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SHORT COMMUNICATION

Mapping the distribution of invasive shrub *Austroeupatorium inulifolium* (Kunth) R. M. King & H. Rob: A case study from Sri Lanka

I. P. K. Piyasinghe[1,2], J. Gunatilake[3] and H. M. S. P. Madawala[1]

[1]*Department of Botany, Faculty of Science, University of Peradeniya, Peradeniya, Sri Lanka*
[2]*Postgraduate Institute of Science, Peradeniya, Peradeniya, Sri Lanka*
[3]*Department of Geology, Faculty of Science, University of Peradeniya, Peradeniya, Sri Lanka*

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Abstract: A light loving invasive shrub, *Austroeupatorium inulifolium* has been spreading many land use types in the Knuckles Forest Reserve (KFR) in Sri Lanka, including man-made grasslands. In developing countries, there are limitations of using novel technologies to quantify and track the distribution of invasive species due to high costs and lack of facilities. This is a setback for their early detection and to introduce effective control measures. This pilot study attempted to map the distribution of *A. inulifolium* in man-made grasslands in KFR using high spatial multispectral images. Unsupervised, supervised and knowledge-based classifications were performed to quantify the spatial distribution of *A. inulifolium* in ERDAS Imagine. The results generated comparable results of the extent of area under *A. inulifolium* by using the unsupervised (108 ha), supervised (94 ha) and knowledge-based classifications (93 ha). They were 18, 15 and 15% from the total area selected for the study (622 - 646 ha), respectively. The results indicated the suitability of high spatial multispectral imageries in quantifying the spatial distribution of *A. inulifolium*. Further studies are recommended to investigate long-term changes in invasive plant population using multi temporal satellite data.

Keywords: Spatial distribution, *Austroeupatorium inulifolium*, Worldview-2, invasive shrub, Sri Lanka.

INTRODUCTION

Mapping the distribution of problematic plant species is critical in order to monitor their future spread and to introduce effective management strategies. Remote Sensing (RS) together with Geographic Information System (GIS) has been successfully used in spatial mapping of plant populations to predict and/or model their future distributions (McCormick, 1999; Haltuch *et al.,* 2000; Stow *et al.,* 2000). Prior to the attention on single species in concern, scientists have been using RS and GIS to detect major ecosystem-level changes over time due to natural and anthropogenic disturbances (Wang, 2008). The canopy species can be easily detected by their unique phenological events, biochemical properties and structural features (McCormick, 1999, Haltuch *et al.,* 2000; Underwood and Ustin, 2007). Müllerováa *et al*., (2017) emphasize the importance of field data to increase the accuracy of pixel- and object-based classifications for mapping herbaceous invasive plants such as giant hogweed (*Heracleum mantegazzianum*) and knotweeds (*Fallopia japonica*, *F. sachalinensis* and their hybrid *F.* ×*bohemica*). Previous studies stated that RS together with field data can provide a successful combination in mapping invasive plants in the understory (Jones *et al*., 2011; Somodi *et al.,* 2012; Delalieux *et al.,* 2012; Shouse *et al*., 2013; Müllerováa *et al*., 2017).

When selecting satellite imagery for mapping the distribution of an invasive species, the prospects of the final outcome and sensor characteristics are need to be considered. The changes associated with reflection and absorption patterns are used to identify individual species with high accuracies and also allow mapping plants in low densities (Underwood and Ustin, 2007). Previous studies successfully used WorldView-2 to map the distribution of invasive herbs and shrubs (Dlamini, 2006; Sankey *et al.,* 2012; Sankey *et al.,* 2014; Lin *et al.,* 2015; Peerbhay *et al.,* 2015; Immitzer *et al.,* 2016). Dlamini (2006) successfully detected two shrubs, *Lantana camara* and *Chromaleana odorata* in ranches of flat terrain in central Swaziland, southern Africa with Worldview-2 and noted its efficacy and applicability. Sankey *et al.,* (2014) effectively detected small populations of *Brassica tournefortii,* an invasive forb in Mojave and Sonoran Deserts in the southwestern USA using WorldView-2, following an object-oriented image analysis approach. The mapping of an invasive shrub, *Hakea sericea* showed user and producer accuracies greater than 93% using WorldView-2 (Alvarez-Taboada *et al*., 2017). Peerbhay *et al.,* (2015) also demonstrated the capability and effectiveness of unsupervised classification in detecting and mapping invasive shrub, *Solanum mauritianum* distributed along forest margins, open grasslands in Sappi Hodgesons Forest Plantation in South Africa using WorldView-2. A pixel-based image analysis carried out in Canada to map the distribution of two small shrubs, Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) showed some promising results with detection accuracies of 80 and 76%, respectively (Chance *et al.,* 2016). Another success story was recorded from the north-west Pilbara region in Australia with *Prosopis sp.* using WorldView-2 (Robinson *et al.,* 2016), highlighting its universal applicability in detecting and mapping the distribution of plants. Müllerováa *et al.,* (2013) also emphasized the use of

**Corresponding Author's Email:* ipkpiya52@gmail.com
http://orcid.org/0000-0003-1958-9508

RS as a tool in monitoring long-term dynamics of invasive herb, *Heracleum mantegazzianum*.

Asutroeupatorium inulifolium, a known invasive species in the tropics, has been steadily invading different landuse types in the KFR in Sri Lanka including degraded *Cymbopogon nardus*-dominated grasslands, natural grasslands, roadsides, *Pinus* and *Eucalyptus* plantations. *A. inulifolium* appears to take over its invasive nature since early 2000s, silently invading many landuse types. Being a sun-loving shrub, *A. inulifolium* rarely found under the canopy of the lower montane forests at KFR. The anthropogenic grasslands dominated by *C. nardus* seem to provide the most suitable micro-climatic conditions for *A. inulifolium,* thus making them the most vulnerable landuse types for its invasion. Precise distribution maps of invasive species can be an important source of information for forest officers, researchers and policy makers to monitor their further spread and also to implement effective management measures. Therefore, this pilot study aimed at mapping the spatial distribution of *A. inulifolium* in a selected area in KFR using high spatial resolution images, Worldview-2.

MATERIALS AND METHODS

Test Species

Austroeupatorium inulifolium (Kunth) R.M. King & H. Rob. (Asteraceae), a native of Tropical South America, was later introduced to Sumatra and Java (Dasanayake, 1994-1995). It was introduced to Sri Lanka during the Second World War II (McFadyen, 2003). The shrub grows up to 1 - 5 m in height with a conspicuous creamy-white coloured inflorescence. Leaves are opposite, deltoid-ovate, petiolate and gradually acuminate at the apex. Margin is shallowly and regularly serrate glandular, pubescent on both surfaces. Flowering occurs mainly in August. Fruit is an achene (Dasanayake, 1994-1995). *A. inulifolium* show high coppicing ability and therefore some mature plants may contain 20 or more stems of varying sizes from a single rootstock (McFadyen, 2003).

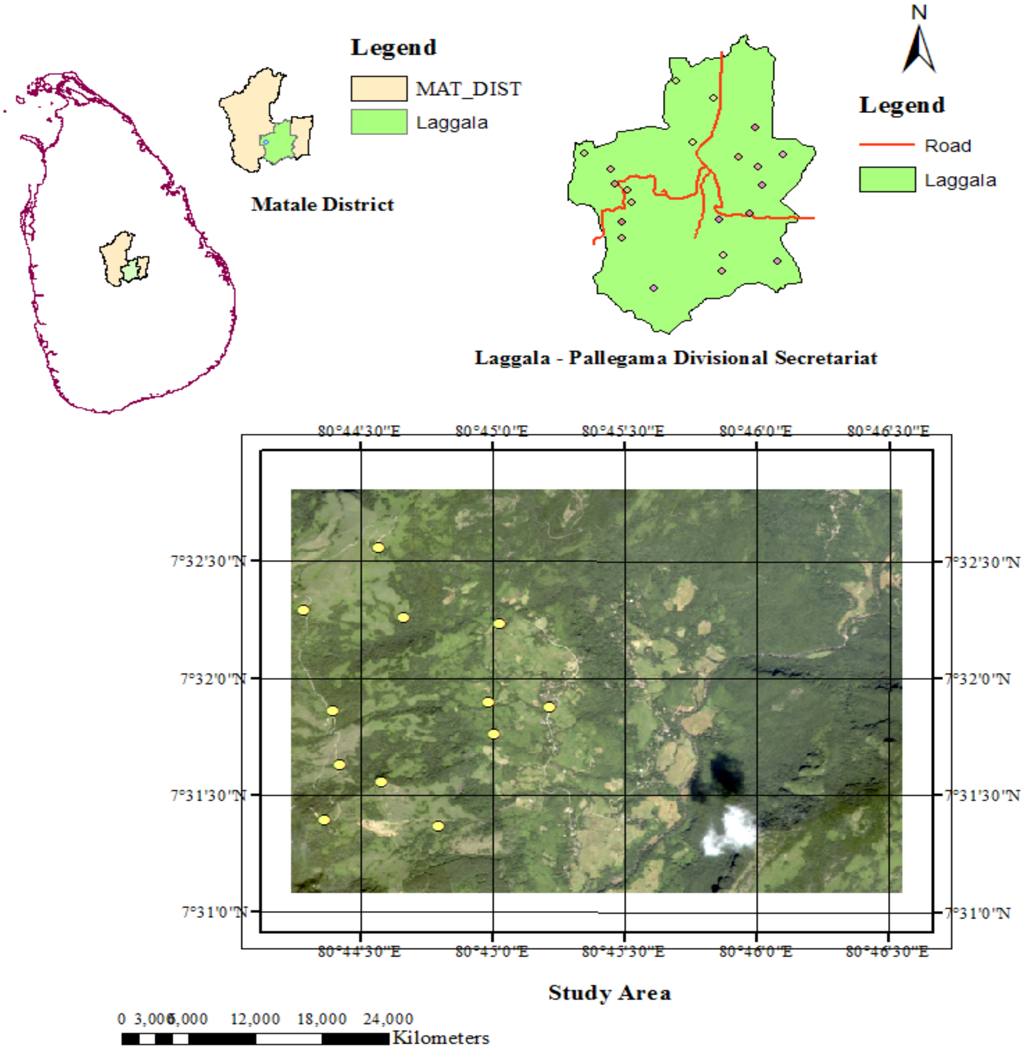


Figure 1: The map showing the selected study site in the Knuckles Forest Reserve in Sri Lanka. The sampling locations are indicated in yellow coloured circles.

Study area

The study area covers an approximately 600 ha in KFR with different landuse types including forests (lower montane forests), *Pinus* plantation, *C. nardus*-dominated grasslands etc. The selected study area was fallen between North-West Latitude = 7.55; North-West Longitude = 80.72; South-East Latitude = 7.51; South-East Longitude = 80.78 (Figure 1).

Pre-processing of satellite images

Image processing was carried out with ERDAS Imagine 2014, while some specific GIS operations were carried out using ArcMap 10.3. Global Positioning System (GPS) locations were collected using a GPS receiver (TRIMBLE Geo XT and Magellan meridian gold) during November, 2014 to April, 2015 to verify the accuracy. A Spectrometer (Spectrometer specifications: Sensor type: - Hamamatsu S 390X (MMS), Sensor size: 256, Spectral Range: 306 – 1129 nm) was used to measure the spectral reflectance values of *A. inulifolium* (Figure 3).

The WorldView-2 image with low cloud cover was acquired from the Digital Globe on 12th February, 2014 (http://www.digitalglobe.com). The WorldView-2 has both panchromatic and multispectral imageries. Sensor resolution for Panchromatic: 0.46 m Ground Sample Distance (GSD) at Nadir and for Multispectral: 1.84 meters GSD at Nadir (https://www.satimagingcorp.com/satellite-sensors/worldview-2). The image acquired was already orthorectified and geometrically corrected to WGS84 UTM zone 44 projection system. Later, the WorldView-2 multispectral imagery was layer analyzed using ERDAS Imagine

Satellite image classifications

Three different classification methods were performed *viz.,* unsupervised, supervised (Long, 2014), and knowledge-based classification (Frick *et al*., 2005). In the unsupervised technique, Iterative Self-Organizing Data Analysis Technique (ISODATA) algorithm was used. The WorldView-2 multispectral imagery (8 bands) was classified for 20 clusters by ISODATA algorithm. Using field information, the classified clusters were correlated and three landuse types were identified *viz.,* forest, *C. nardus*-dominated grasslands and *A. inulifolium* invaded grasslands. Other landuse types such as water, abandoned lands and degraded lands (visible soil layers) were also identified by field information. The classes that obtained were relatively approximate. After the classification was done, classes were overlaid or recoded to test the accuracy of the classification. Finally, the distribution map was illustrated using ERDAS.

In the supervised classification, pixels were classified

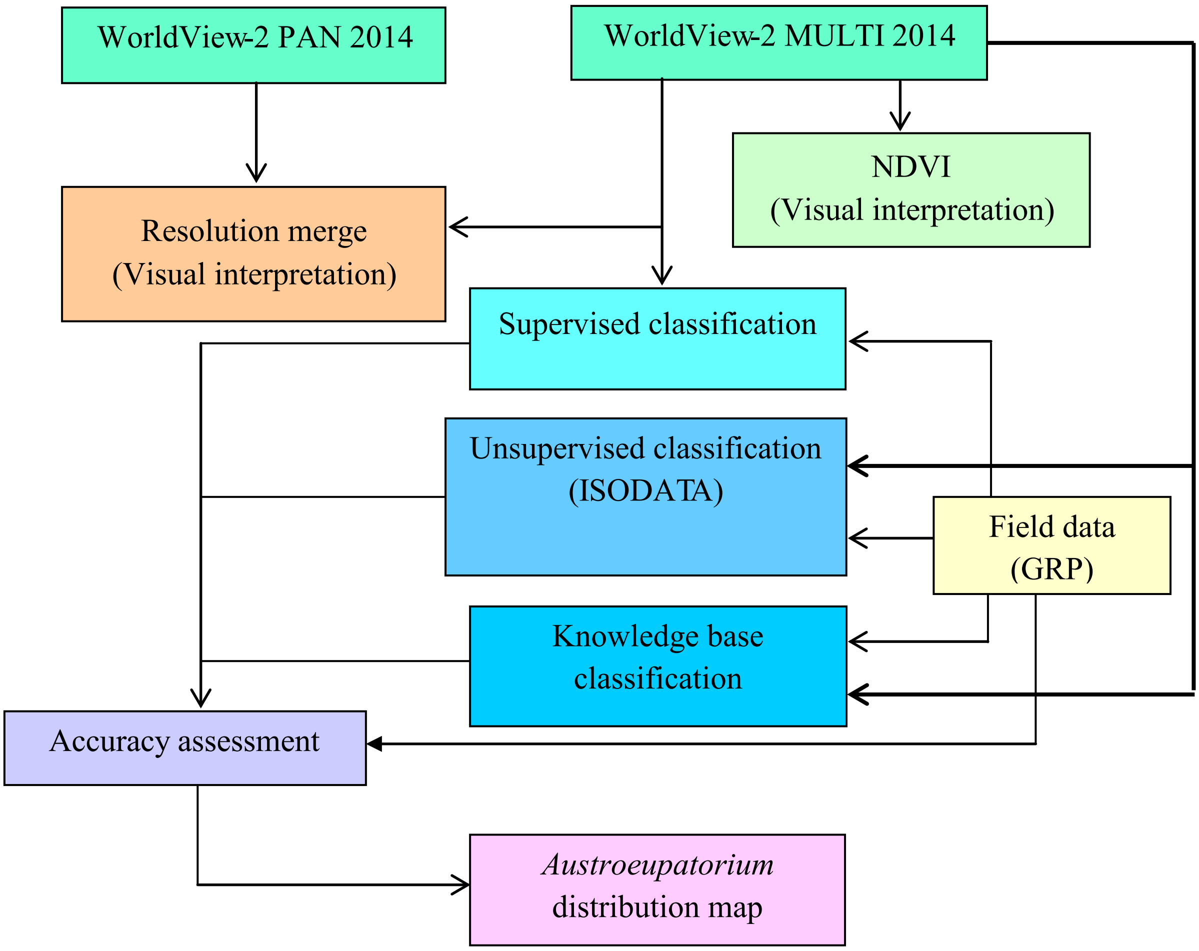


Figure 2: Flow chart depicting the stepwise executions carried out in three different classifications (unsupervised, supervised and knowledge-based) used in the study for preparing spatial distribution maps of *A. inulifolium* in the selected study area in the Knuckles Forest Reserve, Sri Lanka. (GRP: Ground Reference Points)

by setting priorities to identified classes using Maximum likelihood algorithms. The 'Area of Interest" (AOI) tool was used to collect spectral signatures for landuse types such as forest, *C. nardus*-dominated grasslands and *A. inulifolium* invaded grasslands. In addition, water, abandoned lands and degraded lands were also identified. The supervised classification was performed using those recorded spectral signature file. The classified image was visually inspected for accuracy. Specific land cover classes were developed through repeated supervised classifications. An accuracy assessment was performed at the end of the classification.

In knowledge-based classification, the Principal Component Analysis (PCA) was performed for the multispectral image of the WorldView-2 and unique features were analyzed for the components. Number of components desired was set to 8 as it has 8 bands. 'Difference Vegetation Index' (DVI) [*DVI = NIR - RED*] was generated for the above PCA image as given by Graham (2016). Once selected the best bands for DVI, different bands were tested for NIR and RED and preview was checked for different land cover classes while the main focus was given to recognize *A. inulfolium* invaded areas. Band 8 was selected for NIR and band 1 was selected for RED as the best for this classification. The textural differences were recognized as forest, grasslands, disturbed and cultivated lands. After performing DVI using NIR-8 and RED-1, *A. inulifolium* invaded areas were recognized by the histogram of DVI, and was hypothesized that -1320 areas (black colour regions) represented by *A. inulifolium* invaded areas (Graham, 2016). Next, a dendogram was generated using Knowledge Engineer in ERDAS imagine (Graham, 2016). The final classification was executed to isolate *A. inulifolium* pixels. As we gave dark pink to the new hypothesis, dark pink colour regions were detected in the product. Accuracy assessment was done comparing pixels in the classified image file and the class values for the corresponding reference pixels. Reference pixels (points on the classified image) were randomly selected. The stepwise methodology carried out during the three classifications was given in the following flow chart for clarity (Figure 2).

RESULTS AND DISCUSSION

Spectral signature of *Austroeupatorium*

The recorded reflectance values (taken randomly from *A. inulifolium* plants from different locations within the study area) were graphically presented in the figure 3. The spectral reflectance plays a key role in discriminating *A. inulifolium* from co-occuring *C. nardus* in this study. The spectral features specified as a finger print in recognition of invasive plants in RS studies (Underwood *et al*., 2007; He *et al*., 2011).

Distribution of *Austroeupatorium*

In supervised and unsupervised maps, *A. inulifolium* invaded areas are shown in dark pink colour while *C. nardus*-dominated grasslands in yellow (Figures 4a and b). According to the maps, *A. inulifolium* invasion was more or less confined to forest-grassland edges with the trend of spreading towards *C. nardus*-dominated grasslands, often demarcated by lower montane forest patches. An accuracy assessment was carried using overall accuracy and kappa coefficient based on error matrices to compare the classified image with the reference data (Amiri and Hosseini, 2012). According to the error matrix, the producer and user accuracies of the supervised classification were 100%. The Overall classification accuracy was also 100% with Overall Kappa (K^) Statistics at 1.000. Producers and user accuracies of each classified class (Forests, *A. inulifolium* invaded areas, *C. nardus*-dominated grasslands etc.) showed a 100% accuracy.

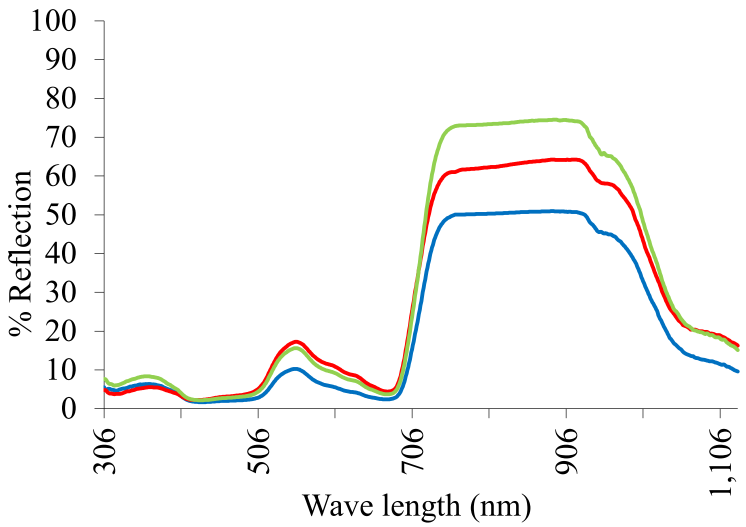


Figure 3: The percentage spectral reflectance [(reflectance of test plant)/(reflectance of white light)]×100) of *Austroeupatorium inulifolium* leaves. Each line of different colours represents measurements taken from separate plants.

Table 1: The area covered by different landuse classes in the selected study area according to the images produced by unsupervised (ISODATA clustering), supervised (Maximum likelihood algorithm) and knowledge-based classifications.

Landuse class	Unsupervised Classification		Supervised Classification		Knowledge-based Classification	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest	353.8	56.9	391	62.8	-	-
Grasslands	85.5	13.8	98.3	15.9	-	-
***A. inulifolium* invaded area**	**108.8**	**17.5**	**93.7**	**15.0**	**92.2**	**15**
Abandoned and cultivated land	58.4	9.4	37.6	6.0	-	-
Water	15.1	2.4	2	0.32	-	-
Total	623	100	623	100	623	100

According to the unsupervised classification, the total extent of the study area selected was 623 ha (by subsetting the selected study area from the originaly classified image), of which *A. inulifolium* invaded area was approximately 109 ha (18%) (Table 1). In the supervised classification, the *A. inulifolium* invaded area was 96.5 ha (15%), while the knowledge-based classification demarcated an area of 93.2 ha (15%) (Figure 5, Table 1). The use of GIS and RS techniques in mapping the distribution of plant species has been explored previously, with varying levels of success. The present study observed a comparable area under *A. inulifolium* invasion (15-18% from the total study area) from all three classification methods. Most applications of RS in mapping plant species are mainly rely on spatial and spectral patterns. The results of the present study further confirmed the potential use of high resolution satellite imagery to create highly accurate and detailed maps of invasive shrubs such as *A. inulifolium*.

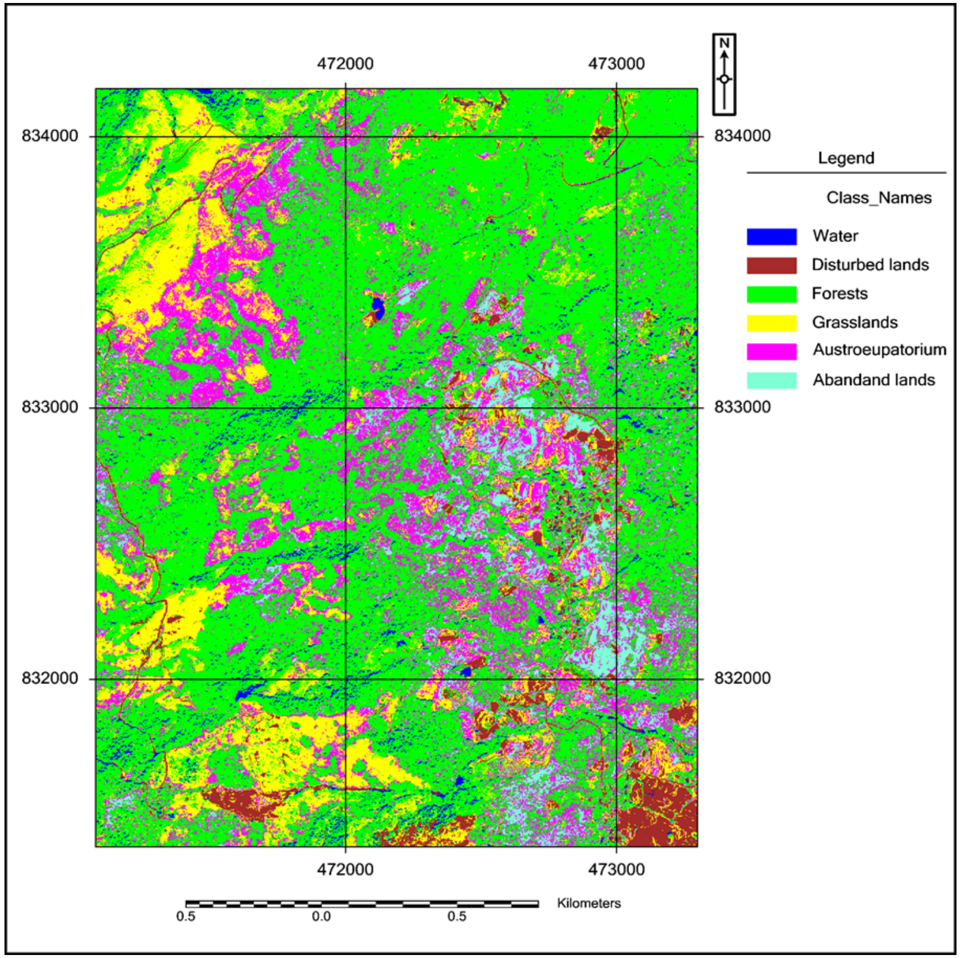
From the three methods used in the study, the unsupervised classification is a fully computer automated method while the supervised and knowledge-based classifications are not fully computer automated methods (Repaka *et al*., 2004; Müllerováa *et al*., 2013; Xu, 2014), where the selection of spectral characters or training samples need to be carried out with the help of field-based knowledge. A thorough knowledge on the study area is critical in these classification methods. In supervised classification, well-defined training areas and pure signatures are essential for accurate results (Repaka *et al*., 2004; Frick *et al.,* 2005). Furthermore, both supervised and unsupervised tools are pixel-based classifications, conversely, in knowledge classifier tool, the decision rules are applied to the base maps to identify vegetation that are not able to be detected based on the pixel-based classification (Xu, 2014).

Comparison of image classifications

All three generated maps indicated that *A. inulifolium* stands are mainly confined to forest-grassland edges and spread towards the man-made grasslands. According to the unsupervised classification, *A. inulifolium* spread was about 18% of the study area, while grasslands encompassed 14%. Supervied classification too quantified the area under *A. inulifolium* as 15%, with almost similar results in the knowledge-based classification as well. In favour, previous studies too showed some promising results where the use of spectral features followed by supervised classification with the help of high spatial resolution imagery (Ustin *et al.,* 2002; Gil *et al.,* 2013; Becker *et al.,* 2013). Early studies highlighted the importance of unsupervised classification including ISODATA clustering for mapping invasive plants successfully (Frazier and Wang, 2011; Müllerováa *et al.,* 2013). However, in this study, all three classifiers produced somewhat comparable outcomes. Based on these results, any of the three tested classfiers can be recommended for detecting and monitoring spread of *A. inulifolium* with the use of high resolution imageries. Rocchini *et al.* (2015) indicate that generating a distribution model for invasive species with environmental parameters may give more accurate estimates for potential invasion. Therefore, generating a distribution model for *A. inulifolium* with environmental data (geology, rainfall, temperature and wind) is also be recommended as a future study. Furthermore, sequential satellite images may produce more accurate estimates for potential invasion.

Discrimination and detection limits

A. inulifolium bear rather distinct creamy-white inflorescences, composed of buds and flowers with different maturity stages, hence may not spectrally homogeneous. High spectral variability within entities could reduce the accuracy of pixel-based classification, known as H-resolution problem and salt-and-pepper effect (Yu *et al.,* 2006; Chen *et al.,* 2012). Therefore, the time of the image acquisition can be highly synchronized with its phenological events (Huang and Asner, 2009; Somodi *et al.,* 2012) and seasonal variations (Morisette *et al.,* 2009). Mapping the distribution of invasive plant species has shown promising results with few exceptions (Underwood *et al.,* 2006). The high costs of satellite imageries, software and hardware can be considered as major barriers in less-developed countries (Turner *et al.,* 2003). In addition, a high technical proficiency is needed for processing hyperspectral images. Even though RS could provide efficient and accurate maps to detect the distribution of plants, the classifying and validating images using *in situ* field measurements is a necessity (Underwood and Ustin, 2007). Though RS is considered as fast and efficient, the



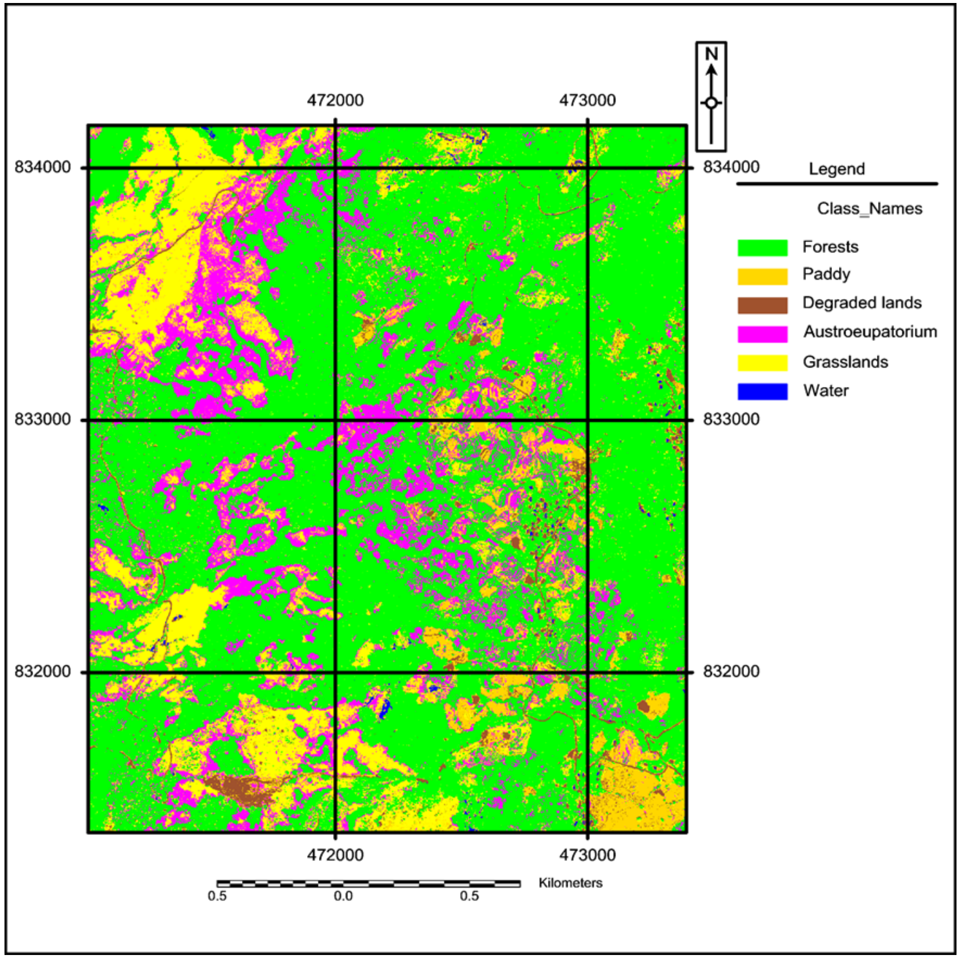


Figure 4: The distribution maps of *Austroeupatorium inulifolium* using A: un-supervised classification and B: supervised classification. In both maps, *A. inulifolium* distribution is indicated in dark pink colour.

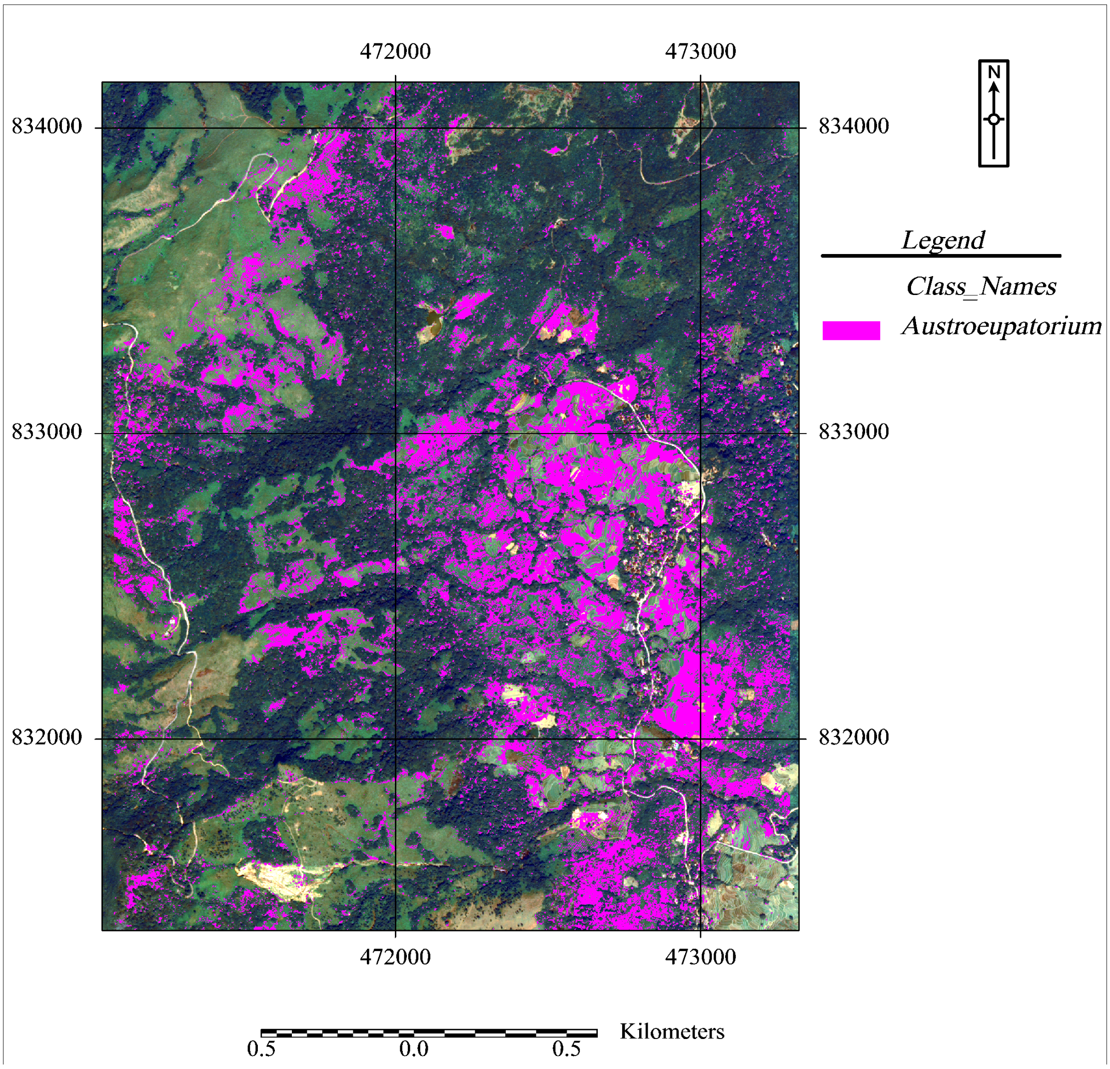


Figure 5: The distribution map of *Austroeupatorium inulifolium* using knowledge-based classification. In the map, *A. inulifolium* invaded areas are denoted in dark pink colour.

best methods in detecting and monitoring of invasive plants need to be identified using further research (Müllerováa *et al*., 2017). With the continuous advancement of satellite imagery and RS technologies besides increasing availability of open access information and open source software, use of RS for mapping invasive plant species will become an essential and readily available tool.

CONCLUSIONS

The study concludes that the distribution of *A. inulifolium* vary from 15 to 18% of the selected study in KFR, indicating that the high resolution WorldView-2 imagery could provide an excellent source to map the distribution of invasive shrub species with a high accuracy.

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