showed a strong relationship between the detected (0.86), accurately detected (0.87) and the undetected (0.91) areas. The opposite was observed for the overestimated areas that a very weak agreement (0.26) between the estimated areas. Both satellite images showed an overestimation in particular classes over the other.

4 | DISCUSSION

The main aim of the study was to detect and map the spatial distribution of IAPs, using the LT8 and S2 multispectral remote sensors in the Heuningnes catchment, Western Cape, South Africa. The accurate detection of the IAPs is important to provide accurate information on their occurrence and their spatial distribution for the rehabilitation of the affected areas and related-management strategies.

The results showed that the S2 image provided a better representation of the distribution of the IAPs and the other land cover types in comparison with the LT8 image. The observed results showing the capability of the S2 in this study are confirmed by other recent studies, which have demonstrated its unique ability to outperform the LT8, with better accuracies. Thamaga and Dube (2018) also found that S2 performed better in discriminating water hyacinth when compared to the LT8. Rajah, Odindi, and Mutanga (2018) reported that the S2 images were appropriate for the mapping invasive species across different seasons.

The higher spatial and spectral resolutions of the S2 when compared to the LT8 contribute to the improved detection of the IAPs. The higher spatial resolution of the S2 reduced the problem of mixed pixels, while the spectral resolution contributed to the better classification of the IAPs because of the improved classes' discrimination (Li, Li, Lu, & Chen, 2019). This is also evident in this study that used 10 bands for the S2, and 7 bands for the LT8 for the image classifications. The S2 has an increased number of four red-edge (RE) bands and two near-infrared (NIR) when compared to the LT8. This increased the ability of the S2 to discriminate vegetation (Cho et al., 2012; Shoko & Mutanga, 2017). Consequently, the S2 had an improved discrimination of the IAPs and the natural vegetation class when compared to the LT8 image. This is evident from the comparison of the overall, user's and producer's accuracy metrics. Other studies have also found that the use of the near-infrared (NIR), red-edge (RE) and shortwave infrared (SWIR 1, SWIR 2) bands improved the discrimination of different vegetation types (Astola, Häme, Sirro, Molinier, & Kilpi, 2019; Dube et al., 2017a,b; Forkuor, et al., 2018; Li et al., 2019; Thamaga & Dube, 2018).

On the other hand, the LT8 showed more overestimation of the IAPs than the S2 image. The high overestimation by the LT8 is evident when analysing the differences in the distribution of the IAPs in comparison with the S2 because the commission errors and omission errors were generally higher for the LT8 than the S2. This can be ascribed to the low ability of the sensor to distinguish between the species and the surrounding vegetation, due to the lack of RE bands. This is evident in this study because the user accuracy for the natural vegetation and the IAPs were similar, although negligible. Possibly, the use of the robust algorithms is required for the detection and monitoring of the IAPs and the use of the combination of both the VIs and spectral bands to improve classification, when using Landsat data series (Matongera, Mutanga, Dube, & Sibanda, 2017; Thamaga & Dube, 2018).

Both the LT8 and S2 had a similar distribution pattern of the invaded areas, thus showing the capability of both satellites in detecting the IAPs and other classes, within the catchment despite the slight differences in the classification accuracies. The McNemar statistical test results confirmed that the classification performance between the two sensors was not significantly different (*p*-value = 0.5254). This observation therefore implied that both the S2 and LT8 can equally be used to map the occurrence of the IAPs, with a reasonable certainty. This was also the case for Sanchez-Espinosa and Schroder (2019), where the distribution of the LULC was similar between the two satellites. The larger patterns of dense stands of the IAPs were similarly detected by both satellite images than the sparse and relatively smaller patches to pixel sizes of the respective satellites. The finer spatial resolution of the S2 has allowed for the better detection and mapping of the IAPs at locations with relatively small or sparse vegetation coverages. The LT8 has a greater limitation over the S2 in adequately detecting the smaller patches of the IAPs. However, the two satellite data sets provide time scale and spatial complementarity required for ecological monitoring.

In addition, there was a strong relationship between the estimation of the accurately detected areas. But the improved spatial and spectral resolutions of the S2 have provided the opportunity for more accurate detection and quantification of the areas invaded by the IAPs (Sanchez-Espinosa & Schroder, 2019). The detection and determination of the spatial extent of the IAPs is valuable as it provides the requisite baseline information for mitigating and rehabilitating the invaded landscapes (Dube et al., 2020; Mudereri et al., 2020). Mapping the spatial distribution of the IAPs is also important for conservation, and the allocation of resources for management and planning purposes (Masocha et al., 2017; Masocha & Dube, 2017; Masocha & Dube, 2018; Mungate et al., 2019). The spatial understanding of the extent and distribution of the IAPs is important for providing the appropriate management strategies (Matongera et al., 2017). The use of the S2 can have a better implication for the management of the IAPs at catchment scale, as it has the potential to provide more detail and accurate information. This information can help in decision-making to inform the clearing and rehabilitation of these IAPs in invaded areas. The freely available multispectral data of the S2 can reduce the cost of management practises when determining the spatial extent of these IAPs (Matongera et al., 2017; Rajah et al., 2018).

5 | CONCLUSION

This study assessed the potential use of the Landsat 8 and Sentinel-2 MSI data in mapping the IAPs. Both sensors were capable to detect and map areas where alien invasive plants were mostly dominant, particularly, within the hillslopes and riparian zones of the catchment. However, the Sentinel-2 demonstrated more potential in the overall classification of the species. The Landsat 8 was not able to detect small patches of alien invasive plants, within the catchment. The unique capability of the Sentinel-2 MSI to discriminate these IAPs is attributed to its improved spatial resolution and the presence of the red-edge bands, which is critical in enhancing the ability to distinguish between different types of vegetation, among other bands that include the NIR and SWIR. Overall, the findings of this work can be used for more extensive analyses of the occurrence and the environmental impact of invasive species and aid in proving the extensive reliable distribution of IAPs using the easily accessible and cost-efficient satellite data, as a surrogate for in-situ measurements in remote areas. Further, these results can be used as a baseline information for the IAPs eradication programmes.

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CONFLICT OF INTEREST

Authors would like to declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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