

Monitoring the critically endangered Clanwilliam cedar with freely available Google Earth imagery

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Monitoring of species and populations is essential for biodiversity observation and reporting at local, national and global scales, but can be an exceedingly difficult task for many, if not most, species. We tested the viability of using Google Earth™ imagery to manually map and monitor all individuals of the critically endangered Clanwilliam cedar, *Widdringtonia wallichii* Endl. ex Carrière, across its global native distribution; the remote and rugged Cederberg mountains. Comparison with sampling from field surveys reveals this to be a highly efficient and effective method for mapping healthy adult tree localities, but it fails to detect small or unhealthy individuals with green canopies $<4 \text{ m}^2$, or discern the number of individuals in clumps. This approach is clearly viable as a monitoring tool for this species and, with the rapid progress being made in machine learning approaches and satellite technology, will only become easier and more feasible for a greater number of species in the near future. Sadly, our field surveys revealed that the number of trees that have recently died (dead leaves still present) outnumbered live trees by a ratio of 2:1.

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2 **with freely available Google Earth imagery**

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17 **Abstract**

18 Monitoring of species and populations is essential for biodiversity observation and reporting at
19 local, national and global scales, but can be an exceedingly difficult task for many, if not most,
20 species. We tested the viability of using Google Earth™ imagery to manually map and monitor
21 all individuals of the critically endangered Clanwilliam cedar, *Widdringtonia wallichii* Endl. ex
22 Carrière, across its global native distribution; the remote and rugged Cederberg mountains.
23 Comparison with sampling from field surveys reveals this to be a highly efficient and effective
24 method for mapping healthy adult tree localities, but it fails to detect small or unhealthy
25 individuals with green canopies <4 m², or discern the number of individuals in clumps. This
26 approach is clearly viable as a monitoring tool for this species and, with the rapid progress being
27 made in machine learning approaches and satellite technology, will only become easier and more
28 feasible for a greater number of species in the near future. Sadly, our field surveys revealed that
29 the number of trees that have recently died (dead leaves still present) outnumbered live trees by a
30 ratio of 2:1.

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32 Introduction

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34 The charismatic Clanwilliam cedar, *Widdringtonia wallichii* Endl. ex Carrière (routinely referred
35 to by the later homotypic synonym *W. cedarbergensis* Marsh), a narrow endemic within the
36 Cederberg mountains, Fynbos Biome, South Africa (32°18'S 19°06'E), has shown precipitous
37 decline in population numbers over the past two centuries. While there are anecdotes of
38 overexploitation in the early 1800s (Smith, 1955), recent evidence from analysis of repeat
39 photographs suggests that mortality has been exacerbated by anthropogenic climate change,
40 particularly over the past 30 years (White et al., 2016). This is consistent with a global analysis
41 revealing increased climate-induced tree mortality over the past 40 years (Allen et al., 2010),
42 with conifer species being especially vulnerable. With increasing evidence of climate change
43 impacts on South African vegetation (Foden et al., 2007; Slingsby et al., 2017; White et al.,
44 2016), it is key that we improve our ability to detect and track these impacts, both to raise public
45 awareness and to improve our understanding of anticipated environmental change.

46 While the monitoring of species and populations is one of the six major classes of
47 Essential Biodiversity Variables “required to study, report, and manage biodiversity change”
48 (Pereira et al., 2013), this can be an exceedingly difficult task in rugged and remote landscapes,
49 or where species are difficult to detect. Fortunately, freely available, high resolution satellite
50 imagery is making this more feasible for large organisms such as trees (Visser et al., 2014; Geller
51 et al., 2017). Here we test the viability of using Google Earth™ imagery to map and monitor all
52 individuals of the Clanwilliam cedar across its global native distribution.

53

54 Material & methods

55

56 Tree localities for the entire species' distribution were manually mapped from high-resolution
57 CNES/Airbus satellite imagery available from Google Earth™ for the year 2013. Trees were
58 identified based on canopy colour, size, shape and shadows, and, where possible, verified with
59 ground photographs from the publicly contributed archives accessible through Google Earth™
60 and a personal collection of ~19 000 georeferenced images from research for the Cederberg
61 hiking map (Slingsby, 2015). Early tests found that we could not detect dead trees, likely because
62 they cast very little shadow and their stems are mostly white and cannot be discerned from the
63 high cover of white rock in the area. Trees with brown canopies were ignored as they were likely
64 dead and/or other species. For visual identification and mapping, Google Earth™ scenes were
65 exported to CorelDRAW® (Corel Corporation, 2016), the colour balance adjusted, and trees
66 marked as points in a layer. The tree points layer was then exported as a vector image and
67 georeferenced and converted to Keyhole Markup Language (KML) in ArcGIS 10.2 (ESRI,
68 2011). Minimum horizontal mapping accuracy was established by opening the KML in Google
69 Earth™ and measuring the distance between 200 mapped points and the trees they represent
70 using the measuring tool. Dense areas were avoided to reduce confusion between target trees.

71 To validate our satellite enumeration approach on the ground, we mapped the GPS
72 location and size class (adult = canopy $>4 \text{ m}^2$, sub-adult = canopy >1 and $<4 \text{ m}^2$, and seedlings =
73 canopy $<1 \text{ m}^2$) of all cedar trees found within three circumscribed field sites across the species'
74 range. We then compared our field survey results with population estimates from our satellite
75 image analysis, exploring the influence of size class on detection from satellite. Since our first
76 site survey revealed that the trees can survive substantial canopy dieback, we also recorded the

77 size of the live canopy of trees for the two subsequent field sites to explore the effect of live
78 canopy size on detection from satellite.

79

80 **Results**

81

82 We mapped 13419 cedar tree localities (Fig. 1), taking an estimated 200 working hours. None of
83 our 200 sample trees fell more than 20 metres from the mapped point, suggesting a horizontal
84 mapping accuracy <20m (~ 1:24 000).

85 Our ground surveys took five days for a team of two to cover 1/20 000th of the
86 Clanwilliam cedar's range. We found 123 live trees (61 adults, 24 subadults and 38 seedlings),
87 while our satellite approach detected only 21 healthy green canopies in the same area (Fig. 1).
88 Our canopy health data from two of the three field sites revealed that of the 25 live adult trees
89 only 10 had healthy green canopies >4 m², while our satellite approach counted 9 trees. Our field
90 survey also revealed 237 dead trees (i.e. a ratio of two dead to every live tree), made up of 109
91 adults, 82 sub-adults and 46 seedlings, still bearing dead leaves.

92

93 **Discussion**

94

95 Our satellite-based approach did very well to provide a near-perfect fine-scale description of the
96 Clanwilliam cedar's distribution, providing a detailed baseline that allows monitoring of future
97 change, and allowing inference of fine-scale habitat preferences that could lead to a better
98 understanding of the species' ecology and causes of its decline. While the satellite image
99 analysis clearly missed smaller individuals and those with unhealthy canopies, and cannot

100 discern between clumps of trees and single individuals, it provides a very good indication of the
101 locations of adult trees with live canopies. We achieved a horizontal mapping accuracy suitable
102 for most applications, but it could likely be improved if all analyses were performed directly in
103 Google Earth™ or Geographic Information System (GIS). This would likely require the ability
104 to modify the colour balance of images directly in the software to aid visual detection. With good
105 field estimates of the species' size class distribution and canopy health it would be feasible to
106 provide a relatively accurate estimate of population numbers based on the locality data. Our
107 small field survey and work by White et al. (2016) both suggest that population structure, canopy
108 health, recruitment (presence of seedlings) and mortality (presence of dead stems) are highly
109 varied across the Cederberg, cautioning against extrapolation without sufficient sampling,
110 stratified across environmental gradients and spanning the species' full range.

111 There was no evidence to suggest there were any errors of commission, whereby
112 individuals of other species were mistaken for the Clanwilliam cedar. The most likely species
113 would have been *Heeria argentea* (Thunb.) Meisn. or *Podocarpus elongatus* (Aiton) L'Hér. ex
114 Pers., but these were readily distinguishable by differences in canopy colour, shape, shadow and
115 habitat. Omission rates may vary depending on topography and the recent occurrence of fire; but
116 error rates for localities with adult trees or clumps >4 m² are likely to be low.

117 This observation method is clearly highly efficient and effective, and has great potential
118 for application to other important plant species worldwide, especially large trees or shrubs that
119 occur in sparse vegetation. Key species in South Africa include the declining *Aloidendron*
120 *dichotomum* (Masson) Klopper & Gideon (Foden et al., 2007), large species in the Proteaceae
121 Juss. (Schurr et al., 2012), or savanna trees.

122 While our approach is far cheaper and more time-efficient than an exhaustive (and
123 exhausting!) field survey, the field of image analysis with machine learning approaches is
124 moving incredibly rapidly (Demir et al., 2018) and will greatly reduce the need for and time
125 spent doing manual digitization of individual localities. This, combined with the growing record
126 of satellite and aerial imagery with continually improving spatial and spectral resolution will
127 soon allow for rapid and cost effective monitoring of many species across their global
128 distribution ranges (Geller et al., 2017).

129

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Figure 1

Clanwilliam cedar size class distribution and tree localities

(A) Barplot of trees of different size classes (A = adult; canopy $>4\text{ m}^2$, SA = sub-adult, canopy >1 and $<4\text{ m}^2$, S = seedling; canopy $<1\text{ m}^2$) within our field sites observed on the ground or using satellite imagery from Google Earth™. (B) Map of Clanwilliam cedar tree localities (black points) mapped from 2013 Google Earth™ imagery showing the Cederberg Wilderness Area boundary (dashed line), and field survey sites (white circles with black centre). Terrain image generated from the Shuttle Radar Topography Mission (SRTM) 90m digital elevation model (Jarvis et al. 2008).

