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Detecting microrefugia in semi-arid landscapes from remotely sensed vegetation dynamics

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Keywords: biodiversity; climate change adaptation; granite outcrops; hydrologic refugia; Landsat time series; southwestern Australia.
Abstract

Microrefugia are sites with stable, high quality habitat within landscapes characterized by dynamic environmental conditions driven by climate variability or ecological disturbances. There is considerable interest in the potential of microrefugia to provide climate change resilience to landscapes and to biodiversity conservation. Although attractive conceptually, there is yet little guidance on how to identify climate change microrefugia in order to study and protect them, and the data required to do so are often lacking. This study demonstrates how time series remote sensing, using all available Landsat images of a study area, can be used to directly detect microrefugia maintained by water subsidies in a semi-arid landscape in southwest Western Australia.

Microrefugia were identified as pixels with abundant vegetation and consistent vegetation dynamics between wet and dry years. At every pixel, a harmonic model was fit to the intra-annual time series of vegetation index values compiled from the wettest years in the Landsat-5 Thematic Mapper (TM) archive. This model was then used to predict the phenological cycle of the driest years at that pixel. Candidate microrefugia were defined to be those pixels with (1) high vegetation activity in dry years and (2) highly predictable phenologies that are consistent regardless of the weather conditions experienced in a given year. Spatial relationships between candidate microrefugia and landscape features associated with elevated moisture availability (thought to drive climate microrefugia in these semi-arid landscapes) were assessed. The candidate microrefugia show great promise. Evaluations against high-resolution imagery reveal that candidate microrefugia most likely buffer against drought, although refugia from other disturbances, especially fire, were also detected. In contrast, spatial proxies of the physical features expected to maintain microrefugia failed to adequately represent the distribution of microrefugia across the landscape, likely due to data quality and the heterogeneity of microrefugia. Direct detection of microrefugia with Earth observation data is a promising solution in data limited regions. Landsat time series analyses are well suited to this application as they can characterize both the habitat quality and stability aspects of microrefugia.

Introduction

Refugia are increasingly seen as essential conservation assets. Refugia, and especially microrefugia, are small sites with stable, high quality habitat in a regional context of change and adverse conditions (Dobrowski, 2011; Keppel et al., 2012); they provide landscape-level resilience to environmental variation (sensu Bengtsson et al., 2003). The refugia concept derives from biogeographical and paleoecological investigations of species’ responses to glacial-interglacial cycles. Unlike macrorefugia (or simply ‘refugia’), which are large areas of suitable habitat for many species during a time of widespread climate-driven range contractions, microrefugia are isolated sites of benign microclimates that allow species persistence within a
broad region of formerly suitable habitat (Rull, 2009). Microrefugia exist because of buffering processes that decouple the site’s microclimate from regional climate (Dobrowski, 2011; Morelli et al., 2016). Because microrefugia allow in situ persistence within the species’ former range, they facilitate species responses to climate change via distribution dynamics, reducing the migration speeds necessary to track climatically suitable habitat (Corlett and Westcott, 2013). Numerous lines of evidence, including fossils, distribution models, and patterns of genetic diversity, support the importance of microrefugia during past climate change (Birks and Willis, 2008; Gavin et al., 2014; Stewart et al., 2010). In Australia, which was not glaciated but experienced widespread conditions of extreme aridity during glacial phases (Byrne et al., 2008), biodiversity appears to have been maintained primarily in microrefugia (Byrne, 2008).

Because of the emphasis on glacial-interglacial cycles in the development of the refugia concept, attention is generally focused on the sites and processes that buffer temperature extremes. However, axes such as moisture availability (hydrologic refugia; Davis et al., 2013; McLaughlin et al., 2017) or disturbance (eg, fire refugia; Ouarmim et al., 2014; Wilkin et al., 2016) are equally important (Reside et al., 2014). In addition, refugia can operate over multiple time frames, determined by their size and permanence (ie, the degree to which they are decoupled from regional conditions). Evolutionary refugia allow population persistence over long time scales, such as glacial phases, while ecological refugia provide stable suitable habitat when processes such as extended drought render the broader area unsuitable for multi-year time frames (Davis et al., 2013; Morton et al., 1995). In arid and semi-arid systems, microrefugia provide critical contemporary habitat. Deserts are highly variable, with vegetation and wildlife populations exhibiting boom-bust dynamics driven by patchy, unpredictable precipitation (Morton et al., 2011). Water supplies that are decoupled from regional precipitation, such as accessible groundwater or springs, maintain consistent resource availability during bust phases. Wildlife populations retreat to these microrefugia, persisting locally despite extended periods of poor conditions regionally (Dickman et al., 2011; Pavey et al., 2014). Conservation strategies may be most effective if they focus on microrefugia, by targeting the sites crucial for population persistence when they are most vulnerable (Pavey et al., 2014).

Similarly, protection of refugia features prominently in general recommendations for climate change adaptation (Groves et al., 2012; Jones et al., 2016). However, while arid-zone refugia provide stable habitat during contemporary climate fluctuations, climate change microrefugia are expected to maintain relictual habitat within larger regions that climate change has rendered unsuitable (Dobrowski, 2011; Keppel et al., 2012; Reside et al., 2014). Such microrefugia may be most valuable as stepping stones facilitating species range shifts, even if they do not provide permanent suitable habitat (Hannah et al., 2014). Modeling studies have found that the availability of microrefugia can substantially reduce predictions of extinction risk due to contemporary climate fluctuations (Céré et al., 2015) and historical (Patsiou et al., 2014) and anthropogenic (Lenoir et al., 2017; Meineri and Hylander, 2017; Randin et al., 2009; Slavich et al., 2014) climate change.
While the conservation of refugia is an intuitive and appealing concept, conservation practitioners are currently unable to operationalize it. There exists much uncertainty over how to identify refugia within landscapes to target management spatially (Ashcroft, 2010). Putative refugia (micro- and macrorefugia) are typically located using simple heuristics, most commonly that areas with high topographic heterogeneity are likely to function as refugia (Ashcroft, 2010; Carroll et al., 2017; Dobrowski, 2011). There is less guidance about identifying refugia in areas of modest terrain (Reside et al., 2014). Another guideline, especially in arid systems, is that sites with access to permanent water sources are refugia (Davis et al., 2013; McLaughlin et al., 2017; Reside et al., 2014).

Refugia may also be determined empirically as areas that are relatively constant bioclimatically. Such sites display reduced contemporary variability or are forecast to experience less climate change relative to their surroundings, and thus meet the condition that refugia are decoupled from regional climate. However, there is uncertainty over how best to quantify this consistency. Measures of the velocity of climate change are becoming popular indicators of refugia (Ackerly et al., 2010; Hamann et al., 2015). Other approaches focus more explicitly on habitat, identifying refugia from species distribution or macroecological model projections (Carroll et al., 2015; Keppel et al., 2015). However, a critique of both of these strategies is that the spatial resolution of the climate data that exists to support them, typically 1-100 km, is too coarse to capture the important microclimates of microrefugia (Franklin et al., 2013; Potter et al., 2013). There is growing interest in developing fine-scale grids of micro- or topo-climate, often with ~30 m pixels, via downsampling techniques (Davis et al., 2016; Dingman et al., 2013; McCullough et al., 2016) or interpolation from dense sensor arrays (Ashcroft, 2010; Frey et al., 2016) to identify microrefugia. An important source of uncertainty is that different measures and different methodological choices identify different sites as candidate refugia (Ashcroft, 2010; Ashcroft et al., 2012; Carroll et al., 2015, 2017).

But a persistent challenge to the mapping of microrefugia is a widespread lack of suitable data. General guidelines about water subsidies, for example, have little use without spatial environmental data of relevant hydrological features. Likewise, bioclimatic data needed to quantify environmental variability at the local scales relevant for microrefugia are vanishingly rare, as fine-scale climate surfaces from dense sensor arrays may often be prohibitive. An alternative strategy that has received little attention is the direct detection of microrefugia with remote sensing.

By collecting repeated, spatially comprehensive observations of Earth over relevant spatial and temporal scales, remote sensing is an excellent means by which to resolve environmental data limitations (Pettorelli et al., 2014). Remotely sensed time series of vegetation activity may indicate stable habitat—sites with high temporal consistency that are decoupled from the larger fluctuations of the surrounding region—and thus the presence of microrefugia, especially in arid regions where patterns of vegetation activity and abundance are related to water availability (O’Grady et al., 2011). To date, there have been several studies to remotely detect ecosystems receiving groundwater subsidies (Barron et al., 2014; Contreras et al., 2011), but only one
application of remote sensing to detect refugia (Mackey et al., 2012), using relatively coarse MODIS data. The current data policy allowing free use of the 40+ year archive of Landsat image data (Wulder et al., 2012) and the novel applications of dense Landsat time series (LTS) that it has stimulated (Kennedy et al., 2014) may support the detection of microrefugia at finer spatial resolution.

The objectives of this study are (1) to demonstrate how LTS data can be used to identify candidate microrefugia, especially hydrologic refugia, in a low-relief semi-arid landscape; and (2) to test the effectiveness of heuristics about physical proxies of microrefugia by evaluating associations between the refugia identified from LTS and landscape features expected to influence water availability. We also assess the robustness of the detected microrefugia to the choice of methods to quantify habitat stability.

**Methods**

*Spatial & temporal extents*

This study was conducted over four conservation stations in Western Australia (Figure 1a; 5300 km²) – Charles Darwin Reserve (formerly Whitewells Station), and Mt. Gibson, Ninghan, and Wanarra Stations. These reserves are former pastoral lands that have been destocked and are now managed for conservation by state government, aboriginal groups, and land management conservation NGOs. Dominant land covers in the study area are open woodlands and shrublands of *Eucalyptus* and *Acacia* species, as well as ephemeral salt lakes. Most of the study area is within the southwestern Australia global biodiversity hotspot, and includes a variety of species and communities of conservation concern. There is little topographic variation across the study area; elevations range from 244 m to 685 m (97% of the area is below 400 m). Some local relief is provided by Mt. Singleton, the Mt. Gibson Range, and numerous granite tors and outcrops. Elsewhere, granite sheets lie beneath shallow soils or are exposed.

Contrasts between vegetation activity in wet and dry conditions provide a measure of temporal consistency that is related to the availability of more permanent sources of water in arid and semi-arid areas (Barron et al., 2014) and is expected to provide an indicator of microrefugia (Griffin and Pearce, 1995). As well, observed changes between wet and dry years are more ecologically meaningful than the generic statistical measures of variability used to detect microrefugia (e.g., Mackey et al., 2012), and have been shown to be more relevant to species distributions (Fox et al., 2016). The temporal extent of this study was set to be the Landsat-5 record (1984-2011), within which we initially targeted all years with annual precipitation outside of the range of mean ± 1 standard deviation (Figure 1b). However, one of the identified years had no image data in the archive; to maintain a balance between wet and dry years, this left us with 3 years of each (wet: 1992, 1999, 2011; dry: 1994, 2007, 2010). All three of the wet and dry years were used to ensure an adequate temporal frequency of observations and to increase representativeness over a single year.
Image analyses

The Landsat Climate Data Record product was used for these analyses. These images have been orthorectified, calibrated to absolute surface reflectance and atmospherically corrected.
(Masek et al., 2006), and include the FMASK cloud mask (Zhu and Woodcock, 2012). This level of processing ensures sufficient consistency between images to support time series analyses. All available images covering the study area (WRS path 112, rows 80-81) acquired by the Landsat-5 Thematic Mapper (TM) sensor were downloaded (http://earthexplorer.usgs.gov/) for the six years analyzed. The image dates used in this study are indicated in Figure 1c.

For each image date, vegetation activity was estimated using two vegetation indices (VIs): (1) the normalized difference vegetation index (NDVI; Tucker, 1979) is a widely used measure of ‘greenness’ calculated from reflectance in the red and near-infrared (NIR) wavelengths; and (2) the normalized difference moisture index (NDMI; Wilson and Sader, 2002; Hardisky et al., 1983; and see Ji et al., 2011 for synonyms of this index), which quantifies the contrast between the NIR and shortwave-infrared (SWIR). The inclusion of SWIR information is a major advantage of Landsat (Cohen and Goward, 2004) and an index calculated with SWIR reflectance measured by Landsat has been recommended for monitoring woody vegetation in the dry forests and woodlands of Australia (Lehmann et al., 2013). NDMI is sensitive to foliar moisture, and may be more effective than NDVI at estimating spatiotemporal patterns in woody vegetation structure. NDVI and NDMI images were masked to remove cloud and cloud shadows using the FMASK layer for each date and compiled into temporal image stacks of the time series of each VI, as depicted in Figure 2. This stack is a data cube (Figure 2a) in which each layer is the VI

Figure 2. Graphical illustration of the information content of temporal image stacks of Landsat time series data. (a) In this image cube, every pixel contains a time series of the six focal years analyzed. The cube face (x- and y-dimensions) is a near-natural color composite (3 February 2011) with (B) red, (G) near-infrared, and (R) shortwave-infrared bands (please refer to the online version of this article for references to color). The streaming z-dimension depicts the time series of vegetation index values for edge pixels. Lighter shades indicate more robust vegetation. (b) Plots the temporal profiles of the vegetation index NDMI (Normalized Difference Moisture Index) for two select pixels from the image cube. Wet years are plotted in black, dry years in grey.
image from a given image date. Every pixel contains the time series of all valid clear-sky observations for the 6 wet and dry years sampled (Figure 2b).

Detection of candidate microrefugia relied on the definition of microrefugia as locations of stable, high quality habitat. Habitat quality was indicated by vegetation abundance, estimated as the average NDVI over the three dry years. NDMI could not be used to estimate vegetation abundance because unvegetated areas with wet soil also received high values of NDMI. Both NDVI and NDMI were used to evaluate habitat stability, which was indicated by the consistency of vegetation dynamics between wet and dry years. For every pixel, the VI observations from the wet years were collapsed into a synthetic wet year indexed by day of year. This annual series depicts the typical pattern of vegetation activity under good conditions at that pixel, which was then modeled using a two-term harmonic model – a function of sines and cosines that captures the phenological cycle of vegetation (Zhu et al., 2012). The ability of this model of vegetation activity to fit the dry years’ observations at the same pixel provided the measure of habitat stability (Figure 3), which was quantified by two alternative metrics of statistical predictability: (1) the $R^2$, and (2) the root mean square error (RMSE) between predicted and observed VI values. We assessed the robustness of the identified patterns of temporal consistency to choice of VI or predictability metric.

In order to capture the potential diversity of microrefugia across the study area, the results of the time series analyses were integrated with an ecological stratification to identify pixels with the most abundant, most

Figure 3. The time series analyses used to estimate the consistency of vegetation dynamics between wet and dry conditions, as illustrated with the NDMI (Normalized Difference Moisture Index) time series of 3 pixels (a-c). The degree to which dry year observations depart from the harmonic model fitted to vegetation activity in wet years, as measured by $R^2$ or RMSE, indicates whether a pixel meets the temporal consistency criterion of microrefugia. Pixel (a) is identified as a candidate refugium by both $R^2$ and RMSE, pixel (b) by $R^2$ but not RMSE, and pixel (c) by neither.
consistent vegetation. The mapping of pre-European vegetation communities (Shepherd, 2003) delineates expected climax communities and was considered a suitable stratification for identifying microrefugia from disturbance or environmental change. This dataset maps 13 vegetation types in the study extent; the 4 classes depicted in Figure 4c comprise >90% of the area. Within each vegetation type, pixels were thresholded into two abundance/consistency classes using the 87th and 95th percentiles (note that the converse thresholds [13th and 5th percentiles] were used for the RMSE measure of consistency). These threshold values were selected after preliminary evaluation of a range of percentiles. Pixels with average dry-year NDVI values above the 87th percentile were identified as ‘abundant’ vegetation, with those above the 95th percentile value ‘very abundant,’ and likewise for the consistency classes. Abundance and consistency classes were overlaid to produce four classes of candidate microrefugia.

Evaluation of candidate microrefugia

The microrefugia results were evaluated at a random sample of 200 pixels (25 pixels in each microrefugia class + 100 pixels not predicted to be a refugium). The locations of all reference pixels were inspected in high spatial resolution imagery available in GoogleEarth. In our study extent, the GoogleEarth archive generally only contains a single date of high-resolution data; acquisition dates range between 2006 and 2017 across the area. GoogleEarth images were true-color mosaics with submeter spatial resolution. Reference pixels were scored as likely to contain a microrefugium if the high spatial resolution imagery revealed patches of distinctly denser vegetation than the surroundings, especially if they were also associated with visible hydrological features such as springs, water-courses, or runoff zones from rock outcrops or nearby hills, or if they were surrounded by conspicuous fire scars (ie, fire refugia).

Environmental associations of candidate microrefugia

Classification tree models were used to evaluate the spatial associations between candidate microrefugia and relevant environmental features under standard heuristics. These included measures of topographic features, hydrologic features, and granite outcrops (Table 1). Topographic variation is often considered to produce favorable microclimates that support microrefugia (Ashcroft, 2010; Dobrowski, 2011) and several topographic variables were developed (Table 1). In arid areas, water availability is expected to drive the distribution of microrefugia. Water subsidies, such as from springs or runoff from rock outcrops and other areas with reduced infiltration, are likely to provide microrefugia from drought (McLaughlin et al., 2017; Reside et al., 2014). In addition, the moderating influence of moisture and humidity are related to the occurrence of thermal microrefugia buffering temperature extremes (Ashcroft and Gollan, 2013) and may provide microrefugia from fire disturbances as well (Ouarmim et al., 2014; Reside et al., 2014; Wilkin et al., 2016). There is limited spatial hydrologic data available for the study area, so only coarse proxies were possible. Water subsidies from the lakes and anthropogenic wells were considered (Table 1). Finally, the most prevalent guideline about the occurrence of microrefugia in southwestern Australia is that they are associated with granite outcrops. Because of the very low infiltration of exposed granite, runoff from granite outcrops...
provides water subsidies to their surroundings, influencing vegetation composition and structure (Schut et al., 2014) and providing valuable resources to wildlife (Withers, 2000). Granite outcrops have also been used as water resources by aboriginal peoples (Bindon, 1997) and western settlers (Laing and Hauck, 1997).

Table 1. Environmental variables used in the spatial evaluation of candidate refugia.

<table>
<thead>
<tr>
<th>Environmental variable</th>
<th>Description</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Topographic features</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>Absolute elevation of a pixel</td>
<td>SRTM (Rabus et al., 2003)</td>
</tr>
<tr>
<td>Topographic heterogeneity</td>
<td>Variance of elevation values in a window surrounding a focal pixel. Calculated for two neighborhood extents: (1) 5x5 pixel window (150x150 m) and (2) 33x33 pixel window (1x1 km).</td>
<td>SRTM (Rabus et al., 2003)</td>
</tr>
<tr>
<td>Relative elevation</td>
<td>Difference between the elevation of a focal pixel and the average elevation of its surroundings. Calculated for two neighborhood extents: (1) 5x5 pixel window (150x150 m) and (2) 33x33 pixel window (1x1 km).</td>
<td>SRTM (Rabus et al., 2003)</td>
</tr>
<tr>
<td>Topographic wetness index</td>
<td>Measure of relative elevation and topographically-related water availability based on local slope and upslope contributing area.</td>
<td>SRTM (Rabus et al., 2003, Gallant et al., 2011)</td>
</tr>
<tr>
<td><strong>Hydrological features</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lakes</td>
<td>Distance to the nearest lake, with distances capped to 1 km*.</td>
<td>GEODATA TOPO 250K (Geoscience Australia, 2006)</td>
</tr>
<tr>
<td>Water constancy</td>
<td>To capture the ephemeral nature of all surface water in the study area, the proportion of images over the 6-year Landsat series (Figure 1) in which a pixel was identified as water was calculated.</td>
<td>FMASK (Zhu and Woodcock, 2012)</td>
</tr>
<tr>
<td>Anthropogenic wells</td>
<td>Distance to the nearest anthropogenic well, with distances capped to 1 km*.</td>
<td>GEODATA TOPO 250K (Geoscience Australia, 2006)</td>
</tr>
<tr>
<td><strong>Rock outcrops</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rock outcrops</td>
<td>Distance to the nearest granite outcrop, with distances capped to 1 km*.</td>
<td>This study (Appendix A; following Alibegovic et al., 2015)</td>
</tr>
</tbody>
</table>

*Distance surfaces capped to 1 km to avoid detecting meaningless associations between microrefugia and landscape features far beyond their reasonable zone of influence.

Classification tree models were used to evaluate if the locations of microrefugia could be predicted by the landscape features described above. Models were trained with a random sample of 5% of the pixels identified as each class of candidate microrefugia by the LTS analyses and a balanced sample of an equal number of random absence points. Binary models were developed to predict the presence/absence of each microrefugia class individually, and for all classes.
aggregated into a single class of candidate microrefugia. Multinomial models predicting membership across all four candidate microrefugia classes were also attempted, but failed to detect any environmental associations. Tree accuracy was calculated as the proportion of training samples that were correctly classified as presence or absence of a microrefugium. Histograms were also used to visualize patterns of the occurrence of microrefugia relative to individual landscape features.

**Results**

Harmonic models effectively captured wet year vegetation dynamics: across the study area, wet year NDVI trajectories were modeled with high $R^2$ (mean ± standard deviation = 0.735 ± 0.157) and low RMSE (mean ± standard deviation = 0.039 ± 0.013). Predictability dropped when applying these models to the dry years’ observations at a pixel (means ± standard deviations: $R^2_{\text{dry}} = 0.329 ± 0.152$; $\text{RMSE}_{\text{dry}} = 0.077 ± 0.025$), which was expected as these were new observations not used to train the models and vegetation in many pixels was impacted by dry conditions. The harmonic models of NDMI trajectories showed similar performance (means ± standard deviations: $R^2_{\text{wet}} = 0.651 ± 0.159$; $\text{RMSE}_{\text{wet}} = 0.046 ± 0.016$; $R^2_{\text{dry}} = 0.235 ± 0.136$; $\text{RMSE}_{\text{dry}} = 0.082 ± 0.030$). Pixel-level $R^2_{\text{dry}}$ and $\text{RMSE}_{\text{dry}}$ for the NDMI time series are mapped in Figure 4d&e, revealing substantial spatial variation in the temporal consistency of vegetation activity across the study area.

There was a reasonable spatial correlation between measures of consistency estimated from NDVI and NDMI time series ($r = 0.42$); these VIs may be interchangeable but NDMI is preferred here given its relationship to foliar water content and its greater sensitivity to variation in woody vegetation. In contrast, $R^2$ and RMSE provided independent measures of consistency and were uncorrelated across the study area ($r = -0.25$). Figure 3 highlights the NDMI trajectories of 3 pixels to illustrate why the results differ when using $R^2$ or RMSE as a measure of consistency. The pixel in Figure 3a has strongly consistent dynamics between wet and dry years, and would be identified as a microrefugium by both metrics. In contrast, the pixel in Figure 3b has reduced foliar water content under dry conditions, but follows a similar phenological cycle as the wet years. Because the dry year trajectory parallels that of the wet years with relatively little scatter, this pixel is identified as a microrefugium by $R^2$, but because of the offset in absolute NDMI values in wet and dry years, it is not identified as a microrefugium by RMSE. Finally, the pixel in Figure 3c has a large NDMI offset between wet and dry years and considerable variability in dry years, thus, it is not identified as a microrefugium by either metric.

When using the RMSE measure of consistency, candidate microrefugia were found over 2.6% of the study area (13,770 ha; Figure 3g). Of these, roughly a quarter was in the very abundant, very consistent vegetation class. Individual candidate microrefugia ranged in size from a single pixel (0.09 ha) to 460 ha. The $R^2$ results (Figure 3f) detected a slightly larger area of candidate microrefugia (24,140 ha; 4.6% of the study area), with 40% in the very abundant, very consistent class and a maximum refugium size of 605 ha. There was low agreement (kappa
Figure 4. Maps providing an overview of the study area (a; near-natural color composite), intermediary products used to identify candidate microrefugia (b–e), and the candidate microrefugia detected (f–g). Microrefugia were identified as sites with (b) high NDVI in dry years and consistent NDMI (Normalized Difference Moisture Index) time series between wet and dry years, as indicated by either the (d) $R^2$ or (e) RMSE measure of statistical predictability, (c) stratified by vegetation type.
= 0.380) between the microrefugia identified by $R^2$ and RMSE when aggregating the 4 classes into a binary microrefugia product; 32% of the microrefugia identified by $R^2$ were also identified by RMSE, while the converse was 55%. The distribution of microrefugia varied between vegetation classes (not shown).

Evaluation of the candidate microrefugia against high spatial resolution GoogleEarth imagery was encouraging, corroborating the detected microrefugia for 60% of reference pixels (Table 2). Interestingly, there was little difference between the 4 microrefugia classes, suggesting that the 5th percentile threshold for the most abundant and most consistent vegetation may be too stringent. Likewise, both measures of consistency (RMSE and $R^2$) performed comparably, although there were some differences in the types of environmental features they identified. The $R^2$ measure of consistency was more likely to identify dense vegetation associated with hydrological features. The top microrefugia class was often associated with large trees. These were generally not considered to be microrefugia in the evaluation, unless they also displayed features associated with hydrologic or fire microrefugia, but this may have been too strict (see Discussion). In contrast, far fewer of the reference pixels where microrefugia were predicted to be absent were interpreted as having microrefugia characteristics in the reference data (Table 2). Many of the false-positives were associated with unburned patches in a matrix of fire scars; the interpretation of the reference imagery was likely too liberal in scoring pixels as fire microrefugia (see Discussion).

<table>
<thead>
<tr>
<th>Microrefugia class</th>
<th>RMSE</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very abundant, very consistent vegetation</td>
<td>15  0.60</td>
<td>15  0.60</td>
</tr>
<tr>
<td>Very abundant, consistent vegetation</td>
<td>15  0.60</td>
<td>17  0.68</td>
</tr>
<tr>
<td>Abundant, very consistent vegetation</td>
<td>13  0.52</td>
<td>19  0.76</td>
</tr>
<tr>
<td>Abundant, consistent vegetation</td>
<td>16  0.64</td>
<td>9   0.36</td>
</tr>
<tr>
<td>Not a microrefugium</td>
<td>18  0.18</td>
<td>18  0.18</td>
</tr>
</tbody>
</table>

Table 2. Number (n) and proportion (p) of a random sample of the candidate microrefugia results, evaluated against high spatial resolution GoogleEarth imagery as likely to contain microrefugia. The abundance of vegetation was evaluated with NDVI; temporal consistency of vegetation was evaluated with NDMI and two alternative measures of consistency: RMSE and $R^2$. Sample sizes were 25 reference pixels for each microrefugia class and 100 reference pixels for the not a microrefugium class.

There were no strong spatial associations between candidate microrefugia and the environmental variables evaluated (Table 3). Classification trees generally contained a single split and had poor performance. The most common patterns were that microrefugia were associated with areas elevated relative to their surroundings and occurred far from lakes (Table 3). The candidate microrefugia were slightly more explainable when identified using RMSE as the measure of consistency: all classes occurred in areas of higher relative elevations, but
decision trees used a different threshold value for each class. As a result, although this association was also identified when aggregating the microrefugia classes into a single class, the decision tree was weaker (accuracy = 58%; Table 3). The histograms of several variables revealed that there may be weak associations between the occurrence of microrefugia and rock outcrops and wells (Figure 5), but these were not strong enough to contribute to the decision tree models.

Table 3. Summary of the decision tree models exploring environmental associations of microrefugia with the variables listed in Table 1. Models were built for individual microrefugia classes and an aggregated class of all identified candidate microrefugia. Analyses evaluated vegetation consistency with NDMI time series and two alternative measures of consistency: RMSE and R2. Decision trees were built using a balanced sample of microrefugia presence and absence pixels; thus, minimum model accuracy is 0.5.

<table>
<thead>
<tr>
<th>Microrefugia class</th>
<th>Modeled environmental associations</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>a. Measure of consistency: RMSE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very abundant, very consistent vegetation</td>
<td>Higher relative elevations (1km), low elevation heterogeneity (1km), far from lakes</td>
<td>0.63</td>
</tr>
<tr>
<td>Very abundant, consistent vegetation</td>
<td>Higher relative elevations (1km)</td>
<td>0.58</td>
</tr>
<tr>
<td>Abundant, very consistent vegetation</td>
<td>Higher relative elevations (1km), far from lakes</td>
<td>0.62</td>
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<tr>
<td>Abundant, consistent vegetation</td>
<td>Higher relative elevations (1km), far from lakes</td>
<td>0.56</td>
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<tr>
<td>Aggregated microrefugia classes</td>
<td>Higher relative elevations (1km)</td>
<td>0.58</td>
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<td><strong>b. Measure of consistency: R²</strong></td>
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<td>Very abundant, very consistent vegetation</td>
<td>Lower topographic wetness</td>
<td>0.56</td>
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<td>Very abundant, consistent vegetation</td>
<td>Far from lakes</td>
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<td>Abundant, very consistent vegetation</td>
<td>Far from lakes</td>
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<td>Abundant, consistent vegetation</td>
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<td>Aggregated microrefugia classes</td>
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<td>0.50</td>
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Figure 5. Histograms of the frequency of pixels that were and were not identified as candidate microrefugia relative to distance from (a) granite outcrops, (b) salt lakes, and (c) wells; and the local elevation relative to the surrounding 1x1km window. Only the patterns in (b) and (d) were strong enough to contribute to classification tree models of environmental associations of microrefugia. This figure presents all classes of candidate microrefugia detected using the RMSE measure of consistency.
Discussion

Time series analyses of Landsat data greatly expand the capabilities of remote sensing to characterize ecological processes with an inherently temporal component (Kennedy, 2014). LTS, which are perhaps most celebrated for characterizing forest dynamics (Wulder et al., 2012), especially disturbances (Banskota et al., 2014), have not yet been used to map microrefugia, but are a logical choice for this application. Microrefugia are defined, in part, by their temporal dynamics, and may be smaller than the pixels of traditional time series instruments such as MODIS or AVHRR but resolvable in 30 m Landsat pixels. In arid and semi-arid systems, such as much of Australia, the spatial and temporal distribution of vegetation abundance and vigor is closely related to water availability, microrefugia are expected to be driven by processes ensuring stable water supplies, and this variation in vegetation can be readily detected remotely. We show that LTS effectively capture spatiotemporal patterns of vegetation related to the attributes of microrefugia: vegetation abundance and marked temporal consistency relative to the broader surroundings.

LTS offer many advantages over traditional multitemporal image analyses of two image dates. For example, Figure 3 suggests that, with unlucky selection of image dates, pairwise change detection may identify the pixel in Figure 3c as a candidate microrefugium, while the complete temporal profiles reveal that wet years and dry years are clearly distinct. Dense time series are sensitive to gradual change and subtle variation in temporal trajectories (eg, Kennedy et al., 2010). The smoothing functions applied to LTS relax difficult-to-meet data requirements for remote sensing change detection, such as the need for cloud-free, near anniversary date, meticulously cross-calibrated images (Banksota et al., 2014). This, too, increases the sensitivity of time series approaches. The use of LTS to detect gradual environmental change is an active field of research. Zhu et al. (2012), in the study that developed the harmonic modeling approach we adapted to detect microrefugia, demonstrated that dense time series of all available Landsat data enabled detection of subtle forest thinning. Other studies, more commonly using time series of annual images (including composite images; eg, Roy et al., 2010), emphasize the power of LTS to detect gradual processes including forest decline due to diffuse disturbances such as insect outbreaks or drought (Ahmed et al., 2017; Cohen et al., 2016; Deel et al., 2012; Kennedy et al., 2010), forest succession and woodland densification (Vogelmann et al., 2012), and variation in ecosystem recovery following disturbance (Kennedy et al., 2007, 2010; Lawrence and Ripple, 1999; Storey et al., 2016).

Inspection of high spatial resolution imagery confirmed that the sites of abundant, consistent vegetation identified from LTS correspond to features expected to be associated with microrefugia, and revealed that there is considerable heterogeneity in the microrefugia detected. Qualitatively, the largest concentration of candidate refugia appears to be associated with runoff from the Mt. Gibson Range. Others seem to occur in basins with reasonable soil depth receiving runoff from granite outcrops or are associated with drainage lines or springs. Finally, some are unburned patches in areas that experienced bushfires over the study’s temporal extent (1992-2011). A number of the candidate microrefugia that had no clear association with surface
hydrology or fire disturbance occurred in areas with large trees. Although these were not generally considered to be microrefugia in the evaluation, it is possible that they are. Large, deeply rooted trees may have access to more reliable water supplies, functioning as hydrologic microrefugia (McLaughlin et al., 2017). Further, Frey et al. (2016) suggest that large trees in old growth forests (admittedly a very different system from that studied here) moderate temperature extremes because of the amount of energy required to warm their large biomass.

However, the candidate microrefugia were too heterogeneous for classification trees to identify simple, strong associations between detected microrefugia and landscape features. Further, the associations that were identified by decision trees tended to be counterintuitive: candidate microrefugia detected with the RMSE measure of consistency tended to be at higher relative elevations; the top class of microrefugia using $R^2$ to indicate consistency were slightly more abundant at lower values of the topographic wetness index (Table 3). However, these associations are likely due to the concentration of microrefugia around topographic features such as the Mt. Gibson Range and tall rock outcrops, and to the large window size (1 km) used to calculate relative elevation. They may also reflect an inability of the SRTM DEM to resolve subtle topographic features associated with microrefugia in this environment. The candidate microrefugia often did correspond to visible runoff zones in high spatial resolution imagery.

The poor ability of decision tree models to detect associations between the candidate microrefugia and physical features thought to control the occurrence of microrefugia underscores several weaknesses in relying on general guidelines to identify microrefugia. In this landscape, heuristics, which emphasize the role of granite outcrops, failed to capture the diversity of microrefugia. For example, some of the detected microrefugia were associated with small wetland features visible in high spatial resolution images that may be associated with the edges of shallow granite sheets and ‘runoff’ aprons analogous to those of exposed granite, but would be missed by rule systems relying on visible outcrops. Furthermore, heuristics are only as good as the data that exists to apply them. For this study, no mapping of granite outcrops existed, we had to develop our own (Appendix A), and proxies calculated from the SRTM DEM did not adequately represent hydrological features.

Given these shortcomings, direct detection of candidate microrefugia from LTS of vegetation dynamics may often be the best alternative, especially in strongly data limited regions. But it is important to note the limitations of this approach. The ecosystem stratification used to develop thresholds to identify microrefugia is the largest source of uncertainty in our analyses (likewise, Gould et al., 2015). There were few good alternatives in this data limited region, and the one chosen was more spatially generalized than the Landsat data. Inevitably, some of identified sites will be due to uncertainties in the stratification – azonal pockets of a more robust vegetation type within a larger area mapped to a different community, or ambiguities in boundary placement – rather than true microrefugia.

Additionally, it is not possible to characterize the type of microrefugia (see Reside et al., 2014 for a typology) from LTS alone. A number of the candidates may be microrefugia from climate variability, especially drought, but others appear to be microrefugia from other
disturbances such as fire. Fire microrefugia are sites that escape burning through repeated fire cycles, generally only burning in the most severe fires (Ouarmim et al., 2014), or that burn at a lower intensity than the surrounding landscape (Wilkin et al., 2016). Fire microrefugia may also be climate microrefugia, since relatively cool, moist conditions determine refugial potential from both drought and fire (Ouarmim et al., 2014; Reside et al., 2014; Wilkin et al., 2016). With short data series, it is difficult to distinguish between true fire microrefugia and patches that happened to be missed by only the most recent fires. We believe that this partly contributes to the number of sites predicted to not be microrefugia in the LTS analyses but interpreted as fire microrefugia in the high spatial resolution data used for evaluation. Because the LTS analyses span a longer time frame than the snapshot of reference data available, they should be less prone to false positive detections of fire microrefugia, but still longer time series would give greater confidence. Another effect of fire disturbances to efforts to directly detect microrefugia is that, in extremely fire prone landscapes such as those of Western Australia, fire microrefugia may dominate the results, limiting the ability to detect hydrologic microrefugia. We did not experience this problem, however, which is likely because of the use of the ecosystem stratification in identifying microrefugia. This partitioned candidate microrefugia among vegetation types; fire microrefugia predominated in the most flammable vegetation type while other types of microrefugia were detected elsewhere.

Finally, questions remain about whether the detected sites serve as microrefugia to the native biota. Our analyses identify the habitat features likely to be associated with microrefugia, but to be a confirmed microrefugium, a site must host relict populations (Hampe and Jump, 2011). Thus, long-term biological monitoring programs both inside and outside of the identified sites are required to determine if the candidate microrefugia provide critical habitat to native wildlife during drought phases (such as Pavey et al., 2014), and flora surveys can determine whether the candidate microrefugia harbor plant species outside of their climate optima (e.g., Abbott, 1984). One characteristic that may influence refugial capacity is site size (Keppel et al., 2015; Stewart et al., 2010). Refugia must maintain viable populations over ecological and/or evolutionary time scales, which may preclude small sites from functioning as microrefugia. The smallest candidate microrefugia we detected were the size of a Landsat pixel (900 m²), and relevant microsites may be even smaller (e.g., Lenoir et al., 2017). However, the minimum size for a microrefugium is unknown, and will be species specific (Stewart et al., 2010). A last caveat is that even if the identified sites are functioning microrefugia, they are contemporary microrefugia. It is unknown if they will continue to provide resilience to climate change, although this source of uncertainty is not limited to remotely sensed refugia (Dobrowski, 2011).

Although this study took advantage of the remarkable Landsat-5 record to identify candidate microrefugia, we do not expect microrefugia detection to be restricted to this sensor. When using image time series to detect microrefugia, the most important criteria are likely to be the duration of the image archive and data cost. The length of the temporal extent spanned by image data will influence the robustness of the analyses. Longer temporal extents are expected to contain a wider range of conditions, ensuring more meaningful contrasts between wet and dry
years. As well, sampling both older and recent years will represent the long-term stability and contemporary presence of the identified microrefugia more effectively. Further, we advocate that including several wet and dry years each will help fill data gaps and reduce the sensitivity of the analyses to short-term variation and individual disturbance events, such as fires. Use of all available image dates within those years should increase the sensitivity and robustness of the analyses. For our study, this required sampling 6 years with >150 images over a 20-year time frame, which would not have been possible without free, high-quality medium-resolution image data. Ongoing Landsat and Sentinel missions extend the archive of freely-available, medium-resolution, full-range optical data (Turner et al., 2015), which will be invaluable to support microrefugia detection and many other applications of Earth observation data to conservation and environmental management. Although the Landsat TM, Landsat-8 OLI, and Sentinel-2 sensors sample slightly different wavelength bands, with careful calibration and co-registration of images, it should be possible to detect microrefugia with time series of multi-sensor data, expanding the temporal extent of similar analyses, and enabling them into the future. In addition, other strategies and other types of remote sensing may contribute to microrefugia detection. For example, there is interest in directly detecting refugial microclimates using thermal remote sensing, although this is challenged by the complex relationships between land surface temperature detected by remote sensors and air temperatures (Pepin et al., 2016). Alternatively, LiDAR data have the potential to indicate microrefugia by characterizing vegetation structures (Frey et al., 2016; Lenoir et al., 2017) or small topographic features (Lenoir et al., 2017) that buffer microclimates, or by detecting the relict vegetation communities occurring within microrefugia (Schut et al., 2014).

Conclusions

Microrefugia offer great potential to maintain resilience to environmental changes in landscapes and reserve networks. To protect microrefugia now and into the future, we must know where they are. However, the identification of microrefugia remains a challenge, not least due to data limitations. Direct detection of microrefugia from Earth observation data may be the most viable approach to map microrefugia, especially in regions lacking sufficiently detailed spatial environmental data characterizing the physical processes hypothesized to drive the occurrence of microrefugia. Here we show how Landsat time series are well suited to characterize the habitat stability and quality components of microrefugia. Our results are encouraging and the microrefugia identified from LTS correspond to distinctive features in the landscape. The two measures of vegetation consistency evaluated (RMSE and $R^2$) identified different microrefugia across the landscape, but both appear to detect meaningful environmental features when evaluated against high spatial resolution image data. In contrast, the general guidelines about drivers of hydrologic microrefugia failed to represent the distribution of microrefugia across the landscape, presumably because of data limitations and the heterogeneity of microrefugia in the study area. Although the results of the LTS analyses are encouraging, they might best be thought of as ‘candidate’ microrefugia until confirmed with ground reference
data revealing their ecological value to native biota. Such long-term monitoring, informed by the candidate microrefugia, has commenced.

Acknowledgements

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References


Appendix A. Mapping granite outcrops from Landsat time series

No comprehensive mapping of surficial granite exists for the study area. The topographic maps (Geoscience Australia, 2006) and the map of pre-European vegetation communities (Shepherd, 2003) identify a small number of large, culturally significant outcrops, although not necessarily the same ones, and many outcrops are excluded from both of these datasets. Consequently, we adapted the methods of Alibegovic et al. (2015) to map granite outcrops from the Landsat data and time series results used to identify refugia (see main text).

Alibegovic et al. (2015) take advantage of the fact that granite outcrops have consistently low vegetation cover in both the summer and winter, which allows them to be discriminated from vegetated areas. We implemented this using a similar logic to our analyses to detect refugia: a pixel was determined to belong to a potential outcrop if its normalized difference moisture index (NDMI) value was low (<-0.10) when averaged across all wet year image dates and when the consistency of NDMI time series was high between wet and dry years (dry year RMSE < 0.065). Thresholds were determined manually by inspection of the known outcrops included in the Geoscience Australia (2006) and Shepherd (2003) datasets.

The result of this procedure is a set of potential outcrops, but it also includes areas that are bare for some other reason. Alibegovic et al. (2015) note that granite outcrops are spectrally dissimilar from bare soil. A final map of outcrops can be produced by performing a supervised maximum likelihood classification on a multi-season composite image capturing summer and winter reflectance differences between outcrops and bare soil. We used images from 18 July 2007 and 23 January 2007, which were both cloud-free over the study area, and developed a sample of training points from the intermediary results classifying bare pixels. Class membership of the training pixels (granite or bare soil) was determined from manual photointerpretation of the high spatial resolution image data available within Google Earth at those locations.

Although we have not formally validated our granite outcrop map, Alibegovic et al. (2015) report high accuracies in their study areas, and visual inspection of our results suggests that they provide a very good representation of the distribution of granite in the study area.