Comparison Of Algorithms For Agave Detection On Unmanned Aerial Vehicle Images

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COMPARISON OF ALGORITHMS FOR AGAVE DETECTION ON UNMANNED AERIAL VEHICLE IMAGES

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Abstract

In this study, six supervised classification algorithms were compared. The algorithms were based on cluster analysis, distance, deep learning and object-based image analysis. Our objective was to determine which of these algorithms has the highest overall accuracy in both detection and automated estimation of agave cover in a given area to help growers manage their plantations. An orthomosaic with a spatial resolution of 2.5 cm was derived from 300 images obtained with a DJI Inspire 1 unmanned aerial system. Two training classes were defined: 1) sites where the presence of agaves was identified, 2) "absence"; where there were no agaves but other plants were present. The object-oriented algorithm was found to have the highest overall accuracy (0.963), followed by the support-vector machine with 0.928 accuracy and the neural network with 0.914. The algorithms with statistical criteria for classification were the least accurate; Mahalanobis distance = 0.752 accuracy and minimum distance = 0.421. We recommend that agave plantation managers use drones for their efficiency and speed. We further recommend that the object-oriented algorithm be used, because in addition to having the highest overall accuracy for the image segmentation process, it yields parameters that are useful for estimating the coverage area, size, and shapes, which can aid in better selection of agave individuals for harvest.

Keywords: algorithms, agave crops, drone, image segmentation, supervised classification, OBIA

Introduction

The genus *Agave* includes 204 species, of which 163 are distributed in Mexico (García-Mendoza et al. 2019). Twenty-five species of agave have been recorded as being used to produce mezcal. The most used species are wild; e.g., *A. durangensis, A. salmiana*, while some are cultivated; e.g., *A. angustifolia* (Carrillo-Trueba, 2007). In the past two decades, the demand and overexploitation of agave for mezcal production has caused wild populations to decline rapidly. One of the main reasons for the decline is that the plants are harvested before sexual reproduction (Rangel-Landa et al., 2015). In Mexico, the main strategy to restore wild and cultivated agave populations is assisted recovery, which consists of in vitro germination and subsequent transfer to restoration sites (Rangel-Landa et al., 2015). However, agave population parameters, including growth rate, recruitment, and presence of nurse plants, are mainly monitored manually, which involves considerable effort (Calvario et al., 2020).

Agaves can be detected and counted by applying algorithms to digital images captured from unmanned aerial vehicles (UAVs). These techniques are widely used in precision agriculture (Tsouros et al., 2019). UAVs can provide high resolution images (1–2 cm), depending on the height of the flight and the focal length of the camera (Torres-Sánchez et al., 2015). This has been very useful for counting and morphometric analysis of agaves; for example, Calvario et al. (2020) conducted a blue agave count using images taken from a DJI Phantom 4 UAV, and applied an algorithm based on mathematical morphology. They found that the estimate of the number of plants identified automatically in the images had an overall precision between 0.830 and 0.980. Another recent study, also carried out with blue agave, was Flores et al. (2021). They applied a convolutional neural network (CNN), in which patterns and textures are learned, and used to carry out automated counts in images taken from UAVs. They report a level of precision of 0.96 for the agave count in their study.

As mentioned above, detection and counting has only been carried out for blue agaves using deep learning algorithms, which require robust knowledge of image processing by users. This study therefore set out to compare supervised classification algorithms for first-time detection of *cenizo* agaves (*Agave duranguensis*), which are in danger of extinction. We compared algorithms based on statistical rules that are commonly used in remote sensing, and deep learning algorithms that are available and contain flowcharts in commercial and free software.

Materials and methods

The Sampling was carried out in the Ejido Nombre de Dios, Durango, that is located at coordinates 23 ° 36 'and 24 ° 05' north latitude, and 103° 56 'and 104 ° 25 'west longitude, at an altitude of 1800 m (Figure 1). In September 2020 along of 10 hectares of *Agave durangensis,* the aerial survey was carried out using a DJI Inspire V.2 UAS (unmanned aerial system) equipped with camera ZenmUSE x3, with a 20 minutes of flight time. To capture images, we use the DJI GS Pro (GSP) application performing the missions with the 3Dmap Area mode. The flight parameters for 10 hectares of coverage using 2 sets of batteries were: definition of 8 lines of course count, the image capture mode was hover and capture at point, flight course mode Inside. The side overlap ratio was a 70% and gimbal angle 90 degrees. The speed of the aircraft was 4.0 m / s and flight height of 50 meters.

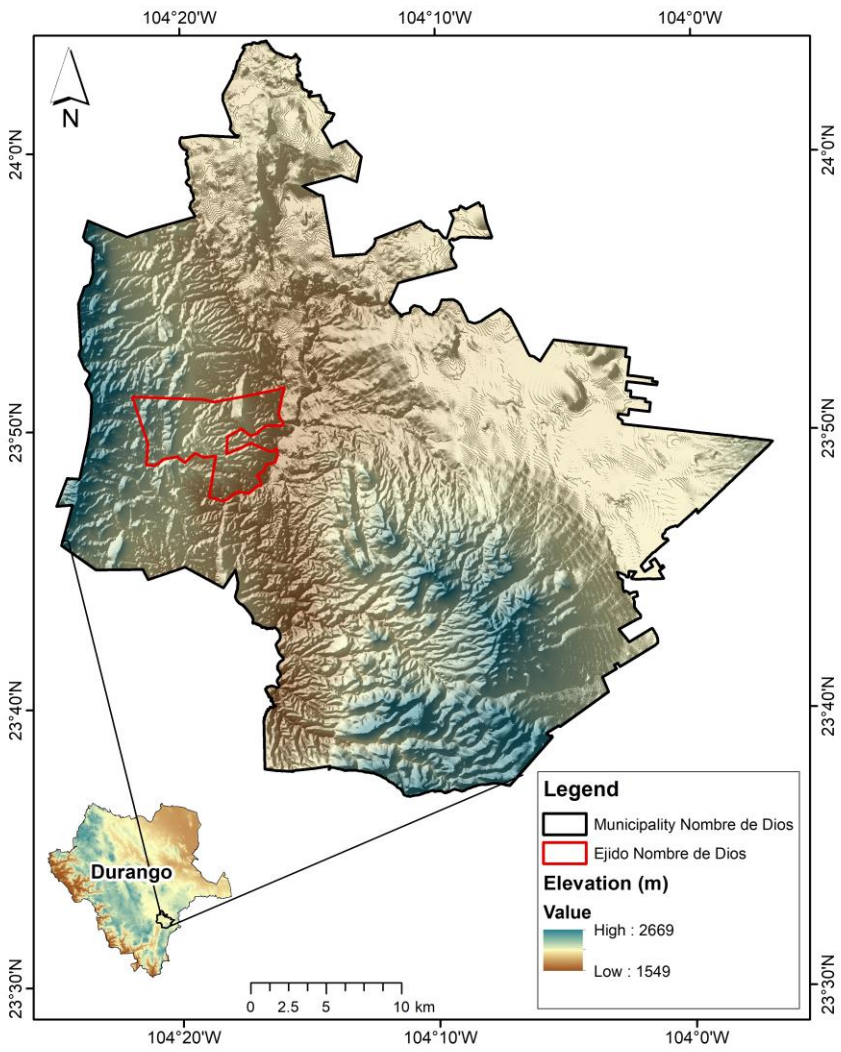

Figure 1. Map of study area of Municipality Nombre de Dios, Durango.

Image processing

The images were georeferenced with DATUM WGS84 Zone 13 using Agisoft Photoscan. To generate orthomosaic the photographs were oriented, establishing 50,000 key points per photograph, and 5,000 link points per photo, generating a point cloud with more than 1 million points. Orthomosaic with a spatial resolution of 2.5 cm/px were derived from the point cloud. The Orthomosaic was exported in JPG format for the supervised classifications in the program ENVI 5.3.

Training sites

A stratified random sampling method (Olofsson et al., 2014) was used to generate the reference data in ArcGis. A total of 860 random points were sampled, with at least 430 points for each class (Goodchild, 1994). The following classes were considered: class a is presences of agaves mescaleros with 430 sites, class b is absences of agaves with sites. These data were contrasted with the category to which each training pixel belongs, corresponding to Georeferenced sites (Datum WGS-84, 13N) obtained in the field in September 2020.

Classification methods

Statistical rule–based algorithms. We used three types. The first was minimum distance, which uses the mean vectors of each region of interest (ROI) and calculates the euclidean distance from each unknown pixel to the mean vector for each class. Pixels are put into the closest ROI class unless the user specifies standard deviation or distance thresholds, in which case some pixels may be unclassified if they do not meet the specified criteria. The second algorithm was Mahalanobis distance. This is a direction-sensitive distance classifier that uses statistics for each class. It assumes all class co-variances are equal and therefore is a faster method. The third algorithm uses maximum likelihood. This method assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified. Each pixel is assigned to the class with the highest probability. The ROIs correspond to the sites with presence or absence of mezcal agaves (Richards, 1999).

Deep learning algorithms. We used two types. The first was a back-propagation artificial neural network (BPNN) (Tan and Smeins, 1996). BPNN is widely used because of its structural simplicity and robustness in modeling non-linear relationships. The first step in BPNN supervised classification is to enter the input layer, which in this study corresponds to the values of the pixel image from the UAV. Weights are then assigned to the BPNN to produce analytical predictions from the input values. We used a logistic function and a training rate of 0.20, previously applied in land cover classification (Hepner et al., 1990; Braspenning & Thuijisman, 1995). The output layer comprised two neurons representing the class of presences or absences of mezcal agaves.

The second type was a support vector machine algorithm. This method is based on statistical learning theory, and often yields good classification results from complex and noisy data. It separates the classes with a decision

surface that maximizes the margin between the classes. The surface can be called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. We used the ENVI implementation of SVM, which uses the *pairwise* classification strategy for multiclass classification (Hsu et al. 2010).

Object-Based Image Algorithm (OBIA). The mezcal agaves were detected using OBIA, a digital analysis of images in which spatially and spectrally similar pixels are clustered into groups called objects in order to then carry out more precise classifications on multispectral images (Blaschke, 2010). The datasets used were the image mosaic with 2.2 cm spatial resolution. The first pass was segmentation of the images using *rule-based feature extraction* in ENVI 5.3, following the workflow: edge scale level 80%; merge settings full lambda schedule 90%. The segmentation was begun using the Full Lambda-Schedule algorithm created by Robinson et al. (2002). The algorithm iteratively merges adjacent segments base on a combination of spectral and spatial information (Eq. 1), where O_i is región i of the image, [O_i] is the área of región i, U_i is the average value in región *i. Uj* is the average value in región j. $\|U_i - U_j\|$ is the Euclidean distance between the spectral values of regions i and j, and of $(\partial(O_i, O_j))$ is the length of the common boundary of O_i and O_j.

$$t = \frac{[O_i] \cdot [O_j] \cdot \|U_i - U_j\|^2}{length\ (\partial(O_i, O_j))} \quad Eq.1$$

The segmentation yielded polygons with similarities in size and shape to agaves. The spatial attributes were analyzed based on a smoothed version of the geometry, not the original geometry (Douglas and Peuker, 1973).

Validation

The classifications were cross-validated (10-fold) estimated the uncertainty of the classification using estimated error matrix in terms of proportion of area and estimates of overall map accuracy ($\hat{O}$), user's accuracy ($\hat{U}_i$) (or commission error) and producer's accuracy ($\hat{P}_j$) (or omission error) recommended by Olofsson et al. (2014): p_{ij} is defined as a cell entry of error matrix of i map classes. A poststratified estimator of p_{ij} is (Eq. 2):

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i.}} \quad (2)$$

where W_i is the proportion of the area mapped as class i. $n_{i.}$ is the total number of sample units in map class i. n_{ij} is the sample count at cell (i,j) in the error matrix.

$\hat{p}_{.j}$ is a poststratified estimator for simple random and systematic sampling (Eq. 3):

$$\hat{p}_{.j} = \sum_{i=1}^{q} W_i \frac{n_{ij}}{n_{i.}} \tag{3}$$

where q is the class number.

An unbiased estimator of the total area of class *j* is then (Eq. 4):

$$\hat{A}_j = A \cdot \hat{p}_{.j} \tag{4}$$

where *A* is the total map area. For $\hat{p}_{.j}$, the standard error is estimated by (Eq. 5):

$$S(\hat{p}_{.j}) = \sqrt{\sum_{i=1}^{q} W_i^2 \frac{\frac{n_{ij}}{n_{i.}}\left(1 - \frac{n_{ij}}{n_{i.}}\right)}{n_{i.} - 1}} \tag{5}$$

The standard error of the error-adjusted estimated area is (Eq. 6):

$$S(\hat{A}_j) = A \cdot S(\hat{p}_{.j}) \tag{6}$$

Finally (Eq. 7),

$$\hat{A}_j \pm 1.96 \cdot S(\hat{A}_j) \tag{7}$$

presents an approximate 95% confidence interval.

The $\hat{O}$, $\widehat{U}_i$ and $\widehat{P}_j$ were calculated with Eqs. (8-10) (Congalton, 1991). $\widehat{U}_i$ of class *i* is the proportion of the area mapped as class *i* that has reference class *i*. $\widehat{P}_j$ of class *j* is the proportion of the area of reference class *j* that is mapped as class *j*.

$$\hat{O} = \sum_{j=1}^{q} \hat{p}_{jj} \tag{8}$$

$$\widehat{U}_i = \frac{\hat{p}_{ii}}{\hat{p}_{i.}} \tag{9}$$

$$\widehat{P}_j = \frac{\hat{p}_{jj}}{\hat{p}_{.j}} \tag{10}$$

Results and Discussion

The supervised classifications obtained using the algorithms with statistical rules had the lowest overall precision; in fact, a very low precision of 0.421 was obtained with the minimum distance algorithm, in addition to overestimation of the area covered by agave (Table 1, Figure 2). For the Mahalanobis distance and maximum likelihood algorithms, which use similar classification criteria, Mahalanobis was slightly better with an overall precision of 0.752. However, this precision is lower than that reported by Carbvalho-Júnior et al. (2011) and Talukdar et al. (2020), who report an overall precision of 0.82 to 0.89 in studies of land use and land use changes. One of the disadvantages of using the Mahalanobis distance algorithm is that it assumes that the histograms of the RGB bands have a normal distribution (Perumal and Bhaskaran, 2010), and when this condition is not met, the overall precisions tend to have lower values, such as the value we report in the present study.

The statistical rule algorithms had the highest errors of omission and commission for agave detection (Table 1, Figure 2). For example, the maximum likelihood algorithm assumes Gaussian multivariate distributions for the classification of the data, but the data in the feature space might not follow the assumed model. Moreover, it is possible that a single class may be represented in multiple places in the feature space (Atkinson and Tatnall, 1997). This particularly affects the analysis when classes are amalgamated at a higher level in the classification system; for example, if shrubs, grasses, and agaves are grouped together (Benediktsson et al., 1993).

The BPNN and SVM deep learning algorithms improved the classification, yielding overall precision levels greater than 0.90 (Table 1). There was less confusion of agaves with other elements of the habitat in the images; however, these algorithms were not perfect since some false positives were found (Figure 2). We achieved slightly lower precision in the detection of agaves with BPNN than that reported by Flores et al. (2021) with the convolutional neural network algorithm (overall precision 0.95), which has the ability to learn patterns and textures. Estimation of the agave area also improved with the deep learning algorithms; the estimation error was less than 40 m² when compared with the estimate obtained in the field (Table 1). The algorithm with the best overall precision and the lowest error in estimating agave area was OBIA, with an overall precision of 0.96, which is slightly better than that reported by Calvario et al. (2020) and Flores et al. (2021) for the detection of blue agave. The deep learning algorithms used in this study have the advantage that during the classification

process they start from a distribution-free assumption; that is, no underlying model is assumed for the multivariate distribution of class-specific data in the feature space.

Table 1. Error matrix of two classes with cell entries (p_{ij}) based on Table 2 and expressed in terms of proportion area. Class a = presences of agave mezcalero Class b = absences

Algorithm	Class	References		Accuracy			Estimated map area (m^2)
		a	b	User´s	Producer´s	Overall	
Minimum distance	a	0.080	0.539	0.129	0.675	0.421	640.06 ± 12.05
	b	0.038	0.341	0.898	0.387		4751.88 ± 8.03
Mahalanobis distance	a	0.083	0.242	0.256	0.933	0.752	271.31 ± 4.66
	b	0.006	0.668	0.991	0.734		2767.78 ± 2.37
Máximum likelihood	a	0.079	0.265	0.229	0.993	0.733	249.95 ± 4.29
	b	0.005	0.654	0.999	0.711		2881.05 ± 0.75
BPNN	a	0.146	0.078	0.652	0.952	0.914	407.94 ± 4.88
	b	0.007	0.767	0.990	0.907		2237 ± 2.34
SVM	a	0.145	0.063	0.696	0.948	0.928	396.49 ± 4.50
	b	0.007	0.783	0.990	0.925		2193 ± 2.38
OBIA	a	0.135	0.030	0.814	0.960	0.963	345.89 ± 2.52
	b	0.005	0.828	0.993	0.964		2112.11± 1.94

In the estimation of errors in the counts of presence and absence of agaves using the Mahalanobis distance and maximum likelihood algorithms, the weight (Wi) assigned to absences was greater than 0.60, which affected estimation of the coverage both of area with agaves and area without the plant (Table 2). The *Wi* were low in the agave-present class in the deep learning and OBIA algorithms (Table 2). This makes sense, because agaves cover less than 20% of the area studied and therefore the estimate of agave coverage improves notably (Figure 2).

Table 2. Estimated error matrix based of sample counts (n_{ij}) from the accuracy assessment sample. Class a = presences of agave mezcalero Class b = absences

Algorithm	class	Total	Wi
Minimum distance	a	44619	0.619
	b	47079	0.380
Mahalanobis distance	a	10082	0.325
	b	52309	0.674
Máximum likelihood	a	45740	0.345
	b	45958	0.657
BPNN	a	15215	0.225
	b	57622	0.774
SVM	a	14208	0.208
	b	58629	0.791
OBIA	a	22641	0.166
	b	59402	0.834

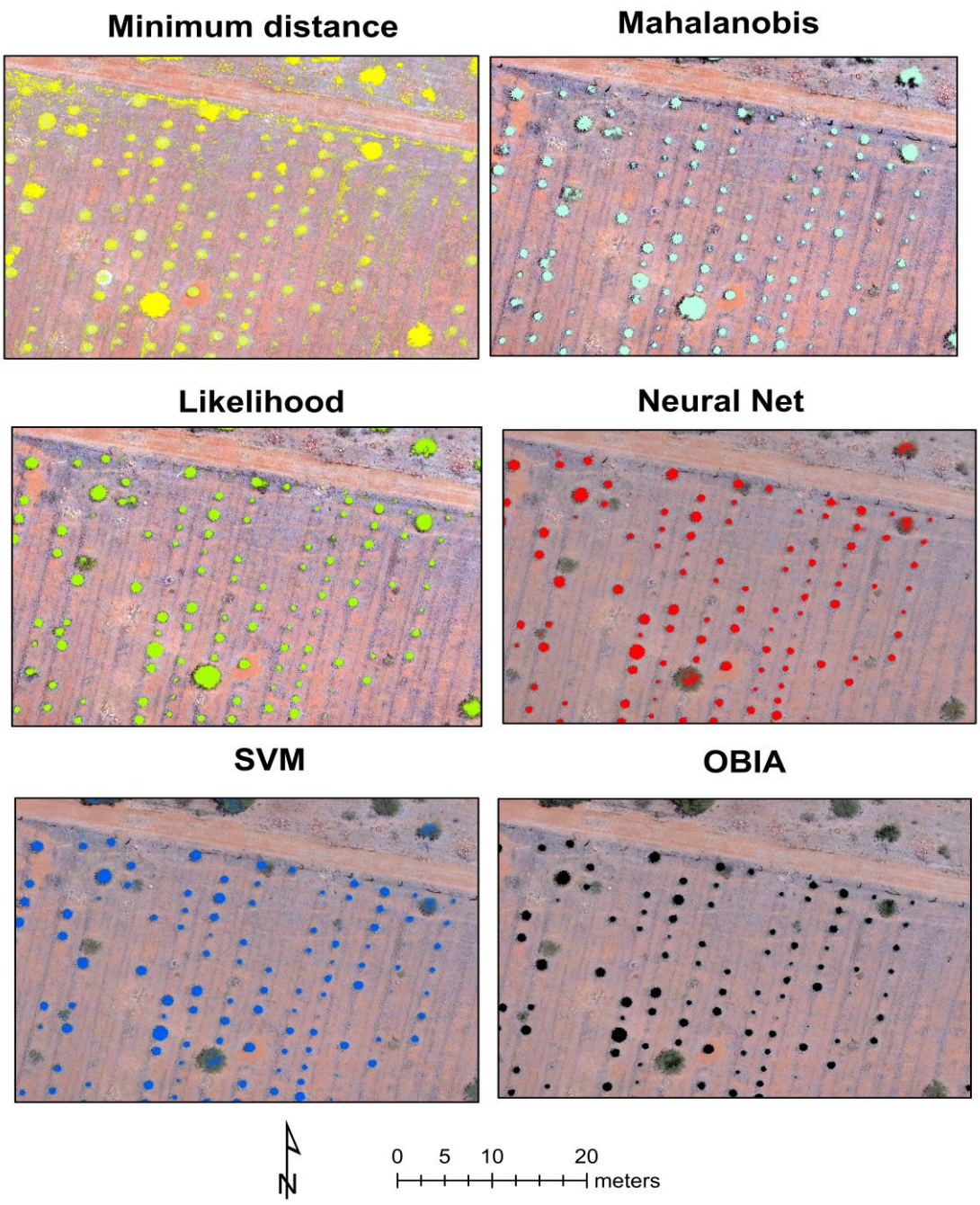

Figure 2. Supervised classifications obtained with the algorithms studied. Greater precision in the detection of agaves is observed with SVM and OBIA.

Segmentation of the image with OBIA clearly differentiated agave with cover greater than 30 cm from other elements of the habitat such as bare soil, grasslands and other herbaceous plants (Figure 3). A main advantage

of OBIA is that it has the ability to detect agaves of a variety of sizes and ages. The algorithm based on mathematical morphology also has this ability (Jean-Philippe et al. 1994; Calvario et al., 2020).

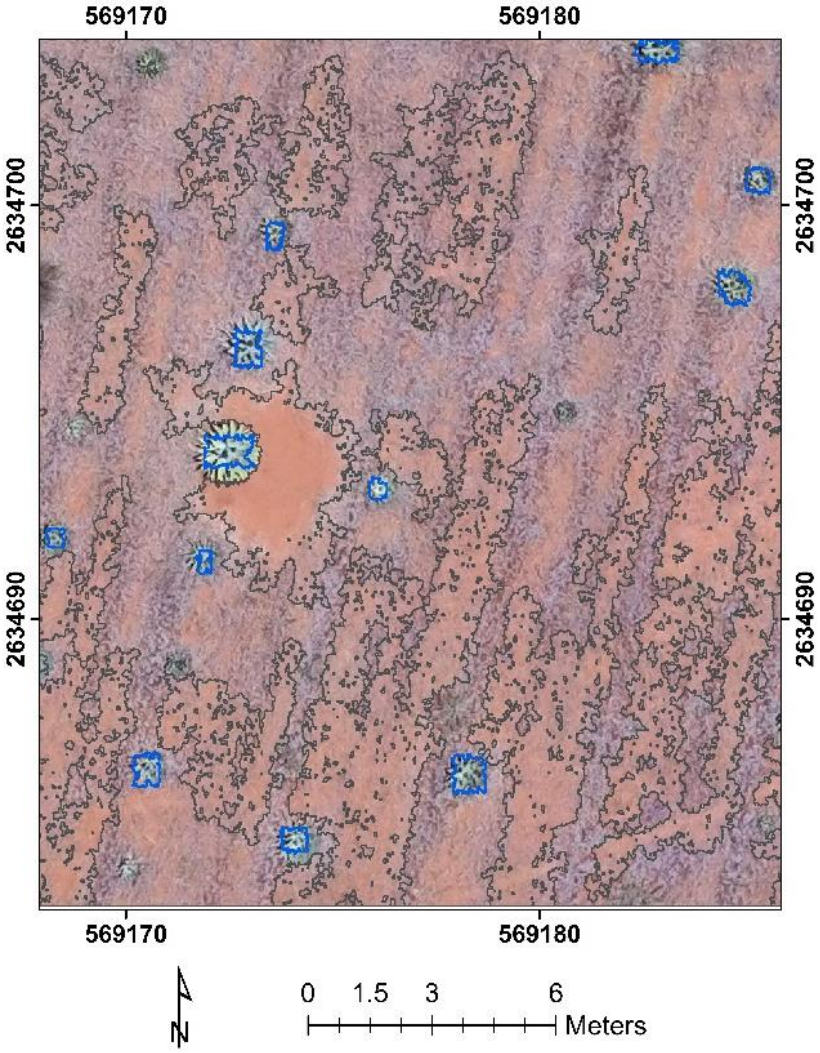

Figure 3. Segmentation of the image of an agave (*Agave durangensis*) crop by the OBIA algorithm

Conclusion

The main difference between algorithms based on statistical rules and deep learning algorithms for the detection of agaves is that the algorithms with a statistical approach depend on an assumed model, while the deep learning algorithims depend on the training data and the histograms of the image. Therefore, we recommend using the OBIA algorithm because it has three advantages over the other algorithms: 1) The global precision level is high

(> 0.90), which is useful in places where the possibility of confusing agaves with others plant species is high, 2) the result of the image segmentation process includes a database of shape parameters (roundness, elongation, cover, compactness, etc.) with which a better selection of agaves can be made in the harvest 3) the Algorithm OBIA is available in both commercial (ENVI) and free (SAGA) software giving you access to many managements and researchers

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Authors' contributions

JE, and SS provide a substantial contribution to the conception and design of this mini-review. JE is the major contributor of literature search and data analysis for this mini review. SS analyzed and interpreted the data for this mini-review article. JE analyzed and interpreted the data for this mini-review article. SS is the major contributor in drafting this mini review. EG contributed to critically revising the article for important intellectual content. All the authors read and approved the final version of this mini-review and agree to approve for sending for publication in this esteemed journal.

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Compliance with ethical standards

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare that they have no competing interests.

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