ESTIMATING CANOPY COVER FROM EUCALYPT DOMINANT TROPICAL SAVANNA USING THE EXTRACTION OF TREE CROWNS FROM VERY HIGH RESOLUTION IMAGERY.

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ABSTRACT:

Very high spatial resolution satellite imagery provides data that enables spatially detailed analysis of landscapes. The identification and extraction of information about tree crowns is one such use. Tree crown or canopy cover is one parameter of vegetation structural classification. The estimation of canopy cover has a wide range if uses related to management and policies. Tree crown extraction of Eucalypts is not without its challenges. The inherent characteristics of Eucalypt crowns include open spaces within the crowns, vertically angled leaves, and the irregular crown shapes provide a number of challenges to remote sensing. This paper proposes an object-based method for extracting tree crowns from Eucalypt dominant savanna in the wet/dry tropics of northern Australia. A two level multi-resolution segmentation was undertaken upon QuickBird data (multispectral, panchromatic and derivatives) covering the area under investigation. The first broader segmentation allowed the differentiation of Eucalypt dominant communities from other vegetation types. The second finer segmentation produced segments smaller than the tree crowns. A rule-set containing a series of classification and object growing algorithms were then used to firstly identify objects within a crown and then to expand the objects to cover the entire crown. Results indicate the potential of this method for delineating tree crowns from Eucalypt savanna and the use of this information to estimate canopy cover. The approach used here offers a method of tree crown delineation where the availability of other forms of data such as hyperspectral and laser scanning imagery may not be available.

1. INTRODUCTION

Very high spatial resolution satellite imagery provides data that enables spatially detailed analysis of landscapes. The identification and extraction of information about tree crowns is one such use. Tree crown or canopy cover is one parameter utilised in the classification of vegetation based on structural formation. The estimation of canopy cover has a wide range if uses related to management and policies. For example, Australia's National Vegetation Information System (NVIS) uses cover characteristics of the dominant growth form as one of the attributes used in the determination of its structural formation classes (Thackway *et al.*, 2008).

The extraction of Eucalypt tree crowns of provides a number of challenges for the remote sensing practitioner. Eucalypts are known for the significant degree of openness and light penetration within their crowns. Typically, this is due to the vertically angled leaves that are characteristic of most Eucalypts (Williams and Brooker, 1997; King, 1997). Other phenomena such as branch shedding (Jacobs, 1955) and disturbances such as fire (Williams *et al.*, 1999) lead to irregular crown shapes, a clumping of foliage and concentrations of leaves around the perimeter of the crown (Jacobs, 1955). All of this contributes to low values for leaf area index (LAI) and foliage cover estimates which makes it difficult to delineate crowns from remotely sensed imagery as most crowns also contain information from the understorey and ground cover directly beneath them.

Within Eucalypt dominant tropical savanna, the leaf area index (LAI) is noticeably lower in the mid-to-late dry season (0.6) compared to the wet and early dry seasons (1.0) (O'Grady *et al.*, 2000). This is considerably lower than the LAI values of between 6 and 10 for plantation conifers (Gower and Norman, 1991) and values of up to 6 for temperate Eucalypt forests (Macfarlane *et al.*, 2007).

Tree crown extraction

The extraction of tree crowns from remotely sensed imagery is based on a number of assumptions. The first assumption is that the crown centre appears radiometrically brighter than the crown edge (Culvenor, 2002). The second assumption is that a tree is a bright object surrounded by darker shaded objects (Leckie *et al.*, 2005). While these assumptions may hold for forested areas with tree crowns all exhibiting similar characteristics (ie plantations) they may not be true when dealing with mature Eucalypt tree crowns in open forest / woodland communities. In some cases, the perimeter of the crown may actually be brighter than the centre and there may be darker shaded areas directly within the tree crown.

The approaches for tree crown delineation do follow these assumptions and indentify crowns through either low intensity (dark) values (spaces between crowns) or high intensity (bright) values (crown centroids). Leckie *et al.* (2003), Leckie *et al.* (2005) and Gougeon and Leckie (2006) use a valley following or low value approach to delineate space between crowns or crown edges from surrounding shadows and then to build crown boundaries. Local maxima approaches use peaks in intensity indicating the brightest spot in the tree canopy, thus showing the location of a tree canopy but not its shape or outline. These spots (local maxima) can then be used to count the number of crowns identified or used as a 'seed' to initiate a region-growing method based on a threshold of intensity within the image (Culvenor, 2002; Tiede *et al.*, 2005; Bunting and Lucas, 2006).

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Culvenor 's (2002) tree identification and delineation algorithm (TIDA) uses a top down approach based on three steps identification of local maximum and minimum values across the image and the clustering of crown pixels. This algorithm was applied to the near infrared band of multispectral video. Eriksen's (2004) tree crown delineation methods were utilised a threshold of near infrared band of near infrared aerial photography. Bunting and Lucas (2006) also use a object/region growing method after identifying object maxima based on ratios of upper and lower red edge bands from hyperspectral (CASI) data.

Other studies using region growing methods have utilised multispectral digital camera data and LiDAR (Light Detection And Ranging) surface models (Tiede *et al.*, 2006; Tiede *et al.*, 2007)

This paper proposes an object-based method for extracting tree crowns from Eucalypt dominant savanna in the wet/dry tropics of northern Australia using very high resolution multispectral data.

2. METHOD

2.1 Study site

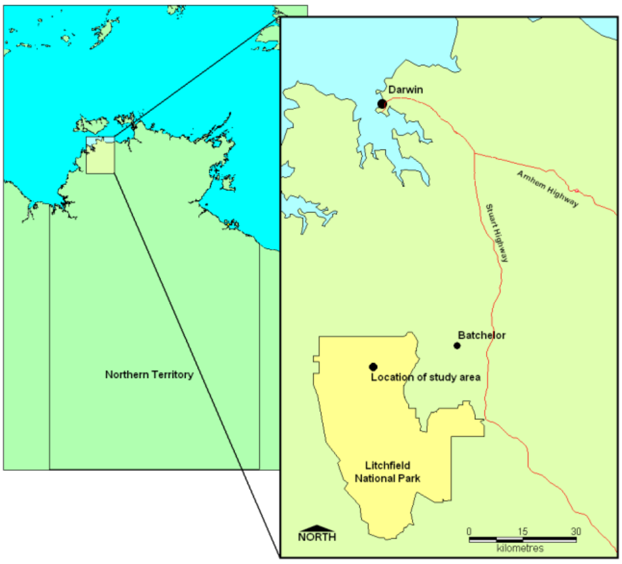


Figure 1: Location of study area.

This study was undertaken in Australia's wet/dry tropics in a 210 hectare area surrounding Florence Creek in Litchfield National Park (figure 1), located approximately 100km south of Darwin, the capital of the Northern Territory (13° 7' S, 130° 47.5'E).

The regional climate displays typical wet/dry monsoonal characteristics consisting of a brief season (December-March) of high intensity rainfall (.1500mm) and a longer period of little to no rainfall (April to November). Maximum daily temperatures in the region vary from just under 32°C in June and July to over 36°C in October and November.

The study area is situated on the north-eastern edge of the Tabletop Range and consists mainly of secondary plateau surfaces, with gentle sideslopes to the south and east and steep hills and slopes in north. The underlying geology is mostly quartz-based sandstone.

On the plateau and gentle slope surfaces the predominant vegetation is *Eucalyptus tetradonta* and *E. miniata* open forest and woodland with understoreys of low shrubs and/or annual grasses including *Sarga* species (Lynch and Manning, 1988). In the lower sandy areas, subject to seasonal inundation, open woodland and grassland communities of perennial grasses and sedges exist with small trees, *Grevillea pteridifolia*, *Banksia dentata* and *Jacksonia dilitata* in the overstorey. There are also linear patches of *Melaleuca* and mixed closed forests along spring-fed creek lines (Griffiths *et al.*, 1997).

Land units and vegetation have been previously mapped across the park based on the interpretation of aerial photography (Kirkpatrick *et al.*, 1987; Lynch and Manning, 1988). Land cover has also been mapped across the study area using ASTER data (Whiteside and Ahmad, 2004, 2005).

2.2 Dataset and pre-processing

The primary dataset for this project was a DigitalGlobe QuickBird image captured at 11.09 am on 28 August 2004. The 16-bit panchromatic and multispectral bands: blue (450-520μm), green (420-600μm), red (630-690μm) and near infrared (NIR) (760-900μm), were utilised. Ground resolution of this imagery is 2.4 metres for the multispectral and 0.6m for the panchromatic at nadir.

August is mid-to-late dry season, by which time the annual grasses have long since 'hayed off' and photosynthetic activity is minimal in the understorey and ground cover. The reduced reflectance in the near infrared should assist in differentiating tree crowns from the understorey and ground cover. However as mentioned previously, LAI for Eucalypt canopy at this time is also quite low (O'Grady, *et al.*, 2000). In addition, as the dry season progresses the area subjected to wildfire increases, adding further challenges.

Data pre-processing was undertaken using ERDAS Imagine version 9.1 image analysis software (Leica_Geosystems, 2005). The image was geometrically corrected to a previously georeferenced aerial photo of the area with an accuracy error of less than 0.5 pixels. A subset for this project was then 'cut' from the image (figure 2a).

An additional derivative data set was also created by conducting a decorrelation stretch of the multispectral data. The result produced four additional 32-bit layers, DS1, DS2, DS3, and DS4, with DS1 being the first order decorrelation stretch, DS2 the second and so on (figure 2b).

2.3 Broad segmentation

The first segmentation involved the creation of objects that could be used to provide a broad classification to determine basic land cover classes to separate Eucalypt or savanna vegetation from closed forest riparian, grassland and flood plain vegetation.

The segmentation was undertaken using the 'Fractal Net Evolution Approach' (FNEA) algorithm (Baatz and Schäpe, 2000) within Definiens Professional V5 software application. The FNEA algorithm is a region growing segmentation algorithm that partitions images into objects based on some homogeneity criteria (Benz *et al.*, 2004). The algorithm balances homogeneity of shape of the objects against spectral homogeneity. The operator is able to place weightings to emphasise either criteria. Further the shape criterion is split into two sub-criteria:

smoothness versus compactness (smooth borders opposed to compact shapes). The algorithm also includes a heterogeneity criterion (scale parameter) which although unit-less determines the size of the objects resulting from segmentation.

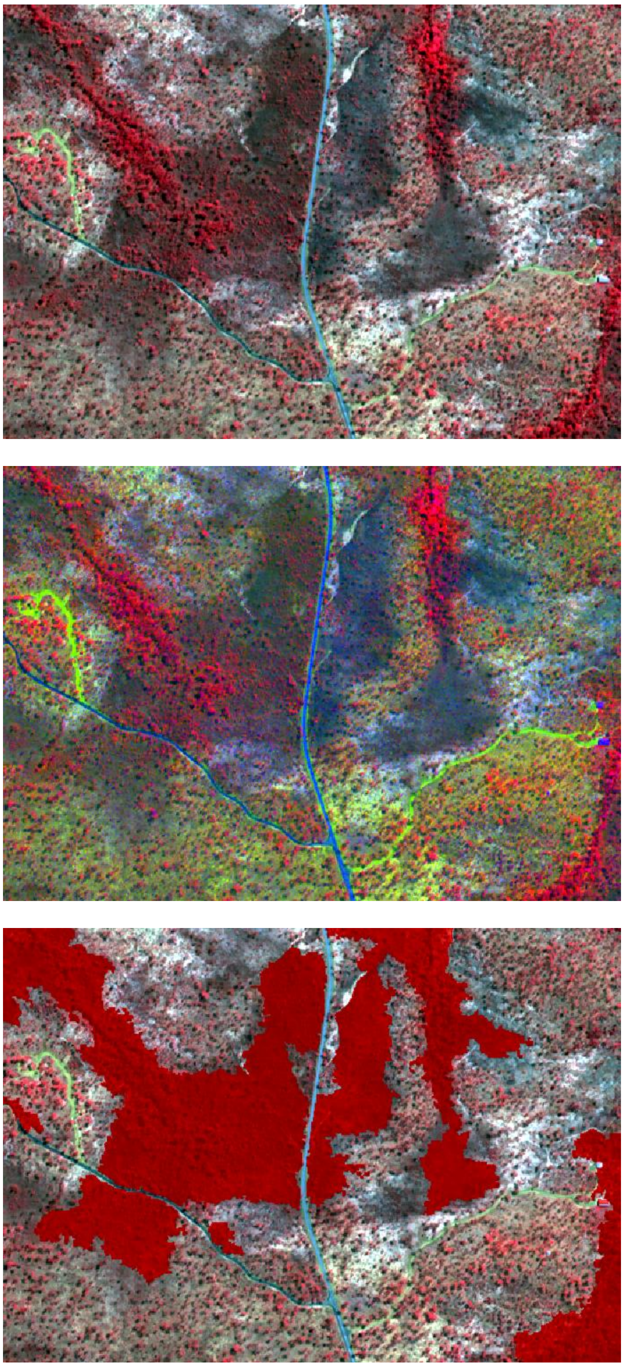


Figure 2: NIR, R, G = RGB (a), DS image DS4, DS3, DS2 = RGB (b), non-Eucalypt vegetation masked out (c).

For this level of segmentation, only the multispectral layers were considered. Table 1 details the parameters for segmentation.

Table 1: Parameters for the broad level of segmentation.

Segmentation method	Scale parameter	Colour /Shape	Compactness / Smooth
Multiresolution	200	0.4/0.6	0.8 / 0.2

Two virtual derivatives (NDVI and NDVI^2) were created from the dataset using the arithmetic feature within Definiens. The NDVI feature applies the Normalised Difference Vegetation Index equation to mean band values and provides mean NDVI values for each object derived from segmentation:

$$NDVI = \frac{Mean\ NIR\ Band - Mean\ Red\ Band}{Mean\ NIR + Mean\ Red\ Band} \qquad (1)$$

Where *Mean NIR Band* = mean pixel value of the near infra-red band for an object
Mean Red Band = mean pixel value of the red band for an object

The second feature NDVI^2 was created by squaring the NDVI feature. This feature intensifies the higher NDVI values against the lower values and as a consequence should highlight the tree crowns within the savanna vegetation.

At the broad segmentation level objects were classified based on a threshold of the DS3 layer. Objects that represented riparian forest and grassland (mean DS3 value equal to or less than 0.345) were classified and excluded from the next segmentation step (figure 2c). Objects possessing a mean DS3 value greater than 0.345 were assumed to represent a Eucalypt dominant vegetation community were included in the finer segmentation.

2.4 Secondary segmentation

The objective of the secondary segmentation level was to create objects that could be utilised as 'seeds' identifying the location of tree crowns. This finer scale segmentation was conducted within the class for Eucalypts. The chessboard segmentation algorithm was used to create square objects 2x2 panchromatic pixels in size (1.44m^2) which equates to one quarter the size of a QuickBird multispectral pixel.

2.5 Tree crown identification

The rule set created to identify tree crowns follows four steps.

Identifying local maxima – The first step was the creation of seed objects that lie within tree crowns. These were created from local maxima based on the square of the mean NDVI value of the objects.

Removal of redundant seed objects - The next step involved removing redundant objects (not lying within tree crowns). This step was based on a threshold mean value of the square of NDVI.

Growing the seed objects to tree crowns – The seed objects created in the above step were used as the starting point for a region growing algorithm based on a mean NDVI value.

Removal of redundant small objects – Small objects considered to be too small in area to represent tree crowns were removed.

2.6 Validation

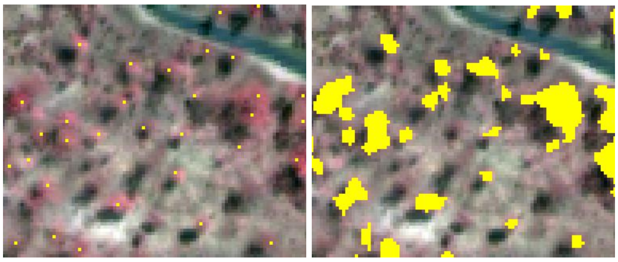
Two validation steps were under taken. Firstly, the seed objects identifying tree crowns were visually assessed to determine whether or not the seeds were located within a tree crown. A grid of 100 x 100 m squares was laid over the study area. Of the

117 squares, 85 contained Eucalypt dominated cover. Within each square the number of seed objects sitting within tree crowns, the number of tree crowns missed by the algorithm and the number of seed objects not within a tree crown were counted. These numbers were then tallied for the entire area.

Secondly, the crown objects grown from the seeds were compared to 112 manually delineated tree crowns created within a GIS. This provided three accuracy measures: the area of overlap between the extracted object and the reference object; the area of reference object not covered by extracted object and area of extracted object not corresponding to the reference object.

3. RESULTS

The seed creation algorithm produced a total of 1406 seed objects (figure 3a). A total of 1604 crowns were counted within the study area (table 2). Of these, 1352 (user's accuracy of 84.3%) were detected by the extracted seeds. In addition, there were 54 seeds created that did not match any observed crowns providing an producer's accuracy of 96.3%.



(a) (b)

Figure 3: Seed objects derived from finer segmentation (a), tree crowns after region growing algorithm applied to seeds (b).

Table 2: Accuracy results of seeds derived from local maxima.

		Reference			
		Crown	Missed	Total	User's %
Extracted	Seed	1352	252	1604	84.3
	Wrong	54	-	-	-
	Total	1406	-	-	-
	Producer's%	96.3	-	-	-

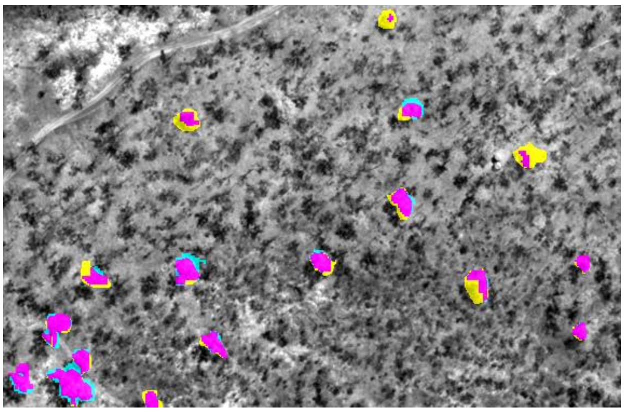
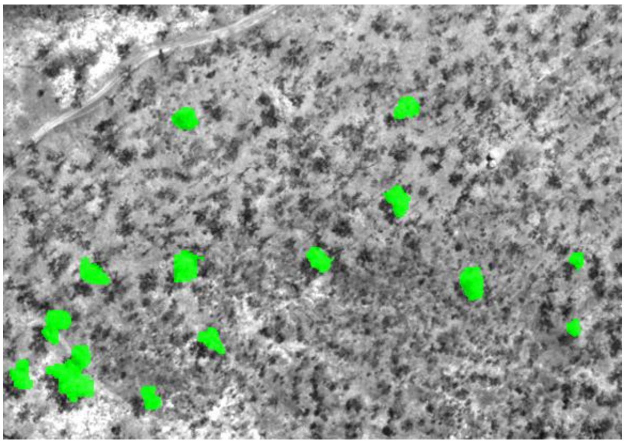
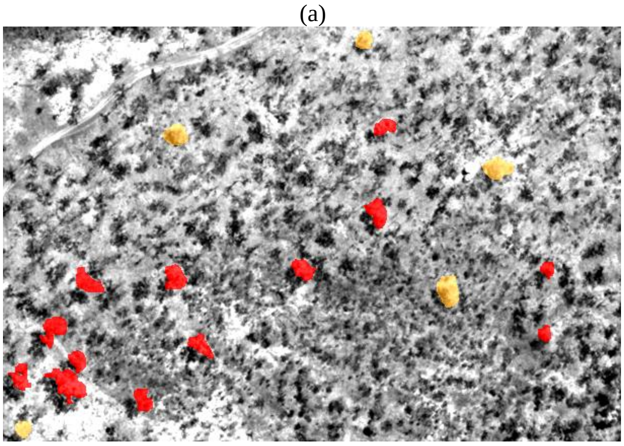


Figure 4: An example from the image showing the degree of matching between extracted tree crowns and reference objects. Magenta is a match between the reference object and the extracted object. Cyan shows the extent of the extracted object not covered by the reference object. Yellow is the extent of the reference object not detected by the extracted object.

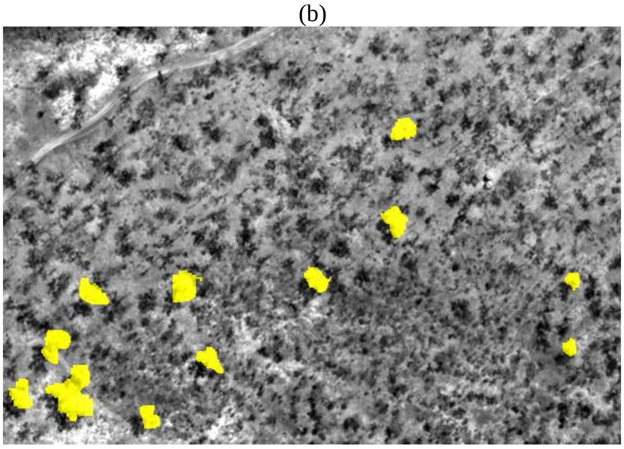
From figure 4, it can be seen that there is a good deal of match between most of the extracted tree crown objects and the reference polygons. The accuracy images created in figure 5 show objects that have greater that fifty per cent overlap between the extracted object and the reference data (Zhan *et al.*, 2005). Figure 5a shows the extracted objects that have fifty per cent overlap with the corresponding reference object. Figure 5b highlights the reference objects with over a 50% match in area with the corresponding extracted object. Figure 5c shows objects that have satisfy both criteria above.



(a)



(b)



(c)

Figure 5: A section of the accuracy images for the tree crown extraction process. Extracted objects that overlap by over 50% (shown in green) with the corresponding reference object (a), reference objects that match in area greater than 50% (shown in red) of the corresponding extracted object (b), and objects that have

greater than 50% overlap against both extracted and reference objects(c).

Over three quarters of extracted tree crown objects overlap with their corresponding reference object by 50 per cent or more of their area (table 3). A similar proportion of the reference tree crown objects overlap their corresponding extracted object by 50 per cent or more of their area. A slightly smaller proportion of objects contain both overlaps.

Table 3: Accuracy results for the extracted tree crowns against reference crowns.

Total reference objects	112	%
Total extracted objects > 50% overlap with reference objects.	89	79.5
Total reference objects > 50% overlap with extracted objects.	84	75
Total objects containing both	82	73

4. DISCUSSION

The accuracy of the seed objects and actual tree canopies is quite acceptable. Several factors could be attributed to the high accuracy of the results. Firstly, the openness of the savanna landscape means that the trees of clumps of trees are well spaced and generally distinguishable as entities from the surrounding understorey and groundcover. Secondly, the date of capture of the imagery enabled the differentiation between the actively photosynthesising tree and the ‘hayed off’ ground cover. Thirdly, the validation was conducted using visual assessment of the seed objects against the image. Obviously, some human error is to be accounted for here. For example, it may be difficult to visually distinguish individual crowns within a clump or cluster. It may also be difficult to detect a very sparse open canopy. Thus the crowns missed by the seed algorithm may also be missed by visual inspection.

Crowns missed by the seed creation algorithm may lack contrast against the surrounding and underlying groundcover and understorey. This in part could be attributed to the sparse nature of Eucalypt crowns or at the other end, similar reflectance from the surrounding vegetation.

Seeds that were created but not spatially matched to tree crowns might have resulted from photosynthesising groundcover or understorey. Alternatively, in areas that are sparsely treed, a local maximum may be detected from a slightly brighter object that is not necessarily a tree crown. These seeds should have been removed by the second step in tree crown identification (section 2.5).

The tree crown objects created from the region growing algorithm were assessed for accuracy against manually drawn tree crowns based on visual interpretation. Again, human error might also influence the reference data in that the polygons drawn may not accurately represent the actual tree crown (due to the spatial and radiometric limitations of the image).

Further work is required to test the process on similar areas of Eucalypt savanna to assess the transferability of the algorithms and the thresholds within.

Accuracy also could be matched against other methods of obtaining crown information and also accurately recorded and mapped tree crowns obtained from field measurements.

The relative area of tree crowns to the super objects created in the broader segmentation should provide an indication of canopy cover changes across the landscape. Further work here is needed to assess these measures against other measures of canopy cover such as estimates for LAI and foliage projective cover.

5. CONCLUSIONS

The approach used here offers a potential method of tree crown delineation where the availability of other forms of data such as hyperspectral and laser scanning imagery may not be available. Further work needs to be conducted to further assess the method’s accuracy, test its transferability and relevance against other measures of vegetation cover.

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