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A spatial vulnerability assessment of monsoonal wetland habitats to para grass invasion in Kakadu National Park, northern Australia

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ABSTRACT

Kakadu National Park and its wetlands are World Heritage and Ramsar listed and are at risk from invasive grasses. However, it appears that not all habitats and native vegetation are equally at risk. We conduct a spatial risk assessment for para grass (*Urochloa mutica*) invasion across seasonally inundated habitats of the 258 km^2 Magela Creek floodplain within Kakadu National Park using Landsat 5 TM time-series imagery. Two maps, representing water depth and fire history, were derived from the imagery using object-based image analyses. Depth was modelled using a linear regression relationship established between 254 known water depth locations and the multi-date spectral index values of segmented image objects at corresponding locations ($R^2 = 0.67$; $p < 0.0001$). Binary fire-scar maps were then produced for each year of a 10-year period using visual interpretation and nearest neighbour classification. A map of the incidence of annual fire over this period was then calculated from the sum of the maps, overlaid. The maps were integrated in a GIS with an existing Landsat vegetation map to measure spatial inter-relationships between para grass, native vegetation, depth and fire. With a highly clustered distribution pattern, para grass occupied 1388 ha or 6% of the total floodplain area. However, its optimal depth habitat, estimated to be from 1.1 to 1.4 m, occurred over a much larger area (7180 ha) or 30% of the floodplain. Only 2% of this optimal area was actually occupied by para grass. Together the low occupancy of 'optimal-depth' habitat and a highly clustered distribution of para grass strongly suggested that, if left uncontrolled, it has capacity to spread further and eventually occupy much larger areas of this floodplain at high density. Landsat provided spatial information of suitable scale and accuracy to understand the landscape ecology of para grass; and from which to design and conduct further research, or trial management interventions to protect wetland vegetation at risk to weed invasion.

1. Introduction

Kakadu National Park and its wetlands include Ramsar (Ramsar, 1971) and World Heritage (UNESCO, 1972) listed areas, internationally recognised for their unique natural and cultural values. These values are in part underpinned by the expansive seasonally inundated floodplain ecosystem which supports important vegetation, including potentially globally significant native rice species *Oryza rufipogon* and *O. meridionalis* (Boyden et al., 2013; Whiteside and Bartolo, 2015; Wurm, 1998). The floodplains are also under threat from invasive grass species including exotic para grass, *Urochloa mutica* (Cowie and Werner, 1993; Douglas and O'Connor, 2003). Such grasses are implicated in causing negative ecological and economic impacts on the abundance and diversity of birdlife, cultural livelihoods of indigenous people and on tourism by restricting access to fish, turtle and native plant foods (McGregor et al., 2011). However, in the case of para grass, it appears not all native vegetation types and freshwater wetland habitats are equally at risk (Boyden et al., 2013; Ferdinands et al., 2005). In order to develop effective strategies to manage para grass, a better understanding of its invasion pattern and the current and potential ecological impacts on different habitats or wetland assets is required.

Spatial relationships measured between different plant species and associated environmental factors can be used to model the impacts and risk of weed invasion on native plant communities (Adams et al., 2015a; Jarnevich and Reynolds, 2011). Based upon niche theory, this approach assumes that known distribution patterns of individual species also reflect the optimal habitat characteristics of those species at the locations each species occupies across a landscape (Barve et al., 2011; Peltzer et al., 2008). This provides a scientific basis from which to predict future distributions of invasive species and to identify strategies

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that deliver site specific and regional weed control, cost-effectively (Joshi et al., 2004; Richter et al., 2013).

Models used to identify and target priority weed invasions are best calibrated with accurate spatial information on both vegetation and the associated habitat factors controlling plant distributions. Yet, it has often been challenging to acquire and integrate enough information in order to characterise the extensive and remote landscapes under conservation at appropriate spatial and temporal scales (Adams et al., 2015b; Harvey and Hill, 2001; Lukacs and Finlayson, 2010; Rodgers et al., 2018). For example, there is a real need for baseline data on hydrological factors known to drive vegetation dynamics on monsoonal floodplains (Setterfield et al., 2013). Such factors, include seasonal-water availability, -flood frequency, -depth, and -hydroperiod. Furthermore, few studies have measured spatial relationships between fire disturbance, as a pervasive factor of tropical savannas, and its influence on floodplain vegetation change (Finlayson, 2005; Miller and Murphy, 2017). Nevertheless, remote sensing methods using Landsat time-series imagery show promise in addressing these knowledge gaps through providing continuous and accurate spatial information at suitable scales on vegetation, hydrological variables and fire history (Boyden et al., 2013; Hawbaker et al., 2017; Smith et al., 2014; Ward et al., 2014).

The objective of this study was to use Landsat 5 TM time series datasets to derive accurate maps of floodplain water depth and annual fire history for a 258 km^2 seasonally inundated floodplain of Kakadu National Park (KNP). Our aim was then to conduct a spatial vulnerability assessment of native vegetation to para grass invasion by integrating these 'habitat factor' maps with an existing vegetation map of the floodplain (Boyden et al., 2013). To achieve this aim, spatial analyses were conducted to: (1) Compare the mapped distribution pattern of para grass with competing native vegetation types; (2) Characterise these vegetation types in context to mapped water depth and annual fire histories; and (3) Determine habitat suitabilities for para grass and native vegetation by the spatial integration of water depth, fire history and vegetation maps. The resulting information products may complement current spread models built on more limited data (Adams et al., 2015a; Ferdinands et al., 2005; Walden et al., 2012), thus enabling more accurate spatial prediction for targeted control of priority weed invasions.

2. Methods

2.1. Site characteristics

The Magela Creek floodplain within KNP and the Alligator Rivers region is shown in Fig. 1. In this region vegetation dynamics is governed by the availability of water and nutrients. This in turn is driven by the monsoonal climate and frequent disturbance events, including fire and extreme weather (Douglas et al., 2005; Finlayson, 2005; Miller and Murphy, 2017). The seasonally predictable wet-dry rainfall cycle is defined by a relatively short period of moderate to intense rainfall followed by a prolonged dry-season in which up to 90% of floodplain areas are usually dry before the next wet season (Russell-Smith et al., 1995). However, the timing, magnitude and duration of the seasonal rains is also highly variable within and between years (Taylor and Tulloch, 1985).

Floodplain habitats are differentiated by low-relief topography, with variable states in vegetation distribution and composition having been linked to shifting hydrological conditions, both within and between years (Finlayson et al., 1989; Smith, 2012). Distribution patterns separating aquatic and semi-aquatic plant communities have been shown to be the result of trade-offs between physiological tolerances of different plants to inundation depth, aeration and drying; as well as different viability and dormancy mechanisms under different environments (Araya et al., 2011; Zedler and Kercher, 2004). Hence, distribution and dynamics of vegetation is dependent on the depth, duration and frequency of annual flooding at any one location (Casanova and Brock, 2000; Finlayson, 2005; Finlayson et al., 1989; Magee and Kentula, 2005; Seabloom et al., 2001; Williams, 1979; Zweig and Kitchens, 2008).

Para grass is thought to have been introduced to the Top End of northern Australia as early as the 1900′s and its presence on the Magela floodplain was first observed in the 1950′s (Christian and Aldrick, 1977; Walden et al., 2012). From the 1980′s, grassy weeds then proliferated on floodplains of KNP as a result of the controlled eradication of grazing water buffalo. Recent reports indicate that para grass continues to increase in extent and abundance on these floodplains (Ferdinands et al., 2005; Finlayson et al., 1997; Knerr, 1998; Walden et al., 2012).

Importantly, the distribution of para grass on this floodplain has predominantly been shaped by natural environmental factors over many decades. It has not been actively controlled within the Magela Creek catchment, which is subject to a natural, unaltered, environmental flow regime. These conditions together with the large area of representative floodplain habitats and vegetation, provided a site model that met key assumptions for niche-based spatial vulnerability assessment (Barve et al., 2011; Peltzer et al., 2008).

2.2. Datasets and analysis framework

Separate maps for water depth, fire history and vegetation (Boyden et al., 2013) were derived from Landsat imagery acquired through the USGS (USGS, 2010). These maps were produced using supervised, object-based image classification methods applied in eCognition ® 8.7 (Trimble, 2011). Spatial relationships between mapped para grass, native vegetation, depth habitat and annual fire frequency, were modelled in a GIS. Details of these steps and datasets used are provided in Fig. 2 and Table 1, respectively.

2.3. Spatial relationships of para grass and native vegetation

Vegetation patterns, and the spatial scales over which they are expressed, can inform of the ecological processes that shape distributions and are therefore useful in calibration of species distribution models (Law et al., 2009; Wiegand et al., 2003; Wiegand et al., 2017). Using statistics for discrete vegetation patches generated in eCognition ® ver. 8.7, we produced graphs for: (a) The frequency distribution by area of all para grass patches; and (b) The proportion of the boundaries of discrete vegetation patches shared with different (adjacent) vegetation patches, including para grass. Using (b), the spatial connectivity between para grass and native vegetation patches was compared at the scale of the whole floodplain (relative to the distribution of all native vegetation patches); and relative to the distribution of para grass only.

In addition, vegetation clustering patterns were measured in context to the total floodplain area using Ripley's K Function (L) for varying distances [Eq. (1)] (Ripley, 1977):

$$L(d) = \sqrt{A \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} k(i, j)/\pi n(n-1)} \quad (1)$$

Where d is the distance, n is the total number of features, A represents the total area sampled and k_{ij} is a weight. In this case the assigned weight indicates presence (= 1) or absence (= 0) of a vegetation class.

Clustering patterns (L) for para grass and native vegetation were measured at distances from 0.5 to 15 km at intervals of 0.5 km, using a 50 m point sample lattice to measure the presence or absence of vegetation. Clustering patterns were identified when the average presence of vegetation, at a given search distance, was statistically greater than the expected presence of vegetation as generated from a random Poisson distribution of all data points. The results were plotted for each vegetation class as the positive or negative deviation from expected distribution over the various distances sampled.

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