An evidence base for improving management effectiveness of alien plants in protected areas: relationships of scale, efficiency and strategy

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Declaration

By submitting this dissertation electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the owner of the copyright thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

This dissertation includes one original paper published in a peer-reviewed journal, one original paper accepted, but not published in a peer-reviewed journal and two unpublished publications (prepared for submission to peer-reviewed journals). The development and writing of the papers (published and unpublished) were my principal responsibility. Declaration has been made indicating the nature and extent of the contributions of co-authors, where relevant.

I am now presenting the dissertation for examination for the degree of Doctorate of Philosophy.

Date: November 2018

Summary

Invasive alien plants (IAP) pose a direct threat to the biodiversity of South Africa. Extensive invasion has occurred in many of the country's protected areas, requiring direct management. In many protected areas, including Table Mountain National Park, the selected study area for this investigation, IAP control programmes were established more than 20 years ago and are well resourced. However, limited tangible success, in terms of reduction of overall alien distribution and density has been achieved. It therefore became necessary, both from an economic and conservation perspective, to investigate the likely future trajectory of control programmes and to determine the main drivers of management success.

This dissertation aims to provide a scientific rationale for improving management of IAP programmes in four key management areas. Firstly, the current accuracy of distribution and abundance data that is used in management decision making, is determined (Chapter 2). This is an important starting point for understanding management effectiveness as decisions to assign resources and treat areas are based on knowledge of IAP species presence and their associated densities in an area. Secondly, the long-term implications of suboptimal treatment quality is examined through modelling the expected density of IAP invasion after 50 years of treatment at 38 levels of clearing efficacy (Chapter 3). Thirdly, the choice of management clearing strategy is thought to play an important role in determining clearing success. Although a number of clearing strategies have been postulated by management and documented in literature, the potential outcomes of these strategies have not been formally tested. These proposed management strategies are modelled to provide insight into the performance of each strategy, also considering the mediating impact of clearing quality (Chapter 4). Last, there exists a management dichotomy between area-based and species-based planning. The shortcomings of these approaches are identified with an alternative invasion-stage-based planning approach that considers a number of scale dependent range properties offered (Chapter 5). To assess these factors, the presence and absence of all identified alien species were mapped at a fine-scale across the Table Mountain National park, producing a systematic sample of species from a total of 10,057 plots.

Results indicated that management data used in decision making largely over estimate IAP distribution and abundance, while under estimating IAP species richness. Fine-scale sampling provided estimates of species richness and abundance that differed in many cases by orders of magnitude from the data that are used by managers. Currently there are adequate resources to deal with the IAP problem, but quality of work is identified as the primary driver

failure to reduce alien species densities over the long-term. The modelling of treatment quality revealed that small increases in clearing efficacy above 80% result in increasingly large gains in the areas that can be covered for the same amount of resources. Conversely, any decrease in clearing efficacy below 80% results in rapidly diminishing areas that can be treated annually with the same resources. A key consequence of the current efficacy levels observed in the clearing programme, is that up to 75% of the future resource costs will be required to treat new infestations resulting from re-seeding of the current standing infestations. With increased efficacy, this future cost can be greatly reduced. The quality of clearing also mediates the choice of clearing strategy. As clearing quality increased or decreased above or below 75%, the best performing strategy changed. This highlights treatment quality as a primary driver of long-term clearing success, while the choice of implementation strategy is a secondary factor. One of the key factors identified for management improvement was the frequency for revisiting previously cleared management units for follow-up treatment. It was found that historical re-visitation to management units has been greater than two years. As many of the targeted species are able to produce seeds within two years, the invasion of such species has been allowed to perpetuate. The last key finding was that through spatial analysis of population data the same species could be at different stages of invasion at different sites with the park. This result suggests that a single management approach for a species is not warranted. The choice of management approach for a species should consider range properties of occupancy, population density and spatial pattern of the species at different sites and scales.

In conclusion, key improvements can be readily integrated into the IAP programme that will lead to substantive improvements in the outcomes of IAP programmes. These include improving the quality data on distribution and abundance IAP and implementing rigorous quality control. Some of the suggested interventions from this work are already being trialled, with marked improvements already visible. Through these improvements, eradication of target species by organised local scale extirpation, is possible.

Opsomming

Indringer uitheemse plante (IUP) hou 'n direkte bedreiging vir die biodiversiteit van Suid-Afrika in. Uitgebreide indringing het plaasgevind in baie van die land se beskermde gebiede, wat direkte bestuur vereis. In baie beskermde gebiede, insluitend Tafelberg Nasionale Park, die geselekteerde studiegebied vir hierdie ondersoek, is IUP beheerprogramme meer as twintig jaar gelede gestig en is dit goed befonds. Beperkte tasbare sukses, in terme van die vermindering van algehele indringer verspreiding en digtheid, is egter behaal. Dit was dus nodig om, vanuit 'n ekonomiese en bewaringsperspektief, die moontlike toekomstige trajek van beheerprogramme te ondersoek en die belangrikste dryfvere van bestuursukses te bepaal.

Hierdie proefskrif poog om 'n wetenskaplike beweegrede te verskaf vir die verbetering van die bestuur van IUP programme in vier sleutel bestuursgebiede. Eerstens word die huidige akkuraatheid van verspreidings- en oorvloeddata wat in bestuursbesluitneming gebruik word, bepaal (Hoofstuk 2). Dit is 'n belangrike vertrekpunt om bestuur doeltreffendheid te verstaan, aangesien besluite om hulpbronne toe te ken en werksareas aan te wys, gebaseer is op kennis van die teenwoordigheid van IUP spesies en hul gepaardgaande digtheid in 'n gebied. Tweedens word die langtermyn implikasies van suboptimale behandelingskwaliteit ondersoek deur die verwagte digtheid van IUP indringing na 50 jaar se behandeling op 38 vlakke van doeltreffendheid skoon te maak (Hoofstuk 3). Derdens word daar gedink dat die keuse van skoonmaakstrategie deur bestuur ‘n belangrike rol speel in die bepaling van die sukses van skoonmaak. Alhoewel 'n aantal skoonmaakstrategieë deur die bestuur voorgestel en in die literatuur gedokumenteer is, is die potensiële uitkomste van hierdie strategieë nie formeel getoets nie. Hierdie voorgestelde bestuurstrategieë word gemodelleer om insig te verskaf in die prestasie van elke strategie, met inagneming van die bemiddelende impak van skoonmaak kwaliteit (Hoofstuk 4). Laastens bestaan daar 'n bestuursdigotomie tussen areagebaseerde en spesiegebaseerde beplanning. Die tekortkominge van hierdie benaderings word geïdentifiseer met 'n alternatiewe indringer-stadium-gebaseerde beplanningsbenadering wat 'n aantal skaalafhanklike omvangseienskappe oorweeg (Hoofstuk 5). Om hierdie faktore te evalueer, is die teenwoordigheid en afwesigheid van alle geïdentifiseerde uitheemse spesies op 'n fynskaal regoor Tafelberg Nasionale Park gekarteer, wat ‘n sistematiese steekproef van spesies uit ‘n total van 10,057 plotte gelewer het.

Resultate het aangedui dat bestuursdata wat in besluitneming gebruik word, IUP verspreiding en oorvloedighed oorskat, terwyl dit die rykdom van IUP spesies onderskat. Fynskaalse steekproefneming het skattings van spesiesrykheid en oorvloed gegee wat in baie gevalle van

grootteorde verskil van die data wat deur bestuurders gebruik word. Tans is daar voldoende hulpbronne om die IUP probleem te hanteer, maar die kwaliteit van werk word geïdentifiseer as die primêre rede hoekom daar gefaal word om die uitheemse spesies digthede oor die langtermyn te verminder. Die modellering van behandelingskwaliteit het aan die lig gebring dat klein toenames in die doeltreffendheid van skoonmaak bo 80% tot toenemende groot winste lei in die gebiede wat vir dieselfde hoeveelheid hulpbronne gedek kan word. Omgekeerd, lei enige afname in effektiwiteit onder 80% in vinnig afnemende areas wat jaarliks met dieselfde hulpbronne behandel kan word. 'n Belangrike gevolg van die huidige doeltreffendheidsvlakke waargeneem in die skoonmaakprogram, is dat tot 75% van die toekomstige hulpbron koste nodig sal wees om nuwe infestasies te hanteer as gevolg van saadskiet van die huidige staande infestasies. Met verhoogde doeltreffendheid, kan hierdie toekomstige koste aansienlik verminder word. Die kwaliteit van skoonmaak bepaal ook die keuse van die skoonmaakstrategie. Aangesien die skoonmaakkwaliteit gestyg of verlaag het bo of onder 75%, het die beste presterende strategie verander. Dit beklemtoon die kwaliteit van behandeling as 'n primêre dryfveer vir die sukses van skoonmaak oor die langtermyn, terwyl die keuse van implementeringstrategie 'n sekondêre faktor is. Een van die sleutelfaktore wat vir bestuursverbetering geïdentifiseer is, was die frekwensie vir herbesoeke van voorheen skoongemaakte bestuurseenhede vir opvolgbehandeling. Daar is bevind dat historiese herbesoek aan bestuurseenhede langer as twee jaar was. Aangesien baie van die geteikende spesies binne twee jaar saad kan produseer, is die indringing van sulke spesies toegelaat om voort te duur. Die laaste sleutelbevinding was dat, deur middel van ruimtelike analise van bevolkingsdata, dieselfde spesie op verskillende stadiums van indringing op verskillende plekke binne-in die park kan wees. Hierdie resultaat dui daarop dat 'n enkele bestuursbenadering vir 'n spesie nie geregverdig is nie. Die keuse van bestuursbenadering vir 'n spesie moet die eienskappe van besetting, bevolkingsdigtheid en ruimtelike patroon van die spesies op verskillende terreine en skale oorweeg.

Ten slotte, kan sleutelverbeterings maklik geïntegreer word in die IUP program wat tot wesenlike verbeterings in die uitkomste van die IUP programme sal lei. Dit sluit in die verbetering van die kwaliteit data oor verspreiding en oorvloed van IUP en die uitvoering van streng gehaltebeheer. Sekere van die voorgestelde ingrypings van hierdie werk word alreeds beproef, met beduidende verbeterings wat reeds sigbaar is. Deur hierdie verbeteringe, is die uitroeiing van teikenspesies deur georganiseerde plaaslike skaaluitsterving moontlik.

Dedication

To my children, Leila and Teighan, who continually supplied me with encouragement and sticky sweets whilst sitting at the computer, may you follow your passion to write your own book one day.

Biographical sketch

I have a broad interest in ecological patterns and processes and enjoy the challenge of attempting to solve big problems. I completed a National Diploma in Nature Conservation (1994) before undertaking a BSc. Honours (1998, University of Natal). I undertook a dissertation that developed a GIS approach to determining the mega-herbivore carrying capacity of the North Eastern Tuli Block, Botswana. This dissertation entailed spatially mapping plant-herbivore dynamics in the presence of large herbivores. I went on to complete my MSc. (Stellenbosch University, 2004) with a dissertation on the Biodiversity Management of Strandveld at Rocherpan Nature Reserve. The work focussed on plant-herbivore dynamics in the absence of large herbivores under the supervision of Prof. Sue Milton, Prof. Karen Esler & Dr. Annelise le Roux.

A career in conservation has enabled me to have fantastic life experiences, while providing important lessons along the way. After being a Section Ranger involved in conservation management for South African National Parks, based in Table Mountain National Park between 2000 and 2005, I moved to conservation planning division of the park, where I am involved in a various conservation projects. I currently work in the science-planning-management interface, looking at ways to improve ecosystem resilience through the reduction of anthropogenic pressures on natural systems. One of the key pressures in the region is invasive alien plants. Due to the immediate management applications provided, the field of invasion biology makes for a productive ground for exploring a range of ecological paradigms. In this regard, I have been intrigued as to why management appears to be losing ground in terms of alien species management, while having more resources and scientific understanding than ever before. A desire to improve the outcomes of conservation management to improve long-term security for protected areas, paved the way for the work presented in this dissertation.

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Chapter 1. Introduction

1.1 Background

Invasion biology encompasses the study of the causes and consequences of introducing organisms to areas outside of their native range (Richardson & Pyšek 2008; Richardson & Ricciardi 2013), and the assessment of risks, costs, benefits and human value perspectives relating to the introduction and management of such species (de Wit *et al.* 2001; van Wilgen *et al.* 2001; Shackleton *et al.* 2018a). The interest in invasion biology has grown substantially over the past 25 years (Pyšek & Richardson 2010), largely driven by a rapid increase in travel and trade, including human-assisted transport at a global scale (Hulme 2009). Introduction pathways for taxa outside their native ranges are numerous and include a variety of intentional and unintentional human-related activities such as direct trade, agriculture and forestry, all of which are capable of moving species from a broad range of taxa (McGeoch *et al.* 2010; Seebens *et al.* 2017).

The small portion of alien species that are able to disperse, survive and reproduce at multiple sites away from the original site are termed invasive alien species (IAS). Introduced species are classified as invasive when multiple individuals of the species disperse and establish multiple populations across habitats (Blackburn *et al.* 2011). Although numerous species are being transported globally, not all introduced species become invasive or cause significant impacts in their new location (Williamson & Fitter 1996; Blackburn *et al.* 2011). Newly introduced species need to overcome several invasion barriers that may restrict individuals from multiplying or moving beyond the site of introduction (Richardson *et al.* 2000b; Theoharides & Dukes 2007; Blackburn *et al.* 2011). In addition, the ecosystem dynamics in the new environment maybe vary, so the arriving species might only be supported for a finite period of time (Simberloff & Gibbons 2004). Much effort has gone into understanding the traits that make a species become invasive. These include genetic variability, population biology, physical morphology and behavioural adaptations (Nel *et al.* 2004; Conser *et al.* 2015; Roger *et al.* 2015). Complementing the species studies are a range of ecosystem studies that attempt to explain invasion dynamics, including biotic resistance from native communities, disturbance, and the role of lag phases, propagule pressure and species interactions (Simberloff & Von Holle 1999; Richardson *et al.* 2000a; Crooks 2005; Lockwood *et al.* 2005).

Invasive alien species can cause a variety of changes in the receiving environment that can result in range of possible impacts (Foxcroft *et al.* 2013; Blackburn *et al.* 2014). These impacts have been widely assessed and include impacts on species and communities (McGeoch *et* *al.* 2010; Pyšek *et al.* 2012), ecosystem properties, for example fire regimes (Brooks *et al.* 2004; Rahlao *et al.* 2009; Alba *et al.* 2015); biogeochemistry, such as altering nitrogen and carbon levels (Ehrenfeld 2003, 2010), ecosystem services, for example water resources (Le Maitre *et al.* 1996; Le Maitre *et al.* 2002) and direct economic costs (van Wilgen *et al.* 2012; van Wilgen *et al.* 2016b). Due to the global nature of assisted species movement, invasive species are one of the primary threats to local biodiversity at a global scale (McGeoch *et al.* 2010).

In order to mitigate the impacts of IAS, deliver ecosystem services and meet biodiversity targets, a number of IAS management programmes have been established globally (Marais *et al*. 2004, Downey 2010). Purposeful management of IAS requires combining invasion theory (species attributes that predict invasiveness and the ecosystem dynamics that make native populations and communities vulnerable or resilient to invasion), with management aspects (strategy, measures, targets and evaluation of outcomes). Management approaches that integrate these factors are in relatively early development (Shea *et al.* 2002; Foxcroft 2009; Downey 2010). The resources and associated costs required for management of IAS is substantial. For example, estimated costs to increase water security in the water catchment areas of the Western Cape, South Africa, could reach about ZAR2436 million over the next 10 years (van Wilgen *et al.* 2016b), while control of alien plants in the iconic Kruger National Park has cost ZAR378 million over a 20 year period (van Wilgen *et al.* 2017).

Due to the high management costs and limited management successes globally, IAS management has drawn a range of scepticism where some have questioned whether the global movement of species is a real ecological problem that warrants investigation (Briggs 2017; Crowley *et al.* 2017; Russell & Blackburn 2017). Contenders argue that as new species are added to ecosystems, they result in new novel systems and can even increase local biodiversity where it has been lost. These novel ecosystems are themselves worthy of study in an increasingly modified world, where altered systems are likely the future norm (Hobbs *et al.* 2006; Hobbs *et al.* 2009; Carroll 2011). Arguments have been put forward that due to the high costs of preventing, controlling and reversing the impacts of alien invasive species, and with many management interventions failing, limited conservation funds should be diverted elsewhere (Davis *et al.* 2011; Vince 2011). In addition, alien species can have a number of positive societal benefits that can improve people’s livelihoods, thus resulting in diverse public perceptions towards invasive species (Tassin & Kull 2015; Shackleton *et al.* 2018b).

In South Africa, the national Working for Water (WfW) programme is one such conservation programme that aims to control IAS, mainly invasive alien plants (IAP). The programme commenced in 1996 as a government benefit scheme that focused on addressing the long history of invasion by IAP's that were driven by a range of complex global, local, social and ecological interactions (Le Maitre *et al.* 2004; Koenig 2009). Many of the IAPs are well-established, with extensive, well-documented negative impacts on biodiversity and ecosystem services (Nel *et al.* 2004; Kotzé *et al.* 2010). Unfortunately many of the heavily invaded areas fall within South Africa's protected area (PA) network, on land that has been set aside for the protection of native biodiversity (Spear *et al.* 2011; Foxcroft *et al.* 2017). Although the WfW programme has been active for more than 20 years in some areas, the rates of control and removal of invasive alien plants have been lower than expected (McConnachie *et al.* 2012; van Wilgen *et al.* 2012; Kraaij *et al.* 2017). This has prompted questions into the probable causes of the perceived under-performance of the programme and was a major incentive for this study.

The central concept for the dissertation rests in supporting an evidence based management approach to IAPs in protected areas that are experiencing low rates of control and removal. Currently management based research on aliens forms less than 10% of research articles pertaining to the WfW programme (Abrahams *et al.* 2018) with an awareness that evidence-based management is often lacking (Legge 2015). This work aims at strengthening the science-management interface, with each chapter providing scientific evidence for particular management applications to ensure an evidence based approach to WfW management. This would provide insights for potential local programme improvements to be implemented and the lessons learnt to be carried forward into the larger WfW programme nationally and further afield.

In order to understand the drivers of invasive alien plant management, the dissertation adopts a simulation model approach as a means to understand the potential outcomes of various management interventions. Simulation models have been widely used to understand the expected outcomes of management intervention, or the lack thereof. Economic models (Higgins *et al.* 1997, de Wit 2001) showed the cost-benefits of area under alien invasion compared to natural systems. Ecosystem services models (mainly relating to water security) have demonstrated the diminishing availability of water and the long-term costs of not treating alien plants in catchment areas of South Africa (Le Maitre *et al.* 1996, 2002). The long-term budgets to undertake clearing have been assessed (Krug et al 2010, van Wilgen 2016). The simulation models developed in chapters 2 and 4 of the dissertation (see section 1.3) align well and follow a similar approach to previous modelling work by making use of published data for the model parameters used for the model variables.

The primary focus of the dissertation is to understand management of invasive alien plants within biodiversity rich areas. Within the species rich fynbos biome of South Africa (Kotzé 2010) (Sup. Mat. Figure 1.1) IAP's have become well established and pose a direct local threat to native biodiversity. The study focuses on the management of a single Protected Area, the Table Mountain National Park that covers an area of exceptional biodiversity across several taxonomic groups (Cowling *et al*. 1996). Along with the importance of biodiversity of the area, the park has collated a number of long-term datasets. This allows for the incorporation of these datasets into the management decision-making environment.

1.2 Table Mountain National Park as a case study

Table Mountain National Park (TMNP) (Fig. 1.1) is a PA where managers have struggled to bring alien plant populations under control. The TMNP was established in 1998 to protect a 'biodiversity hot-spot' on the Cape Peninsula (Cowling *et al.* 1996; Trinder-Smith *et al.* 1996; SANParks 2016). One of the key threats to the biodiversity of the area is the long history of IAS, particularly alien plants (Richardson *et al.* 1996; Higgins *et al.* 1999). The WfW programme in TMNP has been in place for more than 15 years, with a current annual budget up to ZAR20 million (Fig. 1.2). This expenditure has resulted in the TMNP receiving the most funding of all the national protected areas in South Africa with a cumulative investment of ZAR103 million from WfW and ZAR67 million form other funders (SANParks 2015, Foxcroft *el al.* 2017). However despite increased resources into the programme over the years, there has been limited success. (Fig.1.3, Sup. Mat. Table 1.1). This paradox of increasing resources with decreasing returns makes TMNP an attractive case study. Further, TMNP has good IAP distribution and historic clearing data (since 1998), fire history records, climate data and active science-management engagement.

1.2.1 Table Mountain National Park history

Table Mountain National Park is located in Cape Town, on the Cape Peninsula (Fig. 1.1). The park extends from Signal Hill in the north (33° 54' S, 18° 24' E) to Cape Point in the south (34° 21' S, 18° 29' E) and includes international icons such as Table Mountain. The origins of the park can be traced back to the establishment the Tokai, Devils Peak, and Cecilia State Forests in the late 1800s and early 1900s while the Rhodes Will Act (1910) protected the eastern slopes of Table Mountain. This was followed by the declaration of Table Mountain as both a National Monument in 1958 and a Nature Reserve in 1964.

Fig. 1.1 Location of Table Mountain National Park on the Cape Peninsula, South Africa. The Park covers about 250km^2 (25,000 ha) of the Cape Peninsula. Modified from SANParks 2016.

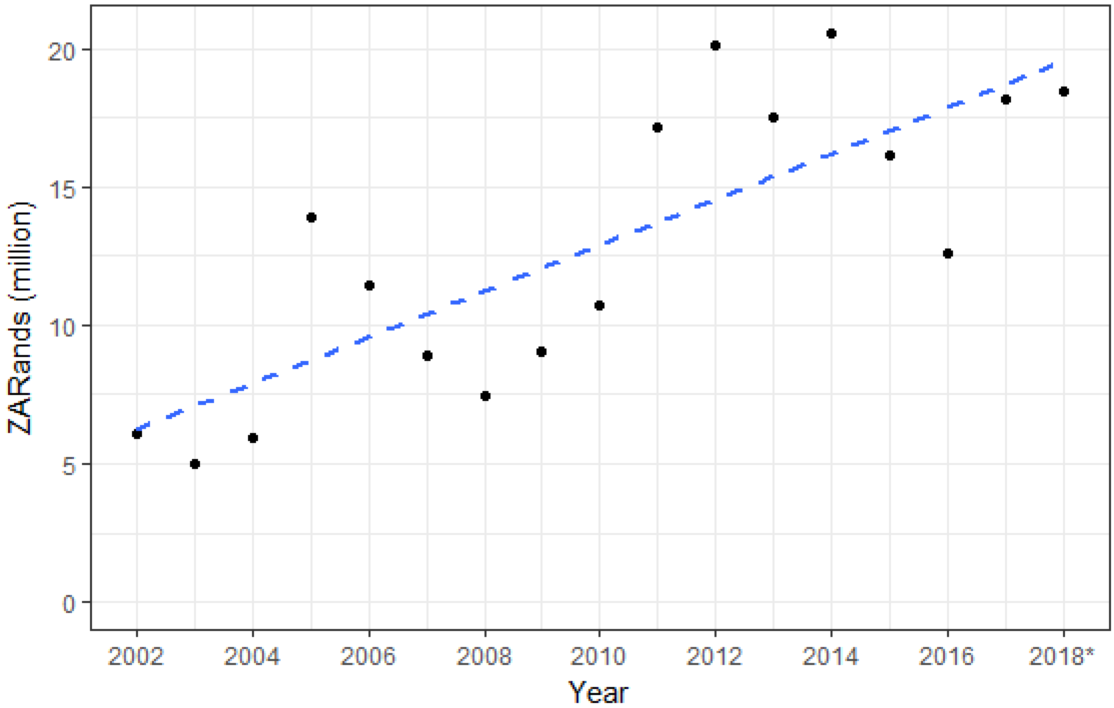

Fig. 1.2 Funding (ZAR) spent in the WfW project between 2002 and 2018* for the control of invasive alien plants in Table Mountain National Park. Expenditure between 2002 and 2017 has been adjusted by the annual Consumer Price Index (CPI) to 2018 values, with a total ZAR219 million spent for the period. CPI sourced from www.statssa.gov.za. (*planned budget)

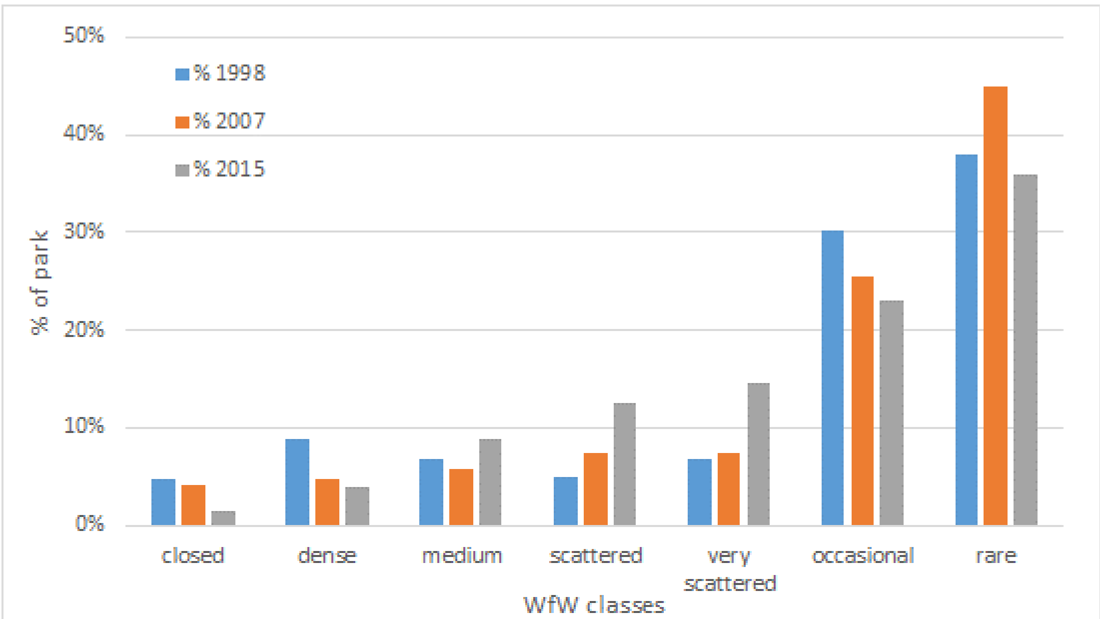

Fig. 1.3 The percentage of the Table Mountain National Park (TMNP) falling into the standard Working for Water alien plant cover classes as measured in 1998, 2007 and 2015.

The greater central area known as Silvermine was declared as a Nature Reserve in 1965, while the southern section of the park, including the areas around Cape Point, was declared under provincial legislation between 1938 and 1964. These original conservation areas were consolidated into the Cape Peninsula Nature Area in terms of the Physical Planning Act in 1983. This was superseded by the Cape Peninsula Protected Natural Environment (CPPNE) in terms of the Environmental Conservation Act in 1989, which in turn has been superseded by the National Environmental Management: Protected Areas Act in 2004 (Act 57 of 2003).

Although the land was protected by conservation legislation, there were 14 different management authorities responsible for the area, resulting in difficult and conflicting land management practices, especially with regard to the management of invasive and alien plants. In 1994, the Kahn Working Group ("Working group to rationalise the management and control of the CPPNE") recommended that a single statutory managing authority be established for the future management of the area (SANParks 2016). The working group recommended that all responsibilities of the existing different management authorities be reassigned and that the land be reallocated for the establishment of a consolidated National Park. In 1996, following a national cabinet decision, the various management authorities (national, provincial and local) undertook to reallocate the available land in the CPPNE for the establishment of the Table Mountain National Park in 1998. In 2004, the area received further recognition of its conservation importance and was inscribed as a natural site of outstanding universal value by UNESCO as part of the Cape Floral Region Protected Area World Heritage Site.

1.2.2 Table Mountain National Park biodiversity

Table Mountain National Park falls within the Cape Floristic Region (CFR) which is the smallest in size of the world's six floral regions, but contains approximately 9,600 plant species of which some 70% (6,200) are endemic to the region (Cowling 1995; Cowling *et al.* 1996). Within the Cape Peninsula (c.a. 471 km^2), 2285 indigenous plant species occur, making the area one of the richest in flora for any similar sized area, both in the Cape Floristic Region and the world. Biogeographically, the flora is unusual in that species typical of the winter-rainfall portions of the CFR as well as species whose ranges extend eastwards into summer rain-fall regions (Simmons & Cowling 1996). This biogeographical mixing probably contributes to the very high floral species richness. As is typical of other areas of the CFR, three major vegetation types are represented on the Cape Peninsula: Cape Fynbos shrubland; Renosterveld shrubland and associated grasslands; with patches of Forest and Thicket (Rebelo *et al.* 2006).

Six nationally threatened ecosystems, as listed in National Environmental Biodiversity Act (NEM:BA 2004), are found within the park, namely, i) Cape Flats Sand Fynbos (Critically

Endangered) occurring on the lowlands in Tokai, ii) Peninsula Granite Fynbos (Critically Endangered) occurring across the Northern, Central and Southern sections of the park, on middle to upper mountain slopes, iii) Peninsula Shale Renosterveld (Critically Endangered) occurring on the lower slopes of Devils Peak and Signal Hill, iv) Elgin Shale Fynbos (Critically Endangered) occurring in small fragments on lower slopes of Newlands and Devils Peak, v) Hangklip Sand Fynbos (Endangered) which occurs in the Fish Hoek and Hout Bay Valleys, and vi) Peninsula Sandstone Fynbos (Endangered) occurring throughout the Park on upper slopes and peaks.

1.2.3 Invasive alien plant management

The unique biodiversity of the TMNP, although largely secure in terms of conservation legalisation, has historically been threatened by IAPs. In the northern section of TMNP, *Pinus* was reported as a problem on Table Mountain as early as the 1930's (Sim 1927 as cited in (van Wilgen *et al.* 2016a). Area-wide surveys between 1961 and 1992 highlighted a constant invasion pressure from a number of species from the genera *Pinus*, *Hakea* and *Acacia* (Hall 1961; McLachlan *et al.* 1980; Moll & Trinder-Smith 1992). Early studies between 1960 and 1980 (Taylor & Macdonald 1985; Taylor *et al.* 1985), already highlighted wide infestation of Acacias in the Cape of Good Hope area. Many of the IAP introductions into the TMNP were deliberate (Shaughnessy 1980, MacDonald *et al*. 1987). Pine species were planted in water catchment and recreational areas, while Acacias were introduced as part of dune stabilisation schemes. Assessments of IAP distribution modelling for the TMNP of *Acacia* and *Pinus* species and the impact on local biodiversity that these species would have (Higgins *et al.* 1999) concluded that, "*The threat posed by alien plants to the plant biodiversity of the Cape Peninsula is severe*.".

Alien species control efforts were established in the early 1970's. The effort was focused on the nature areas of Table Mountain, Silvermine and Cape of Good Hope (Macdonald *et al.* 1985). The control programmes were largely implemented by the various management authorities at the time with un-skilled and semi-skilled labour, with significant support from volunteer groups. With the establishment of the national park the various control programmes were consolidated through the direction of the Global Environmental Facility (GEF) in 1998. This is was followed by commencement of the national Working for Water (WfW) control programme in 2002 with an annual starting budget of ZAR5.6 million (CPI adjusted, SARS 2018). This budget has grown steadily to a current budget of around ZAR18 million per annum (2018 net present value), with the total allocation of funding between 2002 and 2018 reaching ZAR219 million (CPI adjusted) (Fig. 1.2). However, this sizeable investment has not resulted in substantive gains in IAP reduction over 15 years of continuous clearing (Fig. 1.3). Although was a significant reduction in the denser WfW density classes (closed, dense and medium) of 1570 hectares from 5161ha in 1998 to 3591ha in 2015, there has also been a 505 hectare drop in areas that were in a maintenance state (i.e. WfW density class of rare 9620ha in 1988 and 9096ha in 2015) (Sup. Mat. Table 1.1). Of interest is that while management interventions have kept alien density to relatively low levels across most of the park, the relative density of IAPs has shifted around the Park, with peak densities occurring in different areas over time. This reflects an outcome associated with a combination of fire occurrence and management clearing history (Fig. 1.4). The distribution of IAPs in the TMNP is therefore quite dynamic and is determined by ecological drivers and management interventions.

1.3 Dissertation aims and objectives

This dissertation was born out of need to improve the outcome of the alien clearing programme by assessing factors that could enhance the impact of funding spent. Currently, with no definitive management wins, the progress of the IAP control programme has understandably caused some managers to become disheartened. It therefore became necessary, both from an economic and conservation perspective, to investigate the likely future trajectory of alien control and to determine the main drivers of management success (or failure). The idea was to strengthen the science-management interface, with each dissertation chapter providing scientific evidence for particular management applications to ensure an evidence based approach to management. A brief synopsis of the aims and objectives of each of the research chapters is provided below, along with a dissertation roadmap.

Chapter 2: Data quality underpinning management decisions

Managers are required to make decisions, first and foremost of which is the determination of priorities. Decisions about prioritisation include which species and areas to treat, and which pathways to manage given the limited resources available (McGeoch *et al.* 2016). These decisions are frequently, and preferentially, experienced based, rather than evidence based (Cook *et al.* 2009), driven by the urgency for action that supersedes collection of detailed information (Simberloff 2003). However, a balance between conservation action and data gathering is required, with recognition of the shortfalls of the long-term impact of poor information on control programmes. Chapter two assesses the extent of this problem in relation to species occurrence data by generating a fine-scale, comprehensive IAP dataset for the TMNP. This entailed systematically sampling 10,057 plots across the park and counting all alien species falling within the plots. This dataset was then compared with the current management datasets to determine the differences in species listed, distribution estimates, abundance quantification and associated discrepancies in allocation of resources for clearing. *Published: Biological Invasions.*

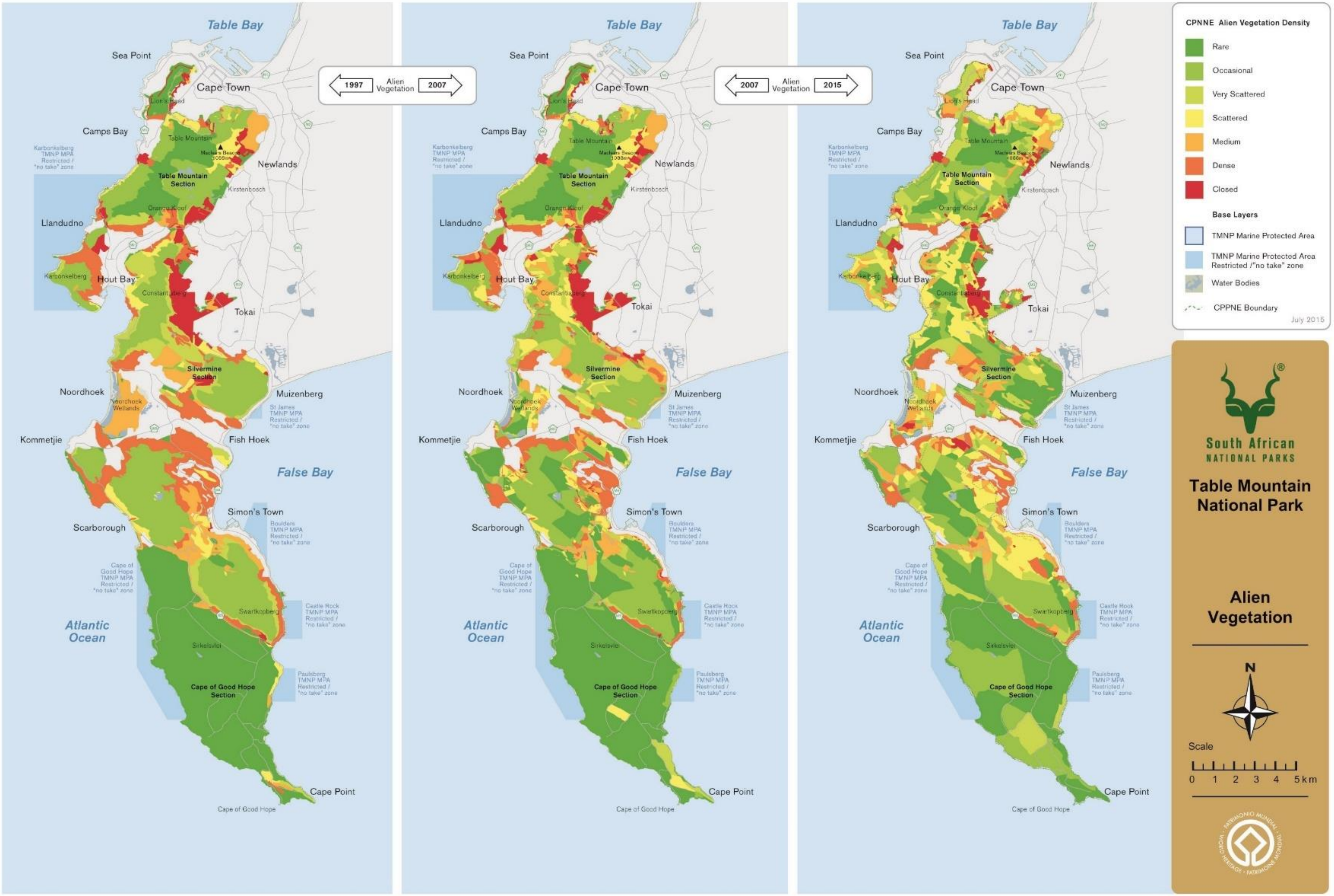

Fig. 1.4 The change in distribution of invasive alien vegetation of specified Working for Water density classes on the Cape Peninsula between 1998 and 2015. Modified from SANParks (2016)

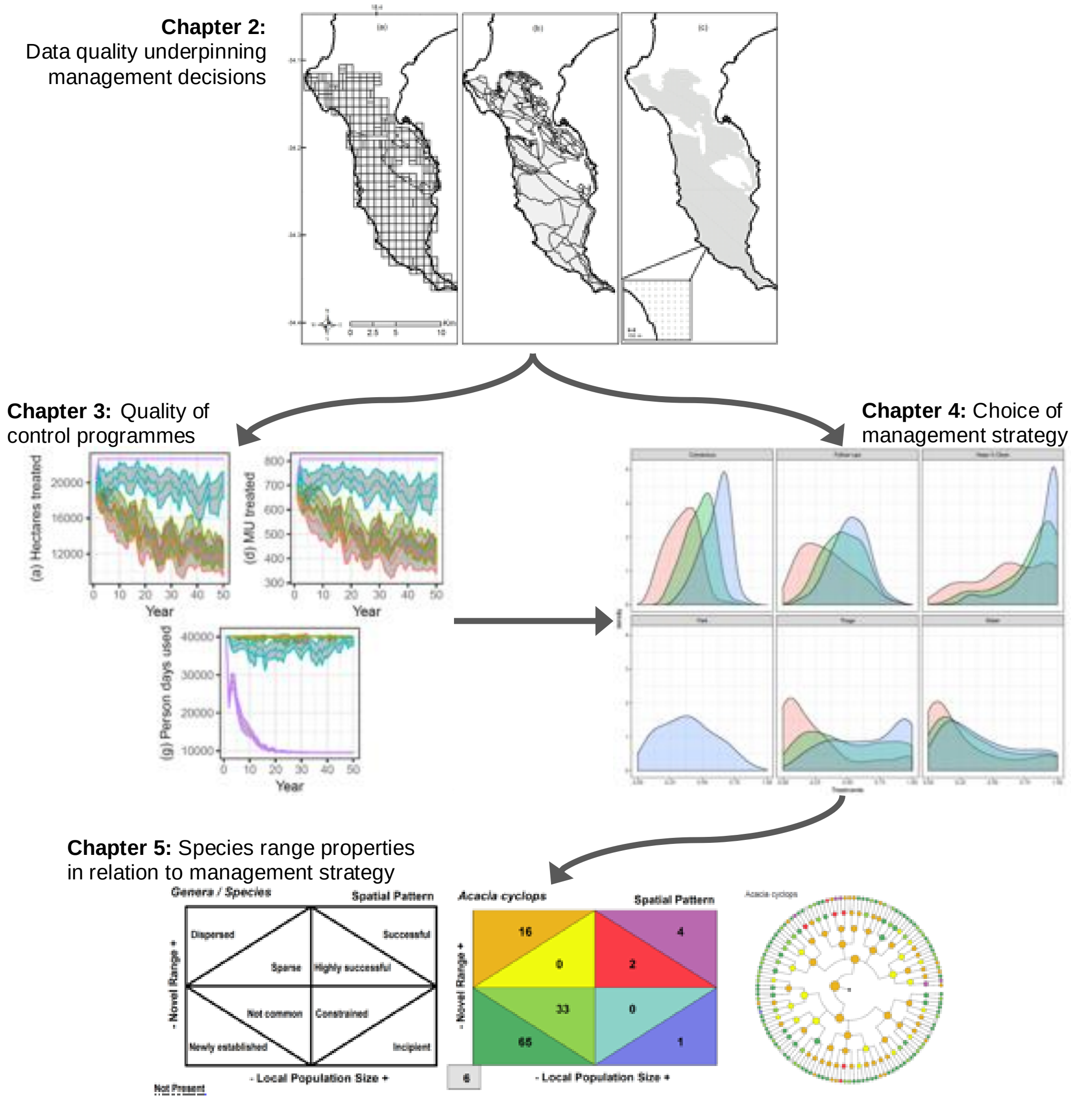

Fig. 1.5 Conceptual roadmap of research chapters (Chapters 2-5) of the dissertation, where:

Chapter 2 investigates data quality issues underpinning management decisions. A high quality dataset of 10,057 infield plots was used to determine the differences from current management datasets in species listed, distribution estimates, abundance quantification and associated allocation of resources for clearing;

Chapter 3 explores the impact that clearing quality has on control programmes. Using the fine-scale alien plant distribution data, a simulation model assed clearing efficacy at 38 incremental levels between 5-100% over a period of 50 years;

Chapter 4 considers the possible long-term outcomes in the choice of management strategy selected for implementation. A simulation model is used to test the performance of five different management strategies against a random selection of treatments, in relation to 20 levels of work quality; and

Chapter 5 presents a novel approach that considers incorporating species range properties into management strategies. The method considers how the range structure (landscape occupancy and population parameters) of invading species can be align with generalised treatment strategies available to management.

Chapter 3: Quality of control programmes

There is increasing evidence that IAP control programmes are 'suffering' the effects of poor implementation quality (McConnachie *et al.* 2012; Kraaij *et al.* 2017). Chapter three assesses programme efficiency, focusing on the quality of work, and the implications poor quality implementation for the long-term outcomes of alien plant control programmes. Using the fine-scale alien plant distribution data generated in Chapter two, a simulation model was developed and used to assess the role of suboptimal clearing efficacy on the long-term potential for success of the clearing programme, focussed on *Acacia* species. In the simulation model, clearing efficacy was set at each of 38 incremental levels between 5-100% over a period of 50 years. The number of hectares and management units treated, the number of these which achieved low alien plant densities, and the associated resource requirements, were assessed for each efficacy level. The model was also run with and without certain ecological processes such as fire and natural seedbank replenishment to assess the main ecological drivers that interact with clearing efficacy to determine programme outcomes. This chapter provides insight into the management effort required to solve the IAP problem going forward. The manipulation of ecological variables in the model also highlights the importance of follow-up clearing to prevent seedlings from reaching maturity in relation to clearing recently burned areas, providing important information for clearing plan prioritization.

Under Review: Journal of Environmental Management.

Chapter 4: Choice of management strategy

Although several management strategies have be adopted by conservation managers, published assessments show that these strategies can be divergent in the spatial areas selected for prioritisation. This results in the prioritisation strategies not converging to meet an overall conservation objective across the landscape (Roura-Pascual *et al.* 2010). Building on chapter three, and the effects of implementation quality on IAP clearing programmes, chapter four looks at how quality issues impact on the choice of clearing strategies available to conservation managers. This chapter assesses the implications of adopting a particular management strategy with respect to determining the spatial prioritisation of treatments. A simulation model is used to test the long-term performance of five different management strategies against a random selection of treatment areas, in relation to varying work quality at 20 levels between 5-100%.

Chapter 5: Species range properties in relation to management strategy

Having evaluated a number of invasion management options, and being aware of the current limitations of treatment prioritisation, a novel method of integrating management approaches is presented in chapter five. The method considers how the range structure (landscape occupancy and population parameters) of invading species can be align with generalised treatment strategies available to management. The approach builds on previous work that considered invasive species as being on a trajectory from being uncommon to becoming common (McGeoch & Latombe 2016). The classification method also considered that management interventions might push the trajectory of populations in the opposite direction, reducing common invasive species towards becoming uncommon. The approach seeks to understand the observed range characteristic spatially across the invasion landscape. Using a combination of local abundance, occupancy and spatial pattern to allow the most appropriate site-specific management interventions to be identified. For example, the application provides insight into whether management should aim to eradicate, control or contain a species in a particular area or at a particular scale, thereby enabling appropriate resource allocation. The approach also allows for the identification of source populations that are isolated within a landscape, that if cleared, could reduce the invasion potential of a species in that area.

Chapter 6: Synthesis

In the synthesis chapter the main findings and conclusions of the research are drawn together. The chapter highlights where park management have adopted already recommendations from the research and outlines the opportunities for future research.

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1.5 Supplementary material

The following supplementary Information may be found in the supplementary section accompanying this thesis.

Sup. Mat. Figure 1.1 Number of alien species across South Africa per Quarter Degree square in relation to the National Protected Areas.

Sup. Mat. Table 1.1 The number of hectares and percentage of the Table Mountain National Park falling into the Working for Water alien plant cover classes.

Chapter 2.

The impact of data precision on the effectiveness of alien plant control programmes: a case study from a protected area

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Cheney C., Esler K.J., Foxcroft L.C., van Wilgen N.J. & McGeoch M.A. (2018). The impact of data precision on the effectiveness of alien plant control programmes: a case study from a protected area. Biological Invasions, 20 11, 3227–3243.

Abstract

Successful long-term invasive alien plant control programmes rely on alien plant distribution and abundance data to assess, prioritise, implement and monitor the efficacy of the programme. Here we assess the impact of data accuracy using the alien plant programme in Table Mountain National Park, South Africa. A systematic plot-based survey method was carried out to assess the distribution of alien plants in the park at a fine scale (systematic sampling). Alien plant richness, total area invaded and the degree of spatial overlap in species' presence were compared between the systematic sample and a protected area (PA) managers' dataset (collated from collective observations by park visitors, rangers and managers) and Working for Water (WfW) project data (data collected for the planning and implementation of the alien plant clearing programme) using a range of confusion matrix-based statistics to assess similarity and error rates between the datasets. A total of 106 alien plant taxa were detected across the three datasets, 12 in PA manager's data, 23 in WfW data and 101 in the systematic survey. Overall, there was substantive disagreement between the datasets on the distribution of alien plants. For example both management datasets estimated species' hectare coverage at orders of magnitude greater than indicated by systematic sampling. The inaccuracy of manager data has direct negative implications for funding allocation, which currently appears to be in excess of what is required. We recommend that contrary to perception, fine-scale surveys are a cost-effective way to inform long-term monitoring programmes and improve programme effectiveness.

Keywords: control programme, confusion matrix, invasive species, protected area management, systematic distribution sampling

2.1 Introduction

Protected areas (PAs) have been established as part of a core approach to biodiversity conservation and the maintenance of functional ecosystem processes (Barr *et al*. 2016; Dudley and Parish 2006; Watson *et al*. 2014). PAs are complex ecological systems and PA managers require high quality and up-to-date information to effectively manage these areas for their intended conservation mandates and objectives (Biggs *et al*. 2003; Pressey *et al*. 2015). One of the primary threats to biodiversity in PAs is the invasion and persistence of invasive alien plants (Foxcroft *et al*. 2013a, b; Spear *et al*. 2011). For example, invasive alien plants can change community structure (Holmes and Cowling 1997), alter energy, nutrient and water flows (Ehrenfeld 2010; Le Maitre *et al*. 2002) and modify disturbance regimes, especially fire (Alba *et al*. 2015; Brooks *et al*. 2004). In most cases, once an invasive alien plant has established, it cannot be removed unless through large control efforts or only at substantial cost (Foxcroft *et al*. 2013a; McConnachie *et al*. 2012; van Wilgen *et al*. 2012b), resulting in permanent effects on native biodiversity (Kettenring and Adams 2011).

There are many potential pathways by which alien and invasive alien plants can be introduced into PAs (Foxcroft *et al*. 2008). PAs have to contend with a legacy of deliberate alien species introductions prior to PA proclamation or as part of the current management practices of a PA in the form of forestry plantation or at tourism facilities (Kueffer *et al*. 2013). Protected area managers are therefore required to continually detect, control or eradicate a range of existing alien plants, and develop strategies to prevent or appropriately respond to the arrival of new alien species that could exacerbate current threats (Pyšek and Richardson 2010).

An invasive alien plant control programme typically comprises a set of actions to achieve objectives that are guided by the strategic aims or goals of the programme (Foxcroft 2009; Tu 2009; Wittenberg and Cock 2001). To implement an effective control programme, PA managers need to consider the achievability of specific objectives, goals and outcomes. Often compromises and prioritization of objectives and goals are required due to constraints on time, financial and other resources, lost opportunity costs and conflicting priorities (Donlan *et al*. 2015; Roura-Pascual *et al*. 2011; Roura-Pascual *et al*. 2009). However, the type and quality of information used to guide prioritization, decision-making and monitoring is an integral, yet often overlooked, component of control programmes (Foxcroft 2009; Gardener *et al*. 2010; McConnachie *et al*. 2012; van Wilgen *et al*. 2012b).

South Africa has a long history of invasion by alien plant species, driven by a range of complex global, local, social and ecological interactions (Le Maitre *et al*. 2004). Many introduced species are well established and substantial negative impacts on biodiversity and ecosystem services have been documented (Kotzé *et al*. 2010; Nel *et al*. 2004). 'Working for Water' (WfW) is a nationally funded invasive alien control programme that aims to restore and maintain habitat structure and function to mitigate the loss of ecosystem services, especially water production through creating employment opportunities and facilitating skills development that contribute to poverty alleviation (van Wilgen *et al*. 2012a).

WfW has historically invested (1995–2015) approximately ZAR 564 million (1 US$ ~ 15 ZAR in 2015) in South Africa's PAs (van Wilgen *et al*. 2012a, 2016). Despite the substantive investment in the programme, annual estimates of the clearing work required remain high, necessitating sustained large or increasing budgets. In PAs, the WfW programme is implemented through projects undertaken as partnerships between PA managers and WfW project teams. For PA clearing projects to be efficient, data on alien plant species richness (McGeoch *et al*. 2012), the distribution of target species across the entire treatment area (Gardener *et al*. 2010; Pyšek and Richardson 2010; Wittenberg and Cock 2001), and a measure of the abundance of the populations are required (Dewey and Andersen 2004). Given the fundamental importance of spatial data for alien plant management, a variety of methods of data collection have been developed and are currently being implemented in the WfW alien control programme. However, there has been no assessment of the best approach for data collection or the effects the various collection methods have. Given the large monetary investment, it is important to determine the role and effectiveness of various types of data in informing alien plant management programme efficacy.

Here, Table Mountain National Park (TMNP) is used as a case study to quantify the adequacy of datasets used in PAs for the management of invasive alien plants. Alien plant species richness, distribution and abundance data from three sources, (i) WfW project managers, (ii) invasions recorded by PA managers and (iii) a fine-scale, in-field systematic survey of alien plant species, were assessed. The assessment aimed to determine the relative error in estimates of the extent of invasion across TMNP from each of the different data sources and the possible role of this information in misinforming management plans and reducing clearing efficiency. The implications of discrepancies between the datasets are discussed and recommendations provided to improve data collection methods and the evidence base used for alien plant species management.

2.2 Materials and methods

2.2.1 Study area

The Cape Peninsula, on the south western tip of South Africa, is a mountainous, topographically diverse area, generally nutrient poor soils, with high levels of species endemism of both plants and invertebrates (Cowling *et al*. 1996). About 2285 plant species have been recorded, with 158 species being endemic (Helme and Trinder-Smith 2006). The Cape Peninsula has experienced a long history of human settlement with the establishment of the City of Cape Town, which has a population of over 3.7 million people (Statistics South Africa 2011). The TMNP was established within the urban matrix in 1998 to consolidate the management of remaining conservation- worthy land on the Cape Peninsula and currently covers about 250 km^2. For over a century the historical land-use and proximity to urbanization has facilitated the introduction and spread of numerous alien plant species into TMNP (Alston and Richardson 2006; Macdonald *et al*. 1985; Shaughnessy 1980; Spear *et al*. 2013).

The TMNP has an intensive long-term alien plant clearing programme in place that is currently implemented through the WfW Programme, and was previously implemented as part of the management function of the PA, employing semi-skilled labour, skilled private contractors and civil society volunteer groups (Macdonald *et al*. 1985). The current alien plant clearing programme is divided into three operational projects covering the northern, central and southern sections of TMNP. This study focused on the southern section of the PA which is the largest in both area, covering approximately 130 km^2, and in funding allocated for alien plant control, which was ZAR R8.7 million for the 2013 financial year (Working for Water 2013). This section of TMNP has a history of woody alien plant species invasion spanning at least 70 years and has had management control programmes in place since the late 1980s (Macdonald *et al*. 1985; Taylor and Macdonald 1985; Taylor *et al*. 1985). Despite these programmes, annual estimates of the clearing work required remain high, necessitating sustained large budgets.

2.2.2 Alien plant management datasets

The implementation of the TMNP alien plant management programme is based on data from two main sources: data collated by the PA managers who maintain records of alien species reported by park rangers and park visitors (hereafter the 'Management' data) and WfW project information, which includes a database of spatially linked historic clearing information (hereafter 'WfW' data). We generated a third dataset using a fine-scale systematic sampling approach to map the richness, distribution and density of all alien species in TMNP (hereafter the 'Systematic' data).

2.2.2.1 PA Managers dataset – 'Management dataset'

Protected area managers are collectively responsible for implementing the daily operations of the park. While the implementation of alien plant control in the PA is undertaken by WfW (see below), the PA managers and rangers collect and collate their own alien plant occurrence data. The dataset is maintained largely as a paper-based file consisting of grid-based area maps where historical records, reports from park visitors and personal observations are recorded on an ad hoc basis. At a group workshop in 2013, 11 managers from the park, were asked to consolidate the alien species and taxa distribution records from this dataset and to add current expert knowledge to these distribution maps for all alien plant species that were common, or considered important for direct control or monitoring. The distribution of the alien plant species was delineated on a colour aerial map (scale 1:20,000) divided into the 0.70 km^2 polygons used for conservation management purposes. Where required, these management units were sub-divided to allow for finer scale delineation per alien plant species or abundance variations. Protected area managers used three measures to estimate alien species abundance, resulting in a combination of percentage cover, density per hectare and descriptive measures (Sup. Mat Table 2.1). The final map was divided into 297 polygons that ranged in size from a relatively fine grain of 0.02 km^2 to a coarse grain of 0.71 km^2 (mean of 0.44 km^2), covering a total area of 130.75 km^2. The data were captured in ArcGIS 10.x (ESRI 2014) (Fig. 2.1a).

2.2.2.2 Working for Water dataset – 'WfW dataset'

Working for Water managers rely on a database of alien distribution information known as WIMS (Working for Water Information Management System) to guide the programmes' implementation. A key component of the WIMS system is the development of an annual plan of operations (APO). These APOs contain a detailed list of all alien plant species and their percentage cover that occur within a project area for a particular year. The project area is further divided into management clearing units known as nBals (National Biological Alien data). The alien species composition and cover for each nBal is updated annually through a combination of in-field visual assessments and rapid plot-based assessments. The WfW dataset for the area comprised 182 nBals which ranged from a relatively fine grain of 0.02 km^2 to a very coarse grain of 12.57 km^2 (mean of 0.71 km^2) and covered a total area of 125.50 km^2 (Fig. 2.1b). Alien species distribution data (species presence and percentage cover; Sup. Mat. Table 2.1) were obtained for each of these nBals for the 2013 project year.

2.2.2.3 Systematic Survey dataset - 'Systematic dataset'

A dedicated survey team systematically sampled the southern section of the PA between April and November 2013. The survey was designed by overlaying the study area with a fine grain (0.02 km^2) sampling grid. A 500 m^2 circular sampling plot was placed at the centre of each grid cell resulting in 5276 plots, evenly distributed across the study area. Within each plot all alien plant species were identified, and richness and abundance quantified. Where the number of individuals for a given species was less than 100, all individuals were counted; where the number of individuals was likely to exceed 100, three randomly placed sub-plots totalling 10 m^2 were sampled. All individuals within the sub-plots were counted and extrapolated by multiplying the mean to a full plot estimate. Where the growth form of the plants did not allow for individual counts (e.g. grasses and creepers), a percentage cover of the full plot was determined using six cover classes (Sup. Mat. Table 2.1). All counts and cover estimates from each sample plot (0.0005 km^2) were extrapolated to the size of the full 0.02 km^2 grid cell for analysis to provide for density estimates across the entire study area of 126.40 km^2 (Fig. 2.1c).

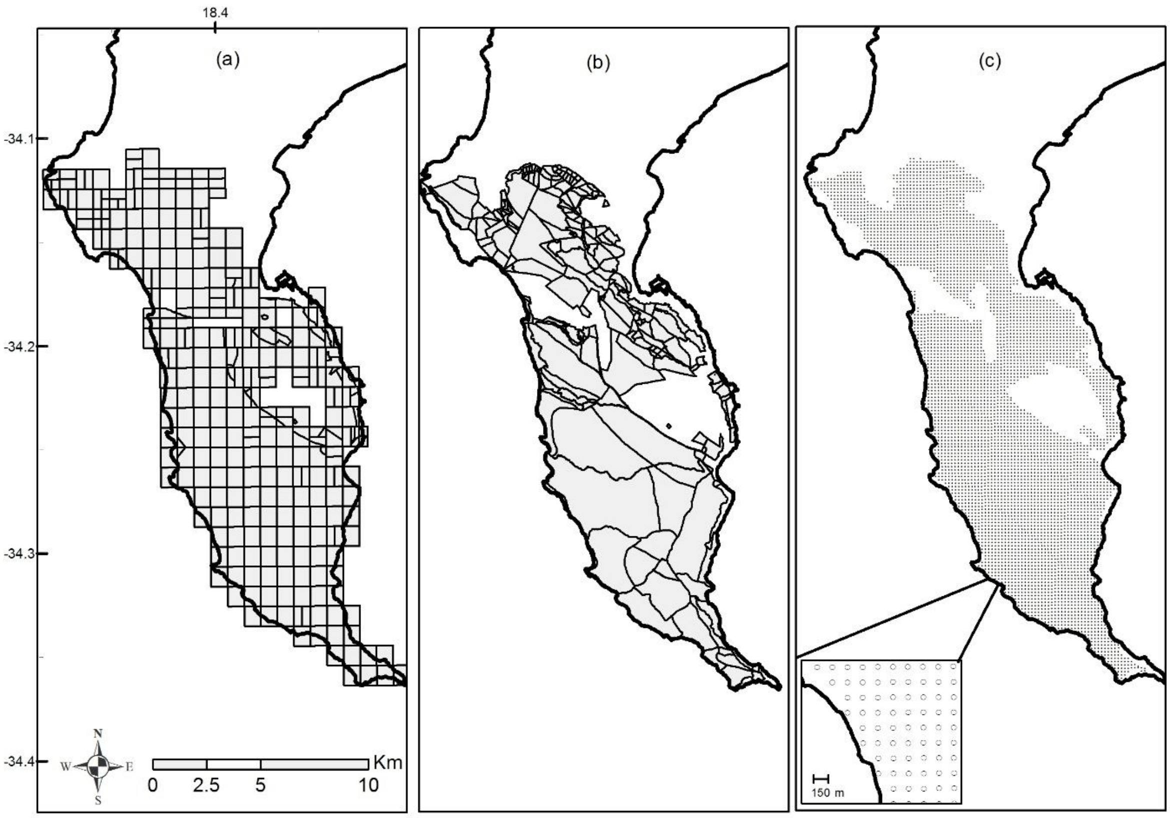

Figure 2.1 Maps depicting the size and distribution of the management/sampling units used a in the Protected Area Manager Dataset (n = 297), b by Working for Water (n = 182), and c for systematic sampling (n = 5276)

2.2.3 Dataset Comparisons

The three datasets had slightly different spatial extents and only the overlapping areas, which covered 125.15 km^2, were included in analyses. These included 295 of the 297 Management polygons and 176 of the 182 WfW nBals. The Management and WfW datasets were compared to the Systematic data in terms of i) the alien plant species richness, ii) the degree of spatial overlap in alien plant species presence and iii) the recorded abundance and area invaded by selected alien plant species.

2.2.3.1 Species Richness within datasets

Species listed within each dataset were checked and verified for taxonomic accuracy and known presence (Spear *et al*. 2011). While most records contained species level information, some records were only identified to genus level (e.g. *Eucalyptus* spp.). For these cases, the records were grouped and treated as a single taxon (e.g. *Eucalyptus* spp.). The Systematic dataset included 12 extralimital species (i.e. a species native to South Africa but outside of its natural distribution range, e.g. *Afrocarpus falcatus* and *Aloe arborescens*) that were excluded from the analysis as they were not specifically recorded in the other datasets. To determine the accumulation rates of alien plants within the three datasets, the mean species accumulation curves, with 95% confidence limits, were plotted based on 100 randomisations using Estimate-S v 9.1 (Colwell 2013). Although not directly comparable due to the different sizes of the individual sample units, the mean, minimum and maximum species richness was calculated for each dataset to allow for overall comparison of the data for the study area.

2.2.3.2 Selection of taxa for comparison

The datasets were checked for species that were common to all three datasets. All records belonging to *Hakea* spp., *Pinus* spp. and *Eucalyptus* spp. in the Management and the WfW datasets were not consistently identified to the species level within these genera and as such were analysed at genus level. The datasets had five species in common identified to species level (*Acacia cyclops*, *Acacia longifolia*, *Acacia saligna*, *Leptospermum laevigatum* and *Paraserianthes lophantha*) which together provided eight taxa (species or genera) for comparative analysis. This selection included the taxa that are the primary focus of the alien plant control programme.

2.2.3.3 Degree of spatial agreement in taxa presence/absence between datasets

Taxa within each sampling unit were scored as present or absent. The degree of spatial matching in taxa presence was assessed between the Systematic data and i) Management and ii) WfW datasets. As the PA managers and WfW data are captured in large polygons (Fig. 2.1), the data from the small plots of the Systematic data that fell within the polygon were pooled for analysis. To determine which plots from the Systematic dataset fell within each polygon, a standard spatial query was performed in ArcGIS (10x).

The data were summarised as cross-tabulates where the Systematic data are regarded as the observed class and either the WfW or Management data the predicted class (Sup. Mat. Table 2.2). The cross tabulates were treated as a confusion-matrix (Fielding and Bell 1997) where *a* is the number of sampling units in which the taxa were recorded in both datasets (*true presence*), *b* where only the Management data or WfW dataset recorded the taxa (*false presence*), *c* where only the Systematic dataset recorded the taxa (*false absence*) and *d* where the taxa was not recorded in either dataset (*true absence*). A range of confusion matrix-based statistics (Accuracy, Prevalence, Sensitivity Specificity and Odds Ratio; see Sup. Mat. Table 2.3 for definition and formulas) were used to assess the degree of similarity and error rates between the datasets (Fielding 2007; Fielding and Bell 1997). In addition two measures of classification accuracy, Kappa (K), and the True Skill Statistic (TSS) (Allouche *et al*. 2006) were calculated to determine the proportion of specific agreement between the Systematic data and WfW data, and the Systematic data and Management data.

2.2.3.4 Total area invaded by taxa and baseline clearing costs

For each dataset the total condensed area covered was calculated by multiplying the taxon percentage cover in each base mapping unit by the area of that mapped unit (Marais and Wannenburgh 2008), which then expresses the area invaded as an equivalent of 100% cover. Where Management data were expressed using a descriptive value, these abundance classes were converted to cover estimates by using the mid-value of the cover class (Sup. Mat. Table 2.1). These mid-point cover estimates have the potential to over or under estimate the cover values and thus the total condensed area. The effect of this was minimised by having a narrow range of cover values available within a class (e.g. 1–10% for low density classes while for higher density sites the over or under estimate is limited by the small size of sample units (0.02–0.03 km^2).

The WfW data are recorded as percentage cover per taxon and therefore these values were used as recorded. The Systematic data density counts were converted to cover values using the WfW Norms and Standards tables (Le Maitre and Versfeld 1994). Each sample unit from the Management dataset and WfW dataset was paired with the Systematic dataset and the total condensed area calculated for the Systematic dataset. The differences between the datasets were tested using a Wilcoxon Signed-Rank Test for paired samples, with the pairs being the sample units. For each dataset the condensed areas were calculated for each taxon and for all taxa together to compare the estimated clearing costs that would be estimated from each dataset. Estimations were based on the WfW norms and standards of 24.65 person days per hectare (0.01 km^2) required to clear adult alien plants at 100% cover (Neethling and Shuttleworth 2013) multiplied by the daily WfW programme's person-day cost of R250 per person per day. This cost is based only on the estimated density and abundance of species to be cleared. It does not consider additional costs incurred though, for example, transport, equipment or herbicide requirements, which vary according to site topography, species presence and distribution of species within the landscape.

2.3 Results

2.3.1 Alien plant species richness

A total of 106 alien plant taxa from 71 genera were recorded from all three datasets (Fig. 2.2, Sup. Mat. Table 2.4). The most taxa (101 taxa, 95% of the total) were recorded through systematic sampling, followed by the WfW dataset (23 taxa, 22%). The Management dataset had the fewest taxa (12 taxa, 11%). The Management and WfW datasets comprised mainly woody species (9 out of 12, and 15 out of 23 taxa respectively), while woody species accounted for only 38 of the 101 taxa in the Systematic dataset. Only nine taxa (8% of the total) were recorded in all three datasets (Fig. 2.2).

The Systematic dataset had more species in common with the WfW data than the Management data, with 19 (including 14 woody species) of the 106 species in common, but 81 (76%) of the alien plant taxa in the systematic sampling dataset were not recorded in either the WfW or the Management data. The five species recorded in the WfW and Management datasets, but not in the Systematic dataset, comprised taxa only identified to genus level (e.g. *Pinus* sp. which were all identified to species level in the systematic sample) or *Metrosideros excelsa* which only had a single location record.

The rate that taxa were recorded within the datasets was greatest in the Systematic dataset (Fig. 2.3). After reaching a cumulative area of 2.5 km^2 there was no overlap in taxa richness between the Systematic dataset and either the WfW or Management datasets. The alien plant taxa accumulation curve approached an asymptote at approximately 10 km^2 (12% of the total study area) for the Management data, while the WfW dataset continued to accumulate taxa until 120 km^2 (95% of the study area) and the Systematic dataset did not reach an asymptote for the study area.

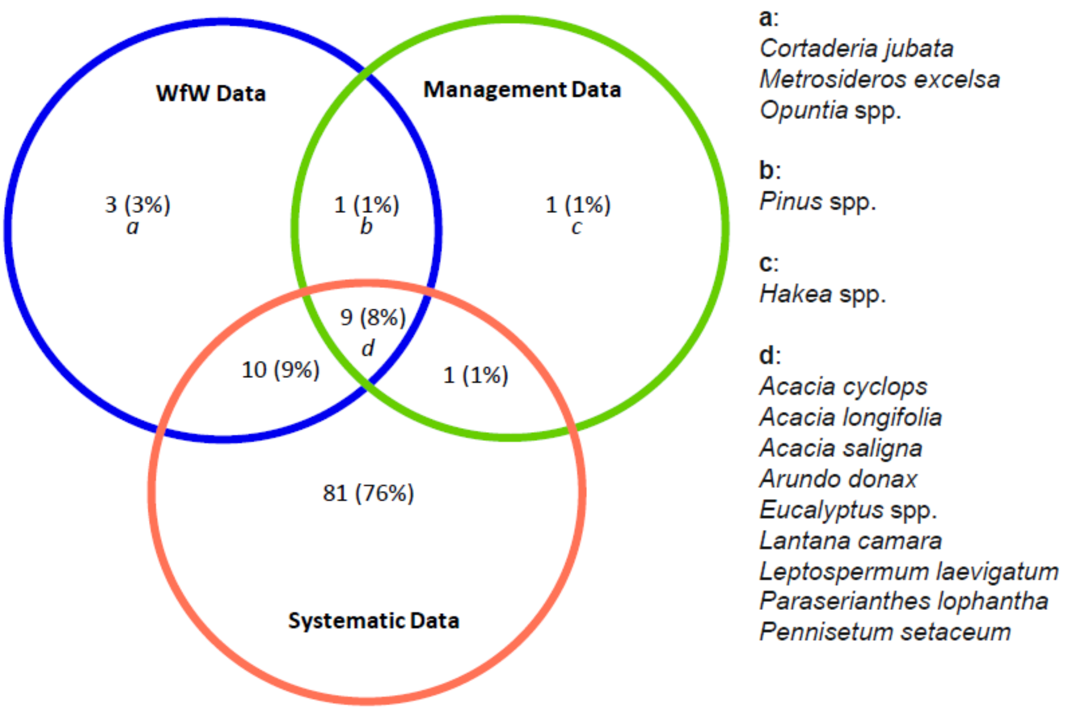

Fig. 2.2 The number of alien taxa unique to and shared between the three datasets: Systematic sampling (101 taxa in total), WfW (23 taxa) and Management Data (12 taxa) with a total of 106 taxa across all datasets. See Sup. Mat. Table 2.4 for full taxa list. Note: for the purposes of this figure data are scored as different between datasets where records are less specifically identified (e.g. *Hakea gibbosa* is different to *Hakea spp.*)

2.3.2 Degree of spatial agreement in taxa presence/absences between datasets

2.3.2.1 Management and Systematic dataset

In the Management dataset, at least one alien taxon was recorded in each of the 295 polygons while the Systematic dataset recorded at least one alien taxon in 266 of the 295 polygons (90%, Tables 2.1, 2.2). According to the Management dataset, *Acacia cyclops* and *Acacia saligna* were widespread in the study area (recorded in 282 and 285 of the 295 polygons respectively), while the Systematic dataset recorded these two species as being scattered in the study area (recorded in 195 and 198 of the 295 polygons respectively).

The overall agreement on alien plant spatial distribution for seven of the eight compared taxa was poor between the Systematic and Management datasets (Table 2.2), with the Kappa and TSS statistics less than 0.4, which is considered to be a minimum threshold designating good agreement (Landis and Koch 1977). Although there was agreement on spatial presence (sensitivity scores >0.9; Table 2.2) for widespread taxa (e.g. *A. cyclops* and *A. saligna*), there was low agreement on absence (specificity scores = 0.06) for these taxa. Localised taxa (e.g. *Acacia longifolia*, *Leptospermum laevigatum*) showed opposite trends with high agreement of absence (specificity scores >0.8; Table 2.2) and fair agreement of presence (sensitivity scores >0.4; Table 2.2).

2.3.2.2 WfW and Systematic dataset

When comparing the WfW and Systematic datasets, at least one alien taxon was recorded in each of the 176 WfW sample units compared to 174 of the 176 WfW nBals for systematic data (Table 2.1 and Table 2.3). In the WfW dataset, only *A. saligna* was recorded as widespread, with *A. cyclops* and *A. longifolia* recorded as scattered within the study area and the remaining five taxa having localised distributions. Overall, the agreement between the Systematic and WfW datasets for all eight compared taxa was very poor (Table 2.3), with the kappa and TSS statistics for all eight taxa lower than 0.4. The WfW dataset was similar to the Management dataset, where widespread species had agreement on presence (sensitivity scores >0.9; Table 2.3), while the agreement on absence was variable (specificity scores 0.37-0.69; Table 3). For localised taxa, the WfW dataset recorded generally good agreement of absence (specificity scores >0.8) while the agreement of presences was generally low (sensitivity scores <0.25). Overall the dataset recorded a mismatch in the distribution of the taxa analysed.

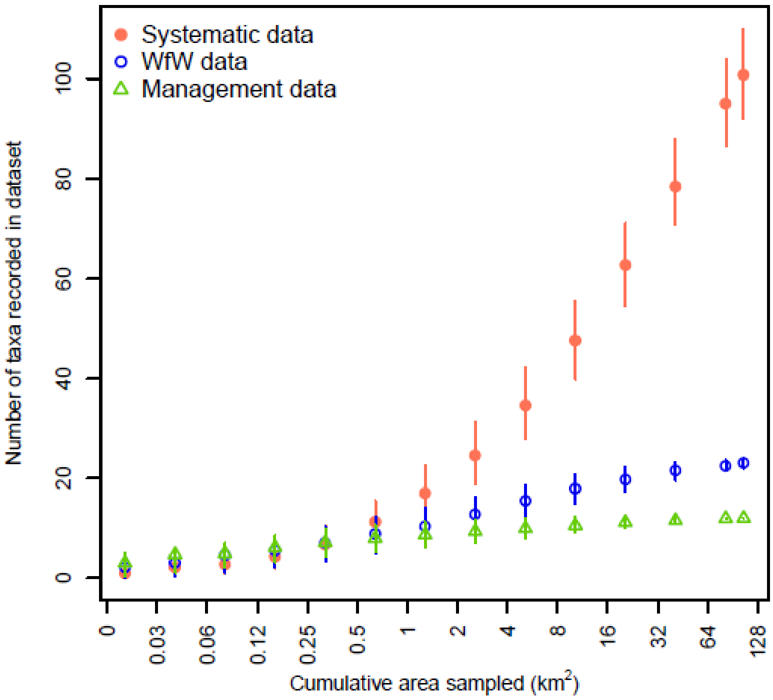

Fig. 2.3 Mean alien plant taxa accumulation curves (100 randomisations) for the Management, Working for Water (WfW) and Systematic datasets plotted on a log scale (base 2; *x*-axis), with error bars indicating 95% confidence intervals as calculated with EstimateS (Colwell R.K., 2013)

Table 2.1 Dataset summary for the Management, Working for Water (WfW) and the Systematic datasets

	Management	**WfW**	**Systematic**
Total extent of survey area	130.75 km^2	125.50 km^2	126.40 km^2
Number of polygons	297	182	5,276
Polygon size range	0.02 km^2 - 0.71 km^2 (mean 0.44 km^2)	0.02 km^2 - 12.57 km^2 (mean of 0.71 km^2)	0.02 km^2
Taxa in dataset	Total: 12	Total: 23	Total: 101
Range of Taxa identified per polygon	Min: 1 Max: 7 Mean: 3.0 (SD=1.40)	Min: 1 Max: 6 Mean: 2.2 (SD=1.37)	Min: 0 Max: 16 Mean: 0.79 (SD=1.51)
Number of polygons occupied by alien plants out of the total polygons for that dataset	297 (100%)	182 (100%)	2,151 (41%)
Range occupied (all species)	130.75 km^2	125.50 km^2	43.02 km^2
Time period collected	All records known by PA managers as at July 2013	January – March 2013	April to November 2013

2.3.2.3 Total invaded area by taxon and baseline clearing costs

In the Management dataset the total condensed area invaded by all alien plant taxa was 28.44 km^2 (equivalent to 22.7% of the study area; Table 2.4). This was significantly more than the total condensed area of 2.43 km^2 measured in the Systematic dataset (equivalent to 1.9% of the study area; Table 2.4: Z = -14.711, p<0.001, r =0.606). All taxa, both widespread species such as *A. cyclops*, *A. saligna*, and localised species such as *A. longifolia* and *Pinus spp*., showed marked, highly significant differences (Table 2.4; p<0.001) in total condensed area invaded, with the Management dataset consistently reporting higher condensed area across all taxa (Fig. 2.4).

The condensed area of all alien plants in the WfW data totalled 15.84 km^2 (equivalent to 12.6% of the study area), which despite being 45% less than the Management dataset, was still significantly greater than the condensed area recorded in the Systematic dataset (Z = - 9.622, p<0.001, r = 0.513, Table 2.5). Like the Management dataset, the WfW data recorded widespread taxa such as *A. cyclops* and *A. saligna* as having significantly greater condensed areas (p<0.001, Table 2.5) compared to the Systematic data. The majority of localised taxa (e.g. *A. longifolia*, *L. laevigatum* and *Paraserianthes lophantha*) had similar condensed density estimates in the two datasets (Table 2.5; Fig. 2.4), but their spatial locations were poorly matched.

Table 2.2 Presence and absence of selected taxa recorded in the Systematic and Management datasets (n= 295). S+ indicates presence in the Systematic data; S- indicates absence in the Systematic data; M+ denotes presence in the Management data and M- denotes an absence from the Management data, with the resulting confusion matrix measures (defined in Sup. Mat. Table 2.3).

Taxa	**M+ S+ (a)**	**M+ S- (b)**	**M-S+ (c)**	**M-S- (d)**	**Accur-acy**	**Prevale-nce**	**Sensit-ivity**	**Specifi-city**	**Odds Ratio**	**Kappa (K)**	**TSS**
All taxa	266 90%	29 10%	0 0%	0 0%	0.90	0.90	1.00	0.00	NS	0.00	0.00
Acacia cyclops	188 64%	94 32%	7 2%	6 2%	0.66	0.66	0.96	0.06	1.71	0.03	0.02
Acacia longifolia	43 15%	38 13%	41 14%	173 58%	0.73	0.28	0.51	0.82	4.77	0.34	0.33
Acacia saligna	194 66%	91 31%	4 1%	6 2%	0.68	0.67	0.98	0.06	3.20	0.05	0.04
Eucalyptus spp.	9 3%	19 6%	21 7%	246 84%	0.86	0.10	0.30	0.93	5.55	0.24	0.23
Hakea spp.	0 0%	2 1%	37 12%	256 87%	0.87	0.13	0.00	0.99	0.00	-0.01	-0.01
Leptospermum laevigatum	15 5%	32 11%	20 7%	228 77%	0.82	0.12	0.43	0.88	5.34	0.27	0.31
Paraserianthes lophantha	19 6%	47 16%	27 9%	202 69%	0.75	0.16	0.41	0.81	3.02	0.19	0.22
Pinus spp.	55 19%	31 11%	30 10%	179 60%	0.79	0.29	0.65	0.85	10.59	0.50	0.50

Overall there was a large discrepancy between the Systematic and WfW data in the estimated budget required to control all invasive alien plants. The Systematic data estimated a person day requirement of ZAR 1.5 million while the WfW data produced a budget estimate of ZAR 9.8 million (Fig. 2.5; recognizing that additional travel and treatment costs are not included in these estimates). The discrepancy in required person day budget to treat invasive alien plants was similar for individual taxa. For example, *A. saligna* in the Management dataset had a total condensed area of 10.78 km^2 and the WfW dataset had a total condensed area 12.85 km^2, while the Systematic dataset recorded only 1.36 km^2 total condensed area (Tables 2.4 & 2.5). Cost estimates to treat *A. saligna* derived from the Management data would be ZAR 6.64 million and ZAR 7.92 million from the WfW data (Fig. 2.5). A person day costing based on the Systematic data indicates that a reduced budget of ZAR 0.84 million would be adequate to treat this species.

Table 2.3 Presence and absence of selected taxa recorded in the Systematic and WfW datasets (n = 176). S+ is presence in the Systematic data; S- is absence in the Systematic data; W+ is presence in the WfW dataset and W- is the absence in the WfW dataset with the resulting confusion matrix measures (defined in Sup. Mat. Table 2.3).

Taxa	**W+ S+ (a)**	**W+ S- (b)**	**W- S+ (c)**	**W- S- (d)**	**Acc-uracy**	**Preva-lence**	**Sensi-tivity**	**Speci-ficity**	**Odds Ratio**	**Kappa (K)**	**TSS**
All taxa	174 99%	2 1%	0 0%	0 0%	0.99	0.99	1.00	0.00	NS	0.00	0.00
Acacia cyclops	61 35%	19 11%	54 30%	42 24%	0.59	0.65	0.53	0.69	2.50	0.19	0.22
Acacia longifolia	24 13%	12 7%	61 35%	79 45%	0.59	0.48	0.28	0.87	2.59	0.15	0.15
Acacia saligna	142 81%	17 10%	7 4%	10 5%	0.86	0.85	0.95	0.37	11.93	0.38	0.32
Eucalyptus spp.	7 4%	10 5%	29 17%	130 74%	0.78	0.20	0.19	0.93	3.14	0.15	0.12
Hakea spp.	6 3%	5 3%	34 19%	131 75%	0.78	0.23	0.15	0.96	4.62	0.15	0.11
Leptospermum laevigatum	6 3%	8 5%	31 17%	131 75%	0.78	0.21	0.16	0.94	3.17	0.14	0.10
Paraserianthes lophantha	12 7%	16 9%	46 26%	102 58%	0.65	0.33	0.21	0.86	1.66	0.08	0.07
Pinus spp.	15 8%	7 4%	48 28%	106 60%	0.69	0.36	0.24	0.94	4.73	0.21	0.18

2.4 Discussion

Understanding the inherent strengths and weaknesses in data that are used to inform decision making will influence the long-term outcomes and sustainability of invasive alien plant management programmes (Cook *et al*. 2009) as data accuracy has a direct effect on the quality of management decisions made for control programmes. Although the accuracy of data collection is consistently emphasised in invasive alien plant control programmes globally (McNaught *et al*. 2008; Rew and Pokorny 2006), these data do not often meet the specific needs for which they are collected (Cook *et al*. 2009) or are inappropriately applied to multiple objectives due to budget and time constraints. However there are seldom multiple datasets available for PA managers to assess the extent to which data types and sources impact on achieving the desired outcome. In this study, the data compiled from three sources in TMNP allow for such detailed analysis.

The positive relationship between grain (size of the minimum mapping unit) and resultant species distribution (area of occupancy) (Foxcroft *et al*. 2009; McGeoch and Gaston 2002) was not properly considered in the Management and WfW datasets. While the datasets agreed on the occurrence of the most common invasive species at a landscape or PA scale (coarse grain), at a finer grain, the systematic sampling approach listed significantly more alien species, smaller distribution ranges of species and lower abundance of the common, widespread species. Not accounting for coarse grain of mapping when estimating area occupied by alien species has significant consequences for the management of alien species in terms of resource allocation and budget and can lead to the failure or delayed success of a control programme (Rejmánek and Pitcairn 2002; Wilson *et al*. 2013).

Table 2.4 Comparison of the total condensed area for selected taxa in the Management data (MD) and the Systematic data (SD). All differences are significant.

Taxa	**Mapping units (n)**	**Data-set**	**Total Condensed Area (km²)**	**Mean (km²)**	**Median (km²)**	***z***	***p***	***r***
All taxa	295	MD	28.44	9.64	4.26	-14.711	<0.001	0.606
		SD	2.43	0.82	0.13			
Acacia cyclops	295	MD	8.94	3.03	1.78	-14.504	<0.001	0.597
		SD	0.32	0.11	0.02			
Acacia longifolia	295	MD	3.19	1.08	0.00	-6.964	<0.001	0.287
		SD	0.52	0.17	0.00			
Acacia saligna	295	MD	10.78	3.65	0.71	-13.204	<0.001	0.544
		SD	1.36	0.46	0.02			
Eucalyptus spp.	295	MD	1.06	0.36	0.00	-3.437	<0.001	0.141
		SD	0.02	0.01	0.00			
Hakea spp.	295	MD	<0.01	<0.01	0.00	-4.521	<0.001	0.186
		SD	0.02	0.01	0.00			
Leptospermum laevigatum	295	MD	0.44	0.15	0.00	-4.616	<0.001	0.190
		SD	0.07	0.02	0.00			
Paraserianthes lophantha	295	MD	0.80	0.27	0.00	-6.228	<0.001	0.256
		SD	0.08	0.03	0.00			
Pinus spp.	295	MD	3.24	1.10	0.00	-7.962	<0.001	0.328
		SD	0.06	0.02	0.00			

The similarity in the species and their abundance collected by PA managers and WfW project managers is not unexpected. The WfW programme prioritises the control of the most abundant, widespread and thus visible species in the PA, which would also be known to the PA managers. However, the long-term success in controlling or eradicating invasive plant species requires an integrated approach (Foxcroft and McGeoch 2011). This includes prevention, early detection and rapid response being implemented in conjunction with on-going control efforts to enable a cost-effective and long-term viable approach (Hulme 2006; Simberloff 2009; Tu 2009; van Wilgen *et al*. 2011). Investing in fine scale and accurate data on alien species within PA's would inform all of these objectives. However, PA managers often prefer experience- based information for decision making (Cook *et al*. 2009; Pullin *et al*. 2004), and even when presented with evidence-based data are reluctant to alter their decisions (McConnachie and Cowling 2013). The inherently social context of the PA decision making environment (including PA policies, management structure, stakeholder base, priorities and capacity) is one of the main reasons given for not implementing evidence-based actions (Ntshotsho *et al*. 2015). In addition, the over-prediction of species presence in control programme plans may appear beneficial to a risk averse manager, who perceives inclusion of false presences as preferable to missing invasion sites (false absences), though we show the latter also has associated risks. Shortfalls in the current PA manager and WfW datasets and their consequences for effective and efficient alien management are discussed below.

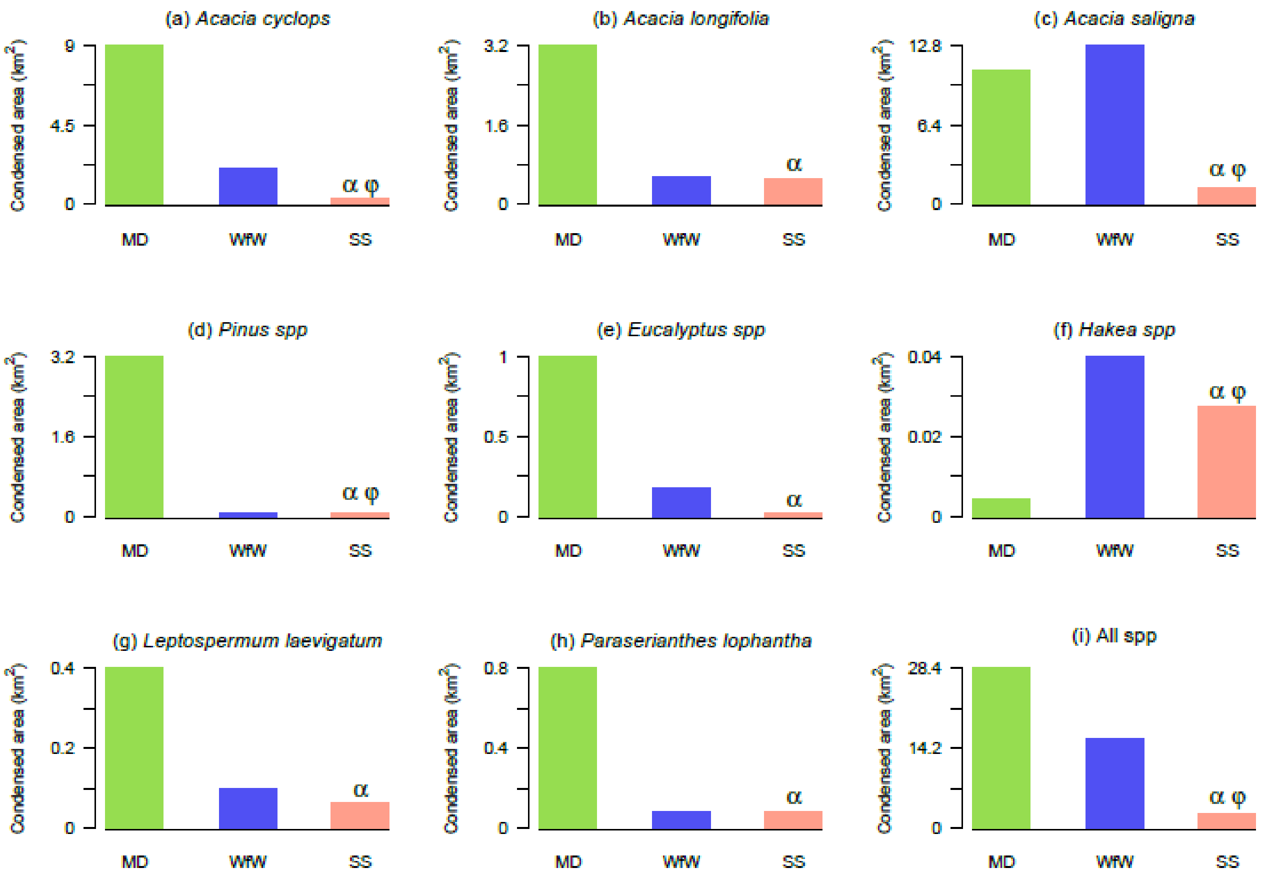

Fig. 2.4 Total condensed area (km^2) for taxa in the Management (MD), Working for Water (WfW) and Systematic (SD) datasets where (α) indicates a significant difference between the Systematic data and the Management data (p<0.01; Table 2.4) and (φ) a significant difference between the Systematic data and the WfW data (p<0.01; Table 2.5)

2.4.1 Incomplete species lists

Large scale alien control programmes typically target common species due to information available to inform programme development and control plans. Incomplete alien plant species lists however, may result in less common species being undetected within a PA (McGeoch *et al*. 2012), losing opportunities for eradication of small populations before they become widespread (Leung *et al*. 2002; Rejmánek and Pitcairn 2002). For example, the systematic sampling detected *Callistemon salignus* (white bottlebrush) and *Centranthus ruber* (red valerian) at a few sites, totalling around 0.01 km^2 that could be targeted for eradication. As urban development and human populations increase around parks, adding to the pathways for alien species, the importance of accurate alien species listing is heightened (Alston and Richardson 2006; Spear *et al*. 2013). The systematic sampling recorded nine species of ornamental garden plants occurring in the PA, along its urban boundary, that were not listed in the WfW or PA mangers datasets (Sup. Mat. Table 2.4). Species accumulation curves indicate that there are likely even more species than indicated by the systematic sample (no asymptote reached, Fig. 2.3), highlighting the need for continued systematic monitoring to detect new invasions. In contrast, both management datasets reached their total species complement after inclusion of few sites (Fig. 2.3), indicating poor ability to identify rarer species.

Table 2.5 Comparison of the total condensed area for selected taxa in the WfW dataset (WfW) and Systematic data (SD). Species where significant differences were detected are indicated in bold.

Taxa	Mapping units (n)	Data-set	Total Condensed Area (km^2)	Mean (km^2)	Median (km^2)	*z*	*p*	*r*
All taxa	176	WfW	15.83	9.00	3.80	-9.622	<0.001	0.513
		SD	2.43	1.38	0.56			
Acacia cyclops	**176**	**WfW**	**2.00**	**1.14**	**0.00**	**-4.882**	**<0.001**	**0.260**
		SD	0.32	0.18	0.02			
Acacia longifolia	176	WfW	0.54	0.30	0.00	-0.822	0.411	0.044
		SD	0.52	0.29	0.00			
Acacia saligna	**176**	**WfW**	**12.85**	**7.30**	**2.24**	**-9.495**	**<0.001**	**0.506**
		SD	1.36	0.77	0.10			
Eucalyptus spp.	176	WfW	0.18	0.10	0.00	-0.191	0.848	0.010
		SD	0.02	0.01	0.00			
***Hakea* spp.**	**176**	**WfW**	**0.03**	**0.02**	**0.00**	**-2.940**	**<0.01**	**0.157**
		SD	0.02	0.01	0.00			
Leptospermum laevigatum	176	WfW	0.11	0.06	0.00	-1.213	0.225	0.065
		SD	0.07	0.04	0.00			
Paraserianthes lophantha	176	WfW	0.08	0.04	0.00	-1.344	0.179	0.072
		SD	0.08	0.04	0.00			
***Pinus* spp.**	**176**	**WfW**	**0.05**	**0.03**	**0.00**	**-3.643**	**<0.001**	**0.194**
		SD	0.06	0.03	0.00			

Complete species lists are also important to enable prioritisation and risk assessment (McGeoch *et al*. 2012). Currently the data from the PA managers or WfW cannot be scaled up to the organisational level to accurately inform national and international indicators relating to species richness and rates of new species arrival1. This results in a missed opportunity that the WfW project can play in the global management of alien species and responses to national and global targets (McGeoch *et al*. 2010). Due to the strength of the systematic sampling approach, the Systematic data can readily be integrated with existing alien species lists at a national and international level (Foxcroft *et al*. 2017; Spear *et al*. 2011).

2.4.2 Species distribution and grain of data collection

Common pitfalls of control programmes include the ability to adequately detect target species prior to treatment and the lack of detection when re-infestation of the treated area from adjacent non-treated areas occurs (Rejmánek and Pitcairn 2002). The coarse grain of the Management and WfW data that are currently used in the PA's alien plant control programme suffer from both these deficiencies. Inadequate detection of the spread of a species across the PA in these management datasets means that new or expanding populations will go undetected. For example, the systematic sampling recorded 41 additional sites for *A. longifolia* where the species had not historically been recorded. Coarse (large) grained data tended to overestimate the occupancy of taxa in this study. Consistent over-estimation of occurrence of widespread species such as *A. cyclops* and *A. saligna* in the management datasets can result in overstating the core invaded area while inadequately delineating outlying satellite areas (He and Gaston 2000; McGeoch and Gaston 2002). Data used by WfW and PA managers to direct the control of alien invasive plants therefore cannot be used to monitor and evaluate the effectiveness of control within monitoring frameworks, for example the Thresholds of Potential Concern Adaptive Management framework (Foxcroft 2009).

2.4.3 Inaccuracy in estimation of species abundance

Measures of abundance (number of individual plants per unit area) are important for developing and monitoring the strategic goals of invasive plant control programmes through understanding the nature and scope of management interventions relative to the impact that the species will have (Latombe *et al*. 2016). In particular, WfW funding is allocated to areas in relation to WfW-estimated alien density data, and until funds are exhausted. This use of funds, in combination with inaccurate data, means that funding may be exhausted before the real priorities have been allocated sufficient funding. For example *A. longifolia* was found to occur in 61 more management units than recorded in the WfW dataset (Table 2.3), meaning these areas would not have been allocated sufficient funding. Key actions recommended for alien plant control programmes include i) reducing the residency time of new invaders, ii) identifying, and focusing on areas of high propagule pressure and iii) maintaining or locally eradicating invaders from lightly invaded areas (Tu 2009). Due to the incorrect abundance estimates in the WfW and Management data, inefficient application of control methods, and improper prioritisation of target areas, misallocation of resources can be expected. The substantial overestimate of costs resulting from WfW data, when compared to systematic sampling data, illustrates the potential extent of the problem. One might expect that a risk adverse approach of overestimating the workload would ensure that areas are completely cleared of alien species. However, the project area still has a wide occurrence of alien species present which means that the currently inflated budget maybe obscuring the appropriate or more effective control methodologies. The misalignment of resource allocation can have long-term negative implications for a control programme where budgets and resources are often limited (Krug *et al*. 2010; Moore *et al*. 2011).

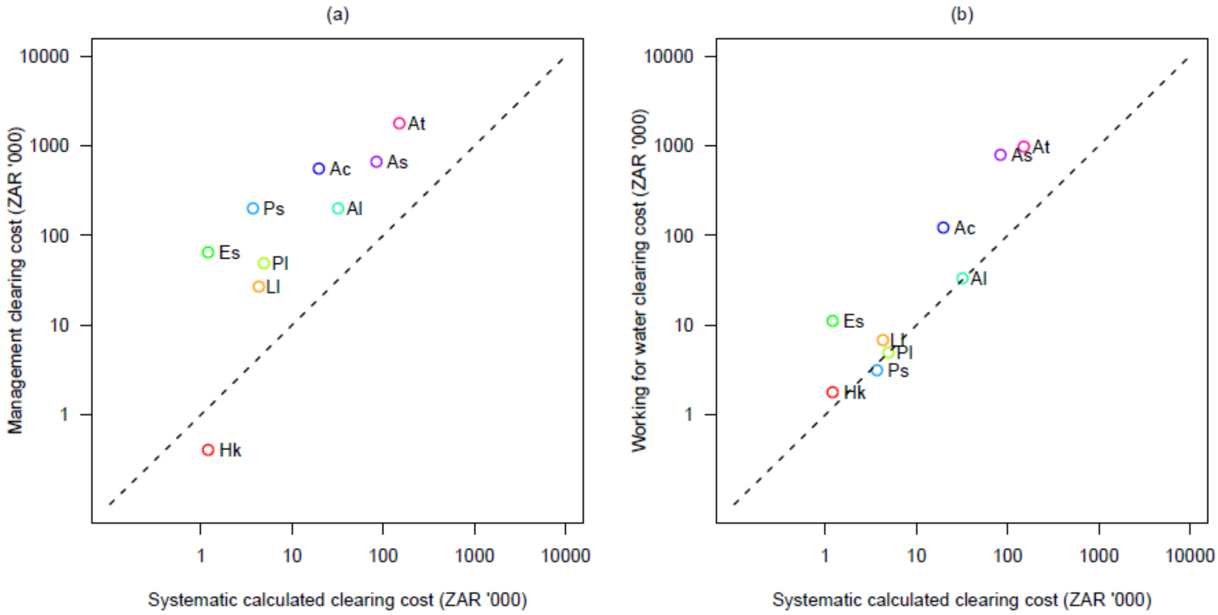

Fig. 2.5 Calculated total clearing cost form the Systematic data and (**a**) the Management data and (**b**) the Working for Water (WfW) data. At-All selected taxa (combined); Ac-*Acacia cyclops*; Al-*Acacia longifolia*; As-*Acacia saligna*; Es-*Eucalyptus spp*.; Hs-*Hakea spp*.; Ll-*Leptospermum laevigatum*; Pl-*Paraserianthes lophantha*; Ps-*Pinus spp.*

Benefits of Systematic Sampling

In managing alien control programmes there is often a budget trade-off between funds available for field sampling and control operations, with intensive sampling being avoided due to the time constraints, costs, and resources required (Hauser and McCarthy 2009). While a variety of invasive alien plant surveys are warranted depending on the management objectives (Dewey and Andersen 2004), survey approaches for alien plant programmes covering large areas should emphasise accurate, consistent and repeatable methodologies (McNaught *et al*. 2008). Currently both the WfW and PA managers approaches fall short of these requirements and produce a skewed picture of the clearing effort and resources required. The poor distribution and abundance records from the WfW and PA manager data commits funding to low priority areas, resulting in inefficient spending. This limits opportunities to expand clearing to additional species, areas, early detection and rapid response (EDRR) programmes and ironically the monitoring that would enable this. Candidate EDRR not recorded by managers in this study would include for example *Acacia pycnantha*, *Centranthus ruber* and *Callistemon salignus*. Using the systematic data it would be possible to cover more management units per year, potentially enabling the achievement of a long-term management goal where every area is treated at least once in a two year cycle. This goal was not being achieved using the management data described.

In addition to the systematic sampling addressing shortfalls in accuracy, this approach enables comparisons to be made across time and as needed through repeated data collection. This will allow for better understanding and management of alien plant species, as the systematic sampling accurately determines where alien plant species are not present in the PA, either though successful control over time or delineation of areas that have not yet been invaded. The systematic mapping exercise cost approximately ZAR 100,000 (<0.1% of the control budget at the time, although this could increase in areas of higher alien density and more mountainous terrain). We propose that when viewed in comparison with the potential budget savings enabled by more accurate plans, the systematic sampling approach is a cost effective addition to the current management approach, providing data that can readily feed into local, national and international monitoring programmes.

2.5 Conclusion

Differences in alien species datasets are expected due to differences in the purpose for and scales at which data are collected. However, as we illustrate here, the urgency of required management actions often results in implementation prior to gaining a full understanding of the problem. Our systematic sampling provided estimates of species richness and abundance that differed by orders of magnitude from the data that are used to make management decisions. While managers may perceive the time and cost required to undertake detailed landscape-scale surveys as wasteful when something could be done about the problem in the interim, we argue that properly assessing the true scope of the problem is critical to optimizing the impact of control work and outputs for budgets spent. Fine-scale alien plant surveys can be used to establish baseline alien plant species information that is suitable for implementing long-term monitoring programmes to assess change as a result of management interventions and environmental factors. This would overcome the current situation where existing management datasets do not allow for the determination of the source, extent, dynamics and realistic clearing costs of alien plants.

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2.8 Supplementary material

The following supplementary Information may be found in the supplementary section accompanying this thesis or along with the online version of the published article.

Sup. Mat. Table 2.1. Standardised classes used to group the relative measures of abundance (percentage cover, density and descriptive) for invasive alien plants invasions from the Management, Working for Water (WfW) and Systematic datasets

Sup. Mat. Table 2.2. Confusion matrix (*sensu* – Fielding and Bell 1997) for comparing presence and absence data from the Management or WfW datasets to the Systematic dataset.

Sup. Mat. Table 2.3. Confusion matrix measures derived from the confusion matrix for the presence and absence data from the Management or WfW datasets and the Systematic dataset. Notation as per Table 2.2.

Sup. Mat. Table 2.4. Alien Species list: Comparison of Alien Plant Species presents between the Systematic Mapping, Working For Water and Management Data, where '1' denotes the presents of that species in the data set and '*' is where data at a Genera level was been collected.

Chapter 3.

Scenarios for the management of invasive *Acacia* species in a protected area: implications of clearing efficacy

This chapter is under review in the *Journal of Environmental Management*.
Cheney C., Esler K.J., Foxcroft L.C. & van Wilgen N.J. (2019). Scenarios for the management of invasive *Acacia* species in a protected area: implications of clearing efficacy. *Journal of Environmental Management*. Under review.

Abstract

In many protected areas in South Africa, invasive Australian *Acacia* species pose on-going management challenges, perpetuating high long-term management costs. Due to limited availability of resources, conservation actions need to be prioritised within and across Protected Areas (PA). Comprehensive datasets spanning over 20 years from the Table Mountain National Park are used to model long-term outcomes of clearing *Acacia* species at different levels of management clearing efficacy. We test a 50 year outlook based on current and 38 incremental levels of management efficacy, ranging from 5-100%, to assess under which scenarios a management goal of reducing *Acacia* density to below 1 plant per hectare for the 22,671 hectare protected area is achieved. With the current clearing resources and maximum clearing efficacy (100% control), it would take between 32 to 42 years to attain the management goal. The modelling revealed two main drivers of *Acacia* persistence. Firstly, germination of seeds added to the seedbank from standing plants made a significantly larger contribution to future clearing requirements than fire stimulated seed germination or the existing (pre-management) seedbank. Secondly the relationship between the number of hectares and management units that could be treated and the efficacy of the treatment was non-linear. When clearing efficacy was decreased from 100% to the current project minimum target of 80% efficacy, the goal was not achieved in all areas, but the area that reached a density of <1 plant per hectare was significantly reduced to 53% of the PA for the simulated 50 years. Results emphasize the need to differentiate between increasing financial resources and increasing efficacy. While increasing financial resources allows for increased effort, this is of little value for *Acacia* management in the absence of an increase in clearing efficacy, as low quality implementation perpetuates the need for large budgets over time. Conversely, improving efficacy allows for decreased budget requirements over time, allowing fund re-direction to additional areas of alien species management such as the early detection and rapid control of newly introduced species.

Keywords:
Alien species, budget requirements, clearing effectiveness, protected area, simulation model, Table Mountain National Park

3.1 Introduction

Protected area (PA) managers are required to respond to a range of biodiversity threats and pressures, including legal and illegal harvesting of resources, pollution and invasion by alien species (Wilson *et al.* 2007; Schulze *et al.* 2018). Conservation targets for managing these threats and pressures are often set through a range of objectives with measureable thresholds (Biggs *et al.* 2003; Foxcroft 2009). The degree to which the specific targets and desired outcomes are achieved influences the overall management effectiveness of the PA (Watson *et al.* 2014). A frequent argument for not meeting conservation objectives is the limited availability of resources or funding (Frazee *et al.* 2003; Bruner *et al.* 2004; van Wilgen *et al.* 2016a). This results in the need to prioritise conservation actions within and across PAs, or to confine actions to particular or vulnerable sections alone. For example, 'conservation triage' (accepting biodiversity loss in lower priority areas over gains or sustained benefits in higher priority areas) has been proposed as an appropriate strategy for apportioning conservation budgets where funds are limited (Downey *et al.* 2010; van Wilgen *et al.* 2016a).

Within South Africa's Cape Floristic Region (CFR), invasive alien plants (IAP) pose one of the largest direct threats to biodiversity and ecosystem services (Richardson *et al.* 1996; Gaertner *et al.* 2009; Le Maitre *et al.* 2011). For example, a conservation status assessment of the region's flora in 2009 found more than 1,000 native plant species were threatened by IAPs (Raimondo *et al.* 2009). To address the negative impact of IAPs, the South African government has for more than 20 years, funded a national invasive alien plant control programme, 'Working for Water' (WfW). A main aim of the programme is to restore and maintain habitat structure and function to mitigate the loss of ecosystem services, especially water, through the control of invasive alien plants (van Wilgen *et al.* 2012). Depending on the implemented management approach, high level budget estimates for IAP control in the CFR are projected to be in excess of ZAR 900 million (1 US$ ~ 16 ZAR in 2017) over the next 20 years (van Wilgen *et al.* 2016a).

Specific IAP genera pose on-going management challenges, perpetuating these high long-term management costs (McConnachie *et al.* 2012), including Australian *Acacia* species which are particularly difficult to control. *Acacia* is a highly diverse genus (~1012 species, Richardson *et al*. 2011), over 20 of which are highly invasive globally (Richardson & Rejmánek 2011). These plants tend to dominate interspecific interactions, having profound impacts on ecosystem processes (e.g. altered community dynamics though changed fire regimes and altered nutrient cycling though changed soil properties) (Le Maitre *et al*. 2011). The genus is a model group for studying many facets of alien plant invasions (Richardson *et al.* 2011; van Wilgen *et al.* 2011). The successful establishment and long-term persistent invasion of *Acacia* species has been attributed to several factors, including early maturity (<2 years), prolific production of long-lived seed (up to 12,000 seeds/m^2/annum) and prolific post-fire germination (Marchante *et al.* 2010; Souza-Alonso *et al.* 2017; Strydom *et al.* 2017).

The Table Mountain National Park (hereafter TMNP or the park) is a well-known protected area in the CFR biodiversity 'hot spot' (Cowling *et al.* 1996), with 158 endemic plant species (Helme & Trinder-Smith 2006). However, the park is facing severe pressure from the invasion of many alien species from the surrounding landscape (Spear *et al.* 2013). Despite a well-established IAP control plan, with over 20 years of continuous implementation, supported by extensive resources, the programme goal of achieving a 'maintenance level' of control, where plants occur at a density of less than one plant per hectare (10,000m^2) (Le Maitre & Versfeld 1994) has yet to be reached (Cheney *et al.* 2018, Chapter 2). This goal, which essentially seeks to reduce Acacias to being 'rare' in the landscape (Le Maitre & Versfeld 1994), is considered feasible within current management time frames and will ensure significant reduction in ecological impact. A common management reaction is to seek additional funding to achieve this maintenance control level, but with studies suggesting that clearing implementation is sub-optimal (McConnachie *et al.* 2012; van Wilgen *et al.* 2016a; Kraaij *et al.* 2017), it is uncertain to what extent larger budgets will address the problem.

We develop a spatio-temporal population model to investigate clearing scenarios for *Acacia* species in TMNP. We assess the potential impact of the currently-available resources under current and incremental levels of management clearing efficacy and determine the long-term resource requirements for optimal management and return on investment. Specifically, we aimed to:

- Assess whether the available resources are adequate to successfully control *Acacia* species in the long-term;
- Determine the extent to which present resources impact current standing plants versus reducing the potential for future invasions (i.e. plants and seedbank increases that result from uncleared plants or remnant seedbanks)
- Determine the optimal clearing efficacy thresholds that achieve the conservation target of reducing invasions to a maintenance level of less than one plant per hectare.

3.2 Materials and methods

3.2.1 Study area

Table Mountain National Park is located on the Cape Peninsula, South Africa, and covers approximately 25,000 ha. For model simulation and analysis we considered 809 management units (Working for Water nBal polygons, Chapter 2) that cover 91% (22,671 ha) of the PA with only the very steep, largely inaccessible areas not included. Each management unit (WfW nBal) currently has, or historically had, different levels of invasion by a range of alien plant species. The dominant alien taxa in TMNP comprise woody alien species from the genera *Acacia*, *Pinus* and *Hakea*. For the purpose of this model only *Acacia* species are considered as they are the most common alien plants in the PA (Cheney *et al.* 2018, Chapter 2) and have been suggested to pose the greatest threat to TMNP's biodiversity (Richardson *et al.* 1996; Higgins *et al.* 1999).

2.2 Model description

A spatio-temporal, polygon-based, population model was developed for the park using Visual Basic in MS Excel (2013 v15.0). The model simulates *Acacia* population size, age structure and area invaded within each management unit. The model's purpose is to estimate the potential future outcomes of the alien plant control programme by varying clearing efficacy (effective permanent removal of alien plants) in relation to two drivers of *Acacia* persistence, namely, ecosystem processes (fire) and plant population dynamics (age, density dependence and seedbank dynamics) (Le Maitre *et al.* 1996; Krug *et al.* 2010). Twelve model scenarios were simulated based on the current levels of *Acacia* abundance as determined by fine scale population data (Cheney *et al.* 2018, Chapter 2), historic fire records spanning 35 years (Forsyth & van Wilgen 2008), and 20 years of alien plant control history for TMNP (van Wilgen *et al.* 2016a).

As a model starting point, population data on *Acacia* species were collected for each management unit as part of a fine scale systematic monitoring programme (Cheney *et al.* 2018, Chapter 2). This entailed sampling 10,057 plots and counting the number of individuals present per alien plant species. The *Acacia* species included in the model were clustered into two groups based on their response to management, i) species that readily coppice if not treated correctly (e.g. through the incorrect clearing method or application of herbicides), such as *Acacia saligna*, *A. mearnsii*, *A. melanoxylon* and ii) species that do not readily coppice, namely *Acacia cyclops* and *A. longifolia*.

The simulation model comprised six time-based modules relating to the management, population dynamics and ecology of *Acacia* species (Fig. 3.1). The population parameters (growth rates, seed production and seed germination) for the coppicing or non-coppicing species were modelled primarily on *A. saligna* for coppicing species and on *A. cyclops* for non-coppicing species. Each module simulated the population dynamics, clearing efficacy and ecological processes influencing the clearing of *Acacia* and each could be included (turned-on) or excluded (turned-off) in a simulation run. For example, the fire module or the seed production module could be turned on or off to test the incremental effect that these processes have on the overall model outputs.

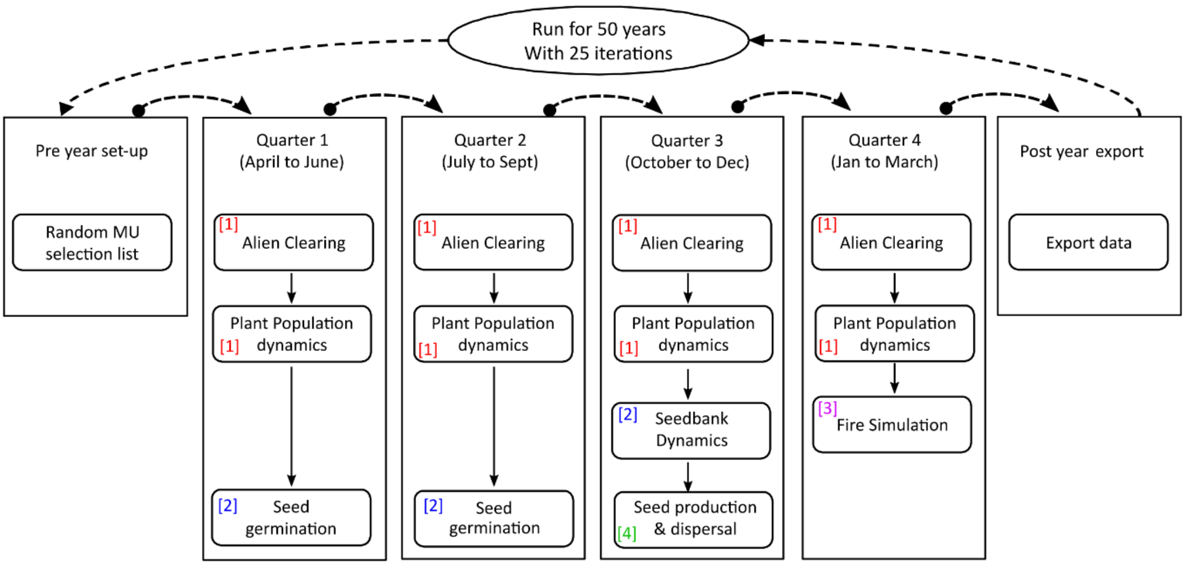

Fig. 3.1 Overview of the modules in the simulation model and the equivalent calendar quarter in which they are called. The growing season is approximated as April to September, during the peak rainfall period. *Acacia* plants flower at the end of the growing season and release seed during October to December. Most natural fires occur in the summer to early Autumn (January to March) which stimulate seeds to germinate from the soil seedbanks following the first rains in April. Numbering [1-4] denote model scenarios described in section 3.2.4 and Figure 3.2.

The model was run for the equivalent of 50 simulation years. Within a simulation year, the model incremented quarterly, in alignment with current IAP clearing operations, *Acacia* population dynamics and ecological processes (Fig. 3.1). Quarter 1 spanned from April to June, with the relevant modules of alien clearing, plant population dynamics and seed germination called within this timeframe. Similarly the modules called in quarter 2 aligned with the alien clearing and plant population dynamics that would occur between July and September.

3.2.3 Module descriptions

3.2.3.1 Alien plant clearing module

The clearing module (Sup. Mat. Fig. 3.1) simulated the control of *Acacia* based on WfW clearing norms and standards (Neethling & Shuttleworth 2013). The standard resource unit for alien plant control is based on the number of person days required to treat an invaded area. The TMNP's 2017 annual allocation of 40,128 person days (ZAR35.4 million, 1 person day = ZAR350) was used as the available resource with which to undertake clearing (Working for Water 2017). The allocation of person days to each management unit was calculated based on the recorded *Acacia* abundance and age class of individuals in each management unit (Neethling & Shuttleworth 2013). The management units for clearing were randomly selected at the beginning of the simulated year. This random selection removes any management bias and allows for the generation of baseline clearing success. The project person days were divided per quarter until the total available person days of 40,128 was reached. Any unused person days in a simulation year were not carried over to the next simulation year. The random selection of management units held 'no memory' of clearing history and each management unit was available for selection at the start of each simulation year. Clearing efficacy was varied for 38 incremental levels of efficacy, from 5-100%, which was taken as the probability that each plant present in a management unit would be treated correctly (i.e. killed via the correct treatment methodology) (Sup. Mat. Fig. 3.1), to test the effect that clearing efficacy would have on achieving management outcomes.

3.2.3.2 Fire simulation module

The fire module (Sup. Mat. Fig. 3.2 and Sup. Mat. Table 3.2) determined i) the number of fire ignition points, ii) the size of individual fires and iii) the total area to be burnt per fire season (quarter 4, January to March). At the beginning of the fire season, the number of fire ignition points and the total area expected to be burnt was determined as a function of the Normal distribution of the fire history dataset of TMNP between 1980 and 2016 (Table Mountain National Park Fire history records 2008-2016, unpublished data). Because certain areas are more prone to frequent burning, management units were assigned to one of five fire frequency classes based on the number of ignitions recorded in the management unit's fire history (Sup. Mat. Table 3.1). For each fire ignition, a fire frequency class was selected at random, adjusted for the probability of each class burning. The management unit within the selected fire frequency class was then randomly selected. To determine if fire ignition would result in the management unit burning, a probability function based on vegetation age was calculated (Sup. Mat. Table 3.2), where vegetation 25 years and older had a probability of 1 (would always burn) and vegetation less than 5 years old would have a probability of 0 (Forsyth & van Wilgen

2008; Van Wilgen *et al.* 2010). Once burning was initiated, additional management units directly adjacent to the source management unit with a vegetation age of 5 years and older burned until the expected size of the individual fire had been reached.

Fire intensity for the individual fires was varied by equating the burn intensity to Fire Danger Index (FDI; South African Government Gazette 37014 No. 1099 of 2013; Sup. Mat. Table 3.3). The FDI, was calculated based on available summer climate data between 1990 and 2008 (2,296 days) from the South African Weather Services' Cape Point weather station. The fire intensity for an individual fire was assigned by selecting one of the days at random. The intensity of the fire effects the proportion of plant mortality between 0.1 (Low fire intensity) to 1.0 (Extreme fire intensity), (Sup. Mat. Table 3.3) as well as seed bank dynamics (see 3.2.3.4). Mortality is assumed to be constant across tree age classes.

3.2.3.3 Seed production and dispersal module

This module simulated the annual rate of seed accumulation within and dispersal to adjacent management units. For plants between the age of 8 and 30 years old, the annual accumulation rate was set to 360 seeds/m^2 (range: 340-380 seeds/m^2) for non-coppicing *Acacia* and 4,250 seed/m^2 (range: 4,040-4,460 seeds/m^2) for coppicing trees (Holmes *et al.* 1987; Correia *et al.* 2014; Strydom *et al.* 2017). For trees younger than 8 and older than 35 years, seed accumulation was reduced using logistic equations (Sup. Mat. Table 3.4). *Acacia* seed dispersal is largely localised, with up to 5% of the annual seed production available to disperse to adjacent areas (Rebelo *et al.* 2013; van Wilgen *et al.* 2016a). Five percent of seeds were made available to disperse to adjacent management units and allocated based on the percentage of common boundary between the seed source and other units.

3.2.3.4 Seed bank dynamics

This module accounted for the seeds in the soil profile, i.e. litter, top soil layers (generally up to 10cm deep) and deep soil layers (greater than 10cm deep). Initial seedbank size was estimated for each management unit by reviewing both clearing and fire history of the management unit. The post-fire residual seed bank of each management unit was taken as between 5-15% of the density of plants that had germinated as a result of the last fire in the management unit (Holmes *et al.* 1987). This seedbank was then adjusted based on the clearing history of the management unit, where additional seed was added to the seedbank in areas where no clearing had taken place within a two year period, because adult plants produce seed and replenish seedbanks. These initial starting seedbank sizes were randomly varied by 5% at the start of each model simulation.

Seeds are deposited through seed production and seed dispersal into the litter layer, where they are held for a year (Milton & Hall 1981; Richardson & Kluge 2008; Strydom *et al.* 2012). Seeds move into deeper soil layers at rate of 10% per year until they reach deep storage after 10 years and are unavailable for germination, except in extreme fire conditions (Holmes 1990; Richardson & Kluge 2008; see Sup. Mat. Table 3.3). An upper limit of seedbank density (seed saturation) of 12,000 seeds /m^2 was set for each management unit (Milton & Hall 1981; Strydom *et al.* 2012; Strydom *et al.* 2017; Sup. Mat. Table 3.5). Within the model, seeds undergo natural decay from the seedbank at a rate of between 10-17%. (Higgins *et al.* 1997; Richardson & Kluge 2008). The model varied fire intensity which removed seeds from the seedbank at differing rates (due to incineration, Richardson & Kluge 2008), for example low intensity fires (FDI<20) only affected the upper soil layers, while extreme fires (FDI>75) affected both the upper and deeper seedbank layers (Sup. Mat. Table 3.6).

3.2.3.5 Seed germination

This module simulated seed germination. A small percentage (up to 3%) of non-coppicing *Acacia* seeds germinate after two years in the seedbank (Holmes *et al.* 1987). Clearing of dense stands of aliens can trigger larger recruitment of seedlings (75-95% of the seedbank) for non-coppicing *Acacia* species and a small proportion of seedling recruitment (1-5% of seedbank) for coppicing *Acacia* species (Holmes *et al.* 1987). The majority of seeds germinate in the winter rainy season (quarter 1 and 2 in the simulation model), following a fire event where up to 95% of the seedbank in the top soil layers and up to 10% of the seedbank in the deep soil layers can germinate depending on the intensity of the fire (see Sup. Mat. Table 3.6 for the effect of fire intensity, as measured by the FDI, on post-fire seedbank mortality and germination rates).

3.2.3.6 Plant population dynamics

The population dynamics module accounted for the mixed age plant population within each management unit and set population parameters that bound the population within observed limits from published sources (Sup. Mat. Table 3.5). These dynamics included maximum seed bank and seedling density (Milton & Hall 1981; Holmes *et al.* 1987; Strydom *et al.* 2017), density dependent competition (Le Maitre & Versfeld 1994), age specific mortality, age dependent seed production (Holmes 1990; Strydom *et al.* 2017), rates of increasing or decreasing invasion and regrowth from ineffective alien clearing (van Wilgen *et al.* 2016a), as determined by the efficacy level set for the particular model.

3.2.4 Simulation Scenarios

To determine the effect of different ecological parameters (as determined by the key model components) and clearing efficacy on *Acacia* population outcomes, four simulation scenarios were run on each of three clearing efficacy levels (varied within the Alien plant clearing module), resulting in twelve simulation outputs. Each scenario included sequential addition of key ecological processes (scenario 1: impact of clearing only, scenario 2: scenario 1 + seed germination, scenario 3: scenario 1 & 2 + fire and scenario 4: scenario 1 to 3 + seedbank replenishment by mature plants; Fig. 3.1). While biologically unrealistic, separating these biological processes can pinpoint the most influential drivers that determine management success or failure. The three levels of clearing efficacy for each scenario were (i) 1.0 for all Acacias (i.e. all plants present in a managed unit were treated 100% correctly); (ii) a mean of 0.8 (Range: 0.6-1.0) across species, which is considered the minimum quality standard for the PA (Working for Water 2015), and (iii) a mean of 0.77 (SD: 0.08) for non-coppicing taxa and 0.54 (SD: 0.15) for coppicing taxa, which is the mean project efficacy (MPE) currently observed for the clearing programme (Working for Water 2018).

Due to the stochastic nature of some of the model variables, the four different scenarios were run for 25 iterations at each of the three efficacy levels. The mean number of person days required by each scenario was considered as the requirement to manage the sub-set of model conditions. The expected change in person days required between two successive simulation scenarios would be the result of the additional conditions added by each scenario.

3.2.5 Clearing efficacy thresholds

The management goal was set to have all management units in TMNP in a maintenance state, where *Acacia* density is <1 plant per hectare, thus classing *Acacia* species as ‘rare’ in the landscape according to the WfW standards (Le Maitre & Versfeld 1994). Fine-scale population data for the park (Cheney *et al.* 2018) found 161 (20%) of the management units and 5,646 hectares (25%) in a maintenance state. Clearing efficacy is expected to impact on the likelihood of achieving this goal, but the relative impact of a given reduction in efficacy on management ability to clear areas is unknown. To test the relationship between clearing efficacy and the extent of *Acacia* invasion, 15 iterations of the fourth simulation model (including all modules) were run at 38 incremental levels of efficacy, from 5-100%. The mean number of years and the cumulative number of person days taken to reach the management goal was calculated at each level of efficacy. Where the management goal was not obtained for a model-run within the 50-year period, the number of management units that had reached the target and the cumulative number of person days used by the end of year 50 was calculated. Model outputs were regressed against each clearing efficacy level. Regression models were fitted to the resultant curve to assess the nature of the relationship between efficacy and clearing outcomes, with the best fit relationship chosen using the Akaike information criterion (AIC).

3.3 Results

3.3.1 Current and Future Resource Allocation

At 100% clearing efficacy, clearing only the current distribution of standing *Acacias* (Scenario 1) to below <1 plant per hectare across all management units would take only 1.8 years (SD=0.4), using 48,590 (SD=5,296) person days (Fig. 3.2a; Sup. Mat. Table 3.7). When clearing efficacy was lowered to 80%, both the time taken (19.1 years, SD=0.4) and the person days required (292,370, SD=4,512) to reach the management goal increased significantly. At current project efficacy rates (approximated across the groups at 66%), clearing only the standing plants would take 25.2 years (SD=0.4), requiring 377,205 person days (SD=5,388).

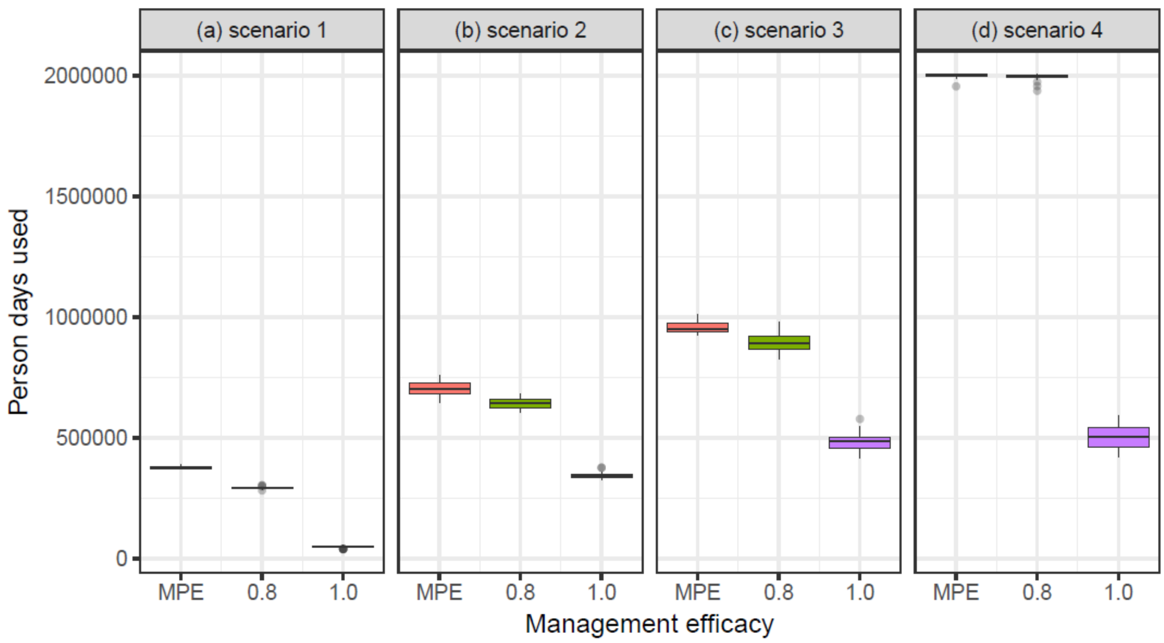

Fig. 3.2 The person days utilised after 50 simulation years to clear: (a) Scenario 1: current standing plants; (b) Scenario 2: current standing plants (a) plus seedlings germinating from non-dormant and post clearing operations; (c) Scenario 3: current standing plants and seedlings germinating from non-dormant post clearing operations (a & b) plus seedlings geminating post-fire; (d) Scenario 4: all propagules considered in a-c, plus plants resulting from additional seed being added to the seedbank from the current population; under 100%, 80% and the mean project efficacy (MPE, approximated across coppicing and non-coppicing species as 66%). For all scenarios, MPE levels required significantly more person days than higher efficacy scenarios, *p* < 0001.

Clearing the seedlings that germinate post-clearing (Scenario 2, Fig. 3.1) required an additional 23 years (in total 24.7 years, SD=2.5, requiring 344,462 person days, SD=13,231) when clearing was 100% effective (Fig. 3.2b, Sup. Mat. Table 3.7). A reduction in efficacy to current implementation levels would require 42.2 years (SD=2.4) and 706,235 person days (SD=31,152). The addition of clearing requirements from seed germination following fire events (Scenario 3) would require an additional 12 years (36.6 years, SD=4.2, and 482,496 person days, SD=36,642.0, in total) at 100% efficacy (Fig. 3.2c, Sup. Mat. Table 3.7). With the addition of fire-induced seedling germination, the management goal was not achievable in all areas with efficacy below 100%. At 80% efficacy, the time taken to achieve the desired target approached 50 years, with an average of only 804.6 (SD=3.5) of a possible 809 management units (mean area of 22,645 hectares, SD=18.8) reaching the goal of < 1 plant per hectare. Similarly, at the current level of efficacy, the management target was only met within a mean of 798.5 management units (SD=8.4), by the end of the 50 years simulation, utilising approximately 957,883 person days (SD= 22,345.5).

When implementing the full model (Scenario 4), the first year in which invasions across all management units reached the desired level of < 1 plant per hectare was 37.2 years (SD=5.3) at a clearing efficacy of 100%. This clearing required a mean of 507,475 person days (SD=50,163) (Fig. 3.2d; Sup. Mat. Table 3.7). Neither the 80% nor current project efficacy levels resulted in a long-term reduction of *Acacia* abundance. At 80% efficacy, after 50 simulation years, 344.1 (43%) management units (SD=54.7) and 58% of hectares achieved < 1 plant per hectare, but required a mean of 1,992,947 person days (SD=16,203). The number of management units reaching the maintenance goal was reduced to 285.4 (SD=53.9, 35%) covering 55% of hectares at current mean management efficacy requiring a mean of 2,000,082 person days (SD=10,366) over 50 years.

For the full model (Scenario 4) at 100% effective control, the current standing alien plants required 9.6% of the utilised resource allocation, while post-clearing seed germination from current seedbanks required the majority with 58.3% (295,872 person days). Post-fire seed germination from current seed banks required 27.2% and clearing plants from future seed banks, the smallest portion of the available effort (4.9% or 24,979 person days). The allocation of resources was significantly different when the clearing efficacy decreased to 80% and lower (p<0.0001). At 80% efficacy, 55.1% (1,099,026 person days) of the utilised person days went to clearing plants from future seedbanks, while current seedbanks collectively accounted for 30.2% (602,046 person days). This outcome was similar to the current project clearing efficacy where 52.1% of the 2,000,082 utilised person days were required for treatment of plants from future seedbanks and 29.0% (580,679 person days) was used for plants from current seedbanks, resulting in the continued need for clearing over time.

3.3.2 Clearing efficacy thresholds

While linear models provided a good fit to the data (Adjusted R-squared > 0.8 in all instances), the best fit models (Adjusted R-squared > 0.95 and ΔAIC in excess of 40) indicated a non-linear, polynomial relationship between the number of hectares and management units treated and the efficacy of the treatment (Fig. 3.3). Below 25% clearing efficacy, there was little difference in the number of hectares or management units achieving a maintenance state in year 50. The achievement of this goal increases steadily to around 80% clearing efficacy, followed by a sharp increase in the impact of increasing clearing efficiency between 80 and 100% (Fig. 3.3 a, c). A similar pattern was observed for the cumulative number of hectares and management units cleared over time (Fig. 3.3 b, d).

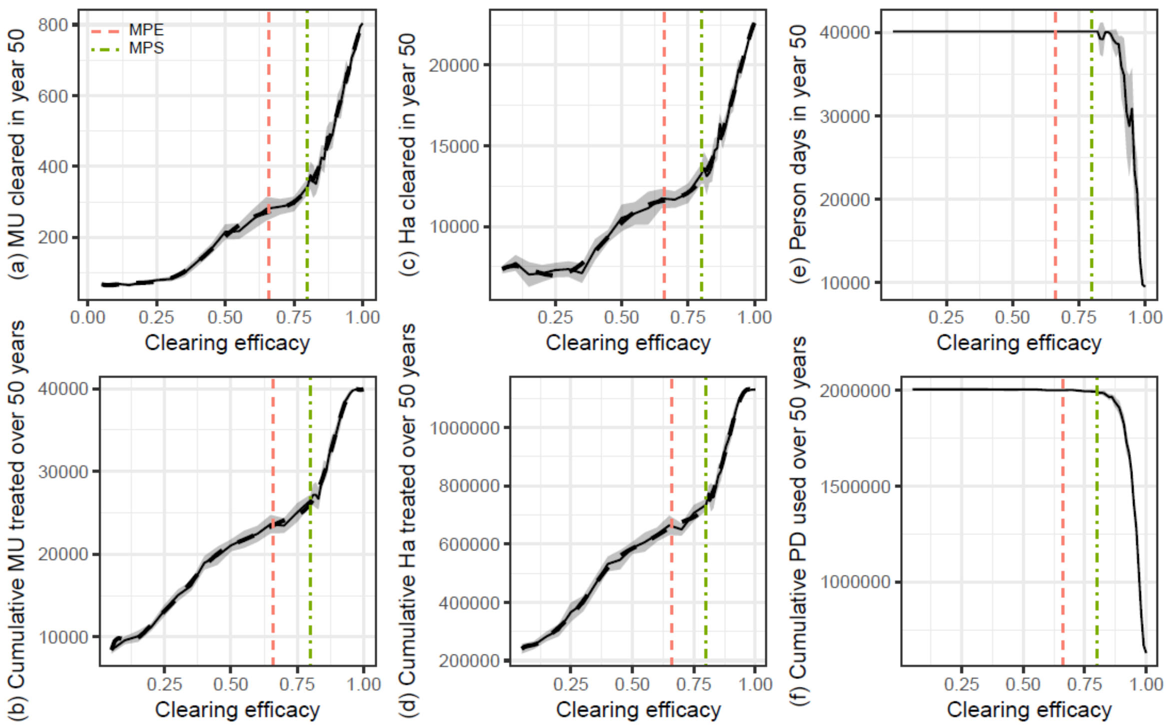

Fig. 3.3. The relationship between clearing efficacy and (a) management units (MU) and (c) hectares, cleared at year 50 and (e) the associated person days required and the respective total cumulative MU (b) and hectares (d) treated over the 50 years with the total cumulative person days (f). Vertical gridlines have been added at 66% and 80% to indicate the current mean project efficacy (MPE) and required minimum project standard (MPS) for clearing. Dotted lines indicate a 4th order polynomial, used to describe the nature of the relationship between management efficacy and measured response: (a) Adjusted R^2: 0.9772, F-statistic: 501.7, p < 0.001, (b) Adjusted R^2: 0.9892, F-statistic: 804.8, p < 0.001, (c) Adjusted R^2: 0.9793, F-statistic: 415.7, p < 0.001, (d) Adjusted R^2: 0.9796, F-statistic: 421.1, p < 0.001. The number of model iterations for each of the clearing efficacy levels was 15.

Due to this non-linear relationship, even a small reduction or increase in clearing efficacy between 80-100% had large effects on the number of hectares and management units that could be treated (Fig. 3.3 a-d; Sup. Mat. Table 3.8). At 90% clearing efficacy, a mean of 527.1

(65%) (SD=53.5) of the 809 management units and a mean of 16,840.7 ha (74%) (SD=1296.3) would be in a maintenance state after 50 years, compared to 99% of management units and 99% of hectares when efficacy is 100% (Sup. Mat. Table 3.8). The model showed that even at 100% efficacy, fire events would stimulate seedbanks in certain management areas that would require continued follow-up work.

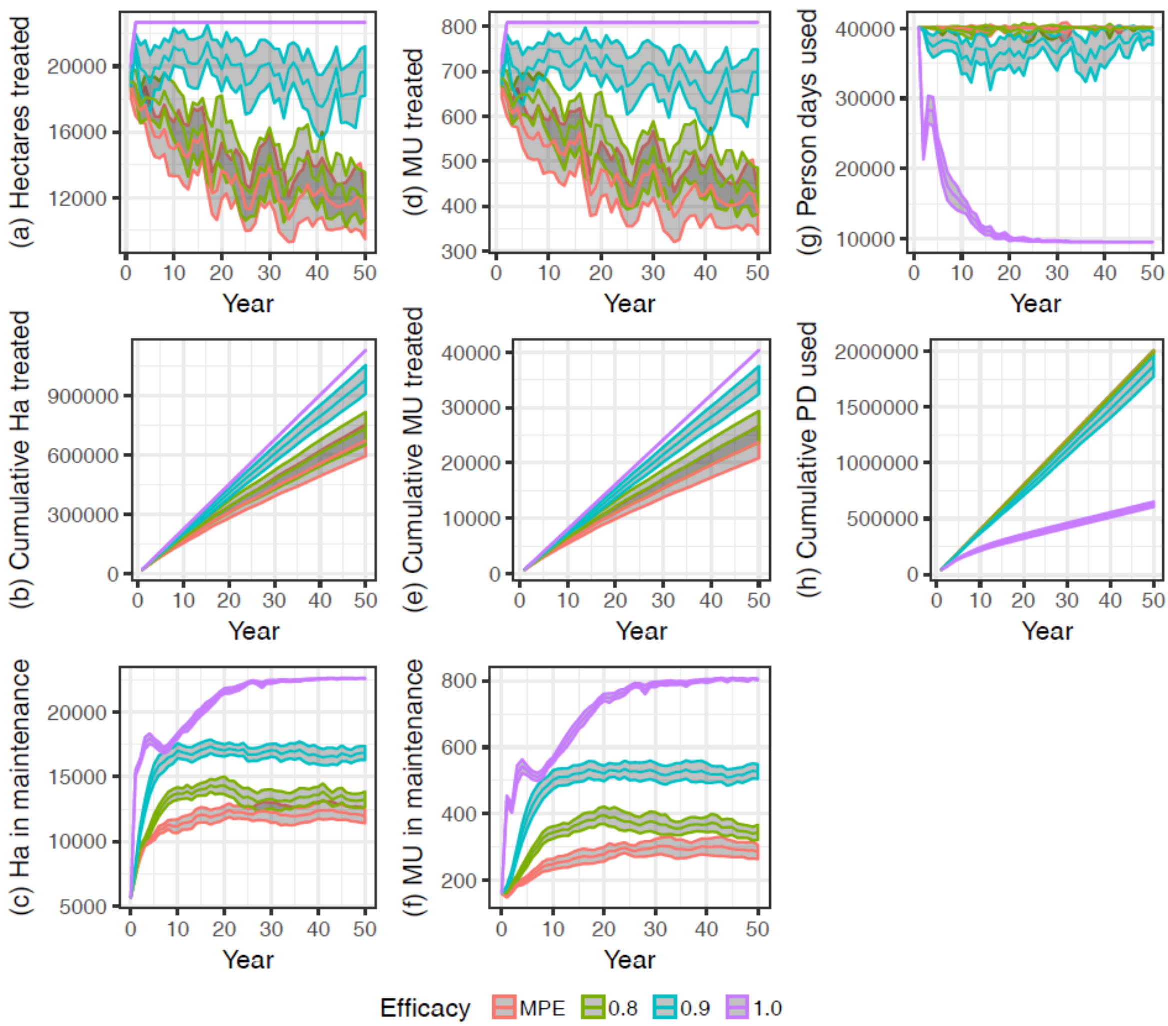

Fig. 3.4 Annual clearing outcomes over time in terms of hectares (a) and management units (d) treated annually and the cumulatively over time (b, d) as well as the number of person days used per year (g) and cumulatively (h) and the resulting number of hectares (c) and management units (f) that achieved a maintenance level (<1 plant /ha) over time at four management efficacy levels (mean project efficacy (MPE, approximated across coppicing and non-coppicing species as 66%), 0.8, 0.9 and 1.0). The number of model iterations for each of the four efficacy levels was 25.

The relationship between the number of person days required and clearing efficacy showed that for the long-term, clearing efficacy below 83% would require all the available annual person days (40,128 person days) for the foreseeable future (Sup. Mat.Table 3.8). Above 83% clearing efficacy, the required person days dropped sharply until 100% clearing efficacy where

9,491.5 person days (SD=7.2; 24% of current annual allocation) would be required from around year 20 to maintain the maintenance state (Fig. 3.3 e-f; Fig. 3.4g). Over the long-term, a decline in clearing efficacy is costly, with a decreasing number of outputs (management units and hectares treated annually), for continued maximum input (Fig. 3.4). Even a clearing efficacy of 90% required sustained high person day use (mean 38,582; SD=2,299.9, Fig. 4g), at levels close to the maximum annual person day allocation of 40,128 for the duration of the model simulation.

3.4 Discussion

Several studies have highlighted that IAP control programmes targeting *Acacia* species can be ineffective (van Wilgen *et al.* 2012; McConnachie & Cowling 2013; Kraaij *et al.* 2017). Studies point to poor treatment of management units where in some instances less than 25% of the treated areas met minimum clearing standards. The long-term implications of clearing inefficiency (e.g. resource allocation, timeliness of clearing, correct treatment and effectiveness of minimum standards) had not yet been quantified, which we set out to do here. We found that the resource allocation of 40,000 person days was adequate to bring the park to a maintenance level (i.e. <1 plant per ha), within 37 years, if clearing was completely effective. There was a positive non-linear relationship between treatment efficacy and the area that could be treated for *Acacia* species in the long-term, with the chance of reaching a maintenance level within 50 years declining significantly at efficacies below 100%. The current minimum clearing standard of 80% efficacy as determined in the WFW norms (Neethling & Shuttleworth 2013), therefore realises slow progress towards the goal of achieving maintenance levels for Acacias, despite using the maximum allowable resources.

In approaching the management of Acacias, the drivers that facilitate successful invaders in many Mediterranean type habitats and climates require consideration (Richardson *et al.* 2011). Much of the invasion success is due to their rapid growth rates, prolific seed production, and persistent seed banks (Milton & Hall 1981; Strydom *et al.* 2012; Souza-Alonso *et al.* 2017). As evidenced by comparison of scenarios, seedbank dynamics played an important role in perpetuating *Acacia* persistence and were the key driver of management resource requirements. Due to the prolific post-fire seed germination by Acacias, stimulating up to 90% of the available seedbanks to germinate (Holmes *et al.* 1987), many management control strategies focus on treating burnt areas within 24 months after fire (Roura-Pascual *et al.* 2010). However, the simulation model showed that for all clearing efficacy levels, more clearing effort would be needed annually in areas that did not burn, due to constant low rates of germination from non-dormant seedbanks, particularly at recently cleared sites (Holmes *et al.* 1987).

Although post-fire germination may be very notable, the actual extent of annual fire events covered <5% of the park (Forsyth & van Wilgen 2008).

The simulation model showed that the potential seedbank contribution from a single mature individual into the population is considerable. This is key for the management of Acacias, as the potential propagule pressure from seedlings and dispersal is pronounced (Rouget & Richardson 2003; Lockwood *et al.* 2005). While areas of low invasion density are often considered lower priority (Roura-Pascual *et al.* 2010), the consequence of not clearing effectively and not reducing propagule pressure increased long-term future resource requirements. In the simulation model as much as 55% of future management resources (effort and costs) would be directed to treating plants that result from seedbank replenishment. This long-term future resource requirement has been observed in rehabilitation of river catchments and headwaters where re-invasion by Acacias is prominent in the absence of follow-up treatment (Galatowitsch & Richardson 2005; Le Maitre *et al.* 2011).

3.4.1 Management implications

Previous models making use of high clearing efficacy parameters have shown a significant reduction in *Acacia* invasion within 20 years (Krug *et al.* 2010; Le Maitre *et al*. 1996). Our models produced similar results at maximum efficiency (Fig. 3.4). However, the modelling scenarios here showed that the long-term resource requirements for the control of Acacias are also directly dependent on the clearing efficacy of current clearing programmes. Although efficacy in this study has largely focused on the treatment of plants, management efficacy can be extended to include several additional management aspects such as area-based, time-based and detection efficacy in the control programme for a protected area.

Area-based efficacy would consider if 100% of the treatment area was actually treated. To adequately manage Acacias, the entire population should be treated, however this is not always the case. In certain control programmes up to 60% of treatment areas did not have full coverage (McConnachie *et al.* 2012; Kraaij *et al.* 2017). Time-based efficacy considers i) when the treatment is scheduled for each area and ii) how much time has been allocated to undertake the clearing. Although considerable effort has gone into IAP planning, the implementation is not always satisfactory (Forsyth *et al.* 2012; McConnachie & Cowling 2013; Kraaij *et al.* 2017). Longer-than-optimal return treatment intervals, allow plants to replenish seedbanks before the follow-up treatment is applied. The amount of time allocated to treat an area has compounding effects on clearing efficacy. Over-allocation of time impacts the total available area that can be cleared with the available budget. This results in areas not being cleared because budgets are depleted before all areas can be scheduled. Under-allocation of time results in 'fast-pace' work and treatment quality deteriorates.

The implications of these sources of management inefficacy are important for control programmes. Currently WfW only records work as completed in terms of area covered and person days used (Marais & Wannenburgh 2008). However, from the simulation models, both the area covered and efficacy should determine if work is considered correctly completed. Red flags should be raised if the follow-up treatment cycle extends beyond two years, since covering the area alone is insufficient for IAP programmes, given seedbank replenishment. A common fall back option for managers is to increase financial resources to allow for more areas to be treated. While increasing financial resources allows for more effort, in the case of poor treatment effectiveness, this works only up to a point. Once an area is ineffectively cleared, it is physically impossible to immediately re-clear the area, as the plants need time to re-grow. Therefore, where funding is available to do the clearing, it is not a budget problem, but a lack of quality that necessitates repeat spending on the same area.

In reality, complete eradication of Acacias is unlikely within in the next 50 years, requiring control programmes to have a very long-term outlook (Rejmánek & Pitcairn 2002; McConnachie & Cowling 2013). This long-term view is not unreasonable when viewed against a lengthy, multi-event invasion history spanning more than 200 years (Shaughnessy 1980). Although managers of control programmes may become disheartened by seemingly slow progress and consider the control efforts a failure (Davis *et al.* 2011; Vince 2011), even at the current levels of efficacy, simulations do predict an increase in the percentage of hectares and units in a maintenance state 50 years from now. Management priorities going forward will include minimizing dispersal into uninvaded and low density sites, through early detection and rapid response as well as focussed clearing of isolated or satellite populations (Zenni *et al.* 2009; Kaplan *et al.* 2012). Managers should further be encouraged by the non-linear relationship between efficacy and clearing effort whereby even small increases in efficacy above 80% result in significant positive long-term improvements. For example improving the efficacy target to 90% would enable 74% of hectares and 65% of management units to reach maintenance levels in 50 years, compared to the current situation of 25% of hectares and 20% of management units.

Even reducing plants to <1 plant per hectare would leave a few scattered plants capable of seeding on the landscape, which could lead to problematic regeneration relatively quickly. Long-term budgets, for at least for the next 100 years, are required for PAs to control IAPs due to incomplete clearing (van Wilgen *et al.* 2016a). The notion that the resources from treated areas can be entirely shifted to other conservation areas is not supported by the model output. Even where clearing efficacy is 100%, about 25% (10,000 person days) of the current person day allocation would be required for maintenance control, due to continual recruitment from the existing seedbank. Instead of reducing budget requirements as programme efficacy improves, resources may be redeployed to other control tasks. For example, if efficacy was improved above 80%, the small unused person day allocation could be redirected to an early detection programme that seeks to ensure rapid control of new arriving species, as such working towards preventing future invasions (Leung *et al.* 2002). This extension of clearing programmes is important to tackle the global challenge of increasing numbers of alien species arriving at a site each year (Seebens *et al.* 2017), coupled with unpredictable responses to climate change (van Wilgen *et al.* 2016b; Slingsby *et al.* 2017) and other global change drivers (van Wilgen & Herbst 2017). Such expansion in the scope of clearing projects without increased budgets is however only possible if the long-term efficacy of current control programmes is improved.

3. 5 Conclusions

Quality of work is a primary driver of control success for invasive alien Acacias. Our model found that incremental improvements in efficacy above 80%, with a key focus on limiting seedbank replenishment, can result in large gains in the realisation of adequate control of Acacias in TMNP. Managers should not see slow progress as control failure as a long-term view of the problem is required. PA managers should undertake regular reviews that can readily identify where short terms gains can be made and where long-term interventions are needed. Going forward, there are already plans in place in Table Mountain National Park to focus on improving quality of work. A new monitoring and evaluation programme now provides an improved focus on quality of work rather than amount of work completed or person days delivered.

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3.8 Supplementary material

The following supplementary Information may be found in the supplementary section accompanying this thesis:

Sup. Mat. Figure 3.1 Clearing module where management units (MU) are selected at random and person days (PD) are allocated for treatment based on the abundance and age class of Acacia species where the probability of effective treatment is varied for 1 of 38 efficacy levels. The process is repeated until the allocation of person days are exhausted with output data supplied to other modules, for example Seed Germination.

Sup. Mat. Figure 3.2 Fire module where the number of fire ignition points and the total expected area to be burnt in a year is determined from the 1980-2016 fire database. For each fire ignition point, the management unit to be burnt is selected and if the management unit (MU) is able to be burnt, the expected size of the individual fire is calculated from the fire history database and additional adjacent MUs are burnt until this value is reached. Fire intensity for the burn is varied by use of a Fire Danger Index (FDI) and output data is fed to other modules for example, Seed Mortality.

Sup. Mat. Table 3.1. Assignment of each management unit to a fire ignition class based on the number of ignitions recorded for the management unit in the TMNP fire history database. Ignition classes were then assigned a probability of being an ignition source in the fire module.

Sup. Mat. Table 3.2. Probability that a Fire Ignition event would result in the entire management unit burning based on vegetation age (Van Wilgen *et al.* 2010). Although ignitions are possible at all vegetation ages, significant portion of the management unit <5 years will not burn given the small fuel loads of young vegetation.

Sup. Mat. Table 3.3. Fire Danger Index (FDI) and Plant mortality where the fire danger rating system is used to provide a measure of the relative seriousness of burning conditions and threat of fire by providing an accurate measure as possible of the relative seriousness of burning conditions by making use of daily maximum temperature, relative humidity, wind speed and recent rainfall (South African Government Gazette 37014 No. 1099 of 2013)

Sup. Mat. Table 3.4. Logistic equations used for annual seed production per m^2 for coppicing and non- coppicing *Acacia* species (Milton & Hall 1981; Holmes *et al.* 1987; Strydom *et al.* 2017)

Sup. Mat. Table 3.5. Fire Intensity as measured by the Fire Danger Index (FDI) effect on proportion of seedbank mortality / seedbank germination. Where cells are blank or '-' indicates no effect by the fire

Sup. Mat. Table 3.6. Plant population parameters that bound the population within observed limits

Sup. Mat. Table 3.7. Mean time (Years) and Person Days required to reach a maintenance level (<1 plant per ha) for the 809 management units before or at 50 years based on model 25 iterations. * indicate that a maintenance level for the 809 management units (MU) was not reached by year 50.

Sup. Mat. Table 3.8. The mean number of Management Units (MU), hectares (Ha) that reached a maintenance level (< 1 plant per Ha) at Year 50, and the number of Person days required at Year 50, for 38 levels of simulated efficacy. n=25 for 1.00, 0.90 and 0.8, n= 15 for all other.

Appendix 1. Visual Basic code of the model

Chapter 4.

Future outcomes of alien plant clearing strategies: Where to from here?

Abstract

Conservation managers are required to make decisions and take action in complex and uncertain systems. To strengthen the robustness of conservation decisions, several approaches have been proposed. These processes involve stakeholder engagement in the setting of conservation management objectives and priority actions. The overall aim of the decision making process should be to encourage participation, accommodate stakeholder differences, allow for the formulation of common values and to incorporate complexity in defining the conservation problems at hand. A number of strategies linked to invasive alien plant management objectives have been formulated in the literature that appear to address management of these species in protected areas. The long-term performance of five of these strategies was tested using empirical data from Table Mountain National Park. A simulation model based on data for *Acacia* species focused on the interaction between strategy performance and clearing efficacy in achieving a management goal or reducing *Acacia* density to below 1 plant per hectare. Results show that at near perfect levels of clearing efficacy, all management strategies converged towards reaching the overall management goal, while at lower efficacy levels the strategies diverged from each other in terms of their ability to achieve desired outcomes. Strategies that focussed on clearing low density invasions managed to clear the most hectares, but maintained the least area in a maintenance state over time. In contrast, strategies that focussed on a mix of post-fire, low density areas and high altitude areas cleared less area annually, but maintained a much greater area in a maintenance state. At higher levels of efficacy, follow-up strategies were even more successful than the consensus strategy. Strategies that focused solely on securing water, performed poorly in maintaining low overall density of aliens. The short falls of the objectives, the importance of improving efficacy and allowing proactive flexible implementation is discussed.

4.1 Introduction

Conservation managers are required to make decisions and take action in complex and uncertain systems (Regan *et al.* 2005; Game *et al.* 2014). These management decisions often have to accommodate biodiversity needs, socio-economic trade-offs, political agendas and conflicting, often diverse interest groups, in the midst of limited resources and data deficiencies (Reed 2008). Many conservation issues can therefore be seen as 'wicked problems' where the real underlying problem is difficult to define and authorities and stakeholders may not agree on the proposed solution (Game *et al.* 2014). The management of invasive alien plants (IAP) is one such wicked conservation problem (Head *et al.* 2015; Seastedt 2015; Woodford *et al.* 2016), which has been widely documented in protected areas (Downey 2013; McNeely 2013).

Several approaches have been proposed to improve the robustness of conservation decision making (Bower *et al.* 2017; Schwartz *et al.* 2018). These processes, such as Structured Decision Making and Systematic Conservation Prioritisation (Bower *et al.* 2017; Schwartz *et al.* 2018), entail inclusive stakeholder engagement in the setting of conservation management objectives and priority actions. The overall aim of the decision making process is to encourage participation, accommodate stakeholder differences, allow for the formulation of common values and to incorporate complexity in defining the conservation problems at hand. In this way, multiple management actions can be prioritized and the required levels of management effort determined. One of the benefits of transparent objective setting is that where conditions fluctuate or have high levels of uncertainty (Regan *et al.* 2005), objectives can be modified through processes such as adaptive management where the focus is on the monitoring and review of conservation actions (Shea *et al.* 2002; Foxcroft & Downey 2008; Foxcroft & McGeoch 2011).

However, the wide range of inputs arising from the inclusion of scientific, political, social and economic stakeholder perspectives may lead to the formulation of excess or conflicting management objectives (Roper *et al.* 2018). This can reduce clarity and obscure the intent of the original conservation intervention. As conservation decision making and objective setting is not an 'exact science', it is possible that convoluted problems result in no clear agreeable solution, or any agreeable solution being deemed better than no solution at all (Saaty 1990). Where management objectives that attempt to reconcile multiple views and agendas are adopted in the absence of better ones (Game *et al.* 2013), the objectives still lead to management actions and resource-allocation decisions that require framing of the 'where, when and what' aspects of the management actions to be carried out (Epanchin-Niell & Hastings 2010). This acceptance by managers of sub-optimal objectives can undermine the effective use of the limited available conservation funding and resources (James *et al.* 1999; Bruner *et al.* 2004; Emerton *et al.* 2006; Ferraro & Pattanayak 2006). The management of invasive alien plants (IAP) is one area of conservation management that requires clear objectives, adaptive planning, adequate resources and budgets for long-term implementation (Esler *et al.* 2010; Foxcroft & McGeoch 2011; van Wilgen *et al.* 2016; Chapter 3). Determining priorities for IAP management requires prediction of the proposed outcomes of management control efforts on the extent of the invasion over time, while accommodating system uncertainty (Epanchin-Niell & Hastings 2010; Regan *et al.* 2011).

Insight into the requirements and expected outcomes of management actions as defined by conservation objectives can be provided by predictive IAP models. These models consider dynamic ecological drivers, for example, fire, rate of invasion, ecological impact and factors that increase uncertainty such as clearing efficiency (Le Maitre *et al.* 1996; Krug *et al.* 2010; Chapter 3). Management prioritisation models for IAPs have been developed for a number of scenarios and include water catchment areas (van Wilgen *et al.* 2007; Forsyth *et al.* 2012), PA management (Forsyth & Le Maitre 2011; van Wilgen *et al.* 2016) and the need to maximise economic cost-benefit ratios (Higgins *et al.* 1997; de Wit *et al.* 2001). However, the prioritisation of areas for management intervention in these predictive models has been shown to be very sensitive to selection criteria, the availability of information and the primary conservation objective that was set (Roura-Pascual *et al.* 2010).

Specific IAP genera pose on-going management challenges, perpetuating high long-term management costs (McConnachie *et al.* 2012). One such group is the Australian *Acacia* species which are particularly difficult to control despite intensive management effort. *Acacia*s are highly invasive globally (Richardson & Rejmánek 2011) and have been considered a model group for studying many facets of alien plant invasions (Richardson *et al.* 2011; van Wilgen *et al.* 2011). The successful establishment and long-term persistent invasion of *Acacia* species has been attributed to a number of factors, including early maturity (<2 years), prolific production of long-lived seed (up to 12000 seeds/m^2/annum) and prolific post-fire germination (Marchante *et al.* 2010; Souza-Alonso *et al.* 2017; Strydom *et al.* 2017). This has resulted in the need for clear objectives that address the management of persistent invasions by *Acacia* species.

Current IAP management strategies applied in the majority of South African protected areas (PA) follow the nationally funded invasive alien control programme, ‘Working for Water’ (WfW). This programme aims to restore and maintain habitat structure and function to mitigate the loss of ecosystem services, especially water production through creating employment opportunities and facilitating skills development that contribute to poverty alleviation (van Wilgen *et al.* 2012a). The overall management goal of WfW is to reduce the occurrence of these IAPs to densities that have no negative impact on native biodiversity. In trying to reach this management goal, a number of area-based prioritization strategies have been employed in PAs, but their long-term outcomes and suitability for reaching the management target have not been evaluated.

Using four major clearing strategies formulated on priorities set by conservation managers and expert information (Roura-Pascual *et al.* 2010), together with a triage strategy the prospects of each strategy for achieving the target alien density for *Acacia* species was tested. In particular the performance of each strategy was assessed at several levels of clearing efficacy in terms of:

i. the number of management units and hectares treated over a 50 year period,
ii. the number of management units and hectares in which the management maintenance goal was achieved over the long-term,
iii. the effect of clearing efficacy on each strategy over 50 years,
iv. changes in the spatial distribution of areas deemed to have reached the management goal under different strategies and clearing efficiencies,
v. the effort (resources) required to implement each strategy, versus alternate strategies, including allowances for variability in implementation.

4.2 Materials and methods

4.2.1 Study area

Table Mountain National Park (TMNP) is located on the Cape Peninsula, South Africa, and covers approximately 25,000 ha. Historical land-use and proximity to the city of Cape Town, has facilitated the arrival and spread of over 200 alien plant species into the park (Shaughnessy 1980; Macdonald *et al.* 1985; Alston & Richardson 2006; Spear *et al.* 2011). Formalised control of IAPs commenced in the late 1980s, employing semi-skilled labour, skilled private contractors and civil society volunteer groups (Macdonald *et al.* 1985; Taylor *et al.* 1985; Moll & Trinder-Smith 1992). Current IAP management is implemented through the WfW programme, which has been in place since 1998. Despite the long history of the control programme, aliens persist in the landscape at densities that require large, long-term budgets (van Wilgen *et al.* 2016).

For model simulation and analysis we considered fine-scale data from 809 Working for Water management units (spatially mapped as GIS polygons) that cover 91% (22,671 ha) of the park (Cheney *et al*. 2018; Chapter 2), excluding only very steep areas that would require rope access. Each management unit currently has, or historically had, different levels of invasion by a range of alien plant species. The dominant taxa in TMNP comprise of woody alien species from the genera *Acacia*, *Pinus* and *Hakea*. For the purpose of this simulation model only *Acacia* species are considered as they are the most common alien plants in the PA (Cheney *et al.* 2018) and have been suggested to pose the greatest threat to TMNP's biodiversity (Richardson *et al.* 1996; Higgins *et al.* 1999).

4.2.2 Setting a management goal for clearing

Since 1998, the park has used a multi-priority management approach, focusing on i) recently burnt areas, thereby targeting young plants, ii) maintenance clearing of lightly invaded areas, to maintain gains of past work, iii) control in areas of medium invasion, iv) removal of pockets of very dense invasions, and v) trying to ensure a 18-24 month return interval to each management unit (i.e. before coppicing/germinated plants produce new seeds). These area-based priorities have the overall objective of long-term IAP eradication or where eradication is not possible, ensuring that the IAP present have no negative effects on native biodiversity.

Due to germination from long-lived, persistent seedbanks and variable clearing quality, it is currently accepted that complete eradication of *Acacia* species within the model period of 50 years is unlikely (Chapter 3). Given the current prevalence of *Acacia* and resources available to conservation managers a realistic management goal needed to be set. Within the current WfW clearing programme three main measures are monitored, based on the programme's objectives that determine successful implementation *i.e.* person day utilised, hectares treated and IAP density reduction (van Wilgen *et al.* 2017). The WfW programme aims to maximize the number of job opportunities provided by allocating work in terms of person days required as a resource input (van Wilgen *et al.* 2012a). Using these available person day allocations, the total number of hectares that can be treated is determined with due consideration of opportunities for reducing alien plant density. Failing eradication of IAPs, the best possible management outcome would be to reduce the target alien species to levels that require only maintenance clearing across the entire park. Thus, for each management unit, the management goal was set for *Acacias* to have a density of less than 1 plant per hectare, and as such being considered 'rare' in in the landscape (Le Maitre & Versfeld 1994).

4.2.3 Simulated IAP management strategies

Four IAP management clearing strategies that were developed through a participatory process with managers, researchers and experts are considered for analysis (Roura-Pascual *et al.* 2009). These are i) follow-up clearing, ii) keep areas clean, iii) water production and iv) management consensus (see Table 4.1, Box 4.1 and Sup. Mat Fig. 4.2 for details). The

Analytical Hierarchy Process (AHP) that was followed in the development of these strategies entailed determining main factors and sub-factors to be considered in the management of IAPs, each of which is assigned a relative importance and weighting (Saaty 1990). In terms of the simulation models the main factors in the AHP are seen as a particular management objective that needs to be attained. Importance weightings for each of the seven main factors (management objectives) summed to 1. Each main factor was further divided into sub-factors, and assigned a weighting that summed to 1 (100% of the main factor). The data used by the main and sub-factors was sourced from existing data, for example the fire history of the PA for vegetation age, DEM modelling of topography (detailed in Table 4.1). In addition to the four management strategies, we considered a Triage management strategy, based on securing a core conservation area of the park and clearing additional areas if resources area available (Box 4.1).

Box 4.1. Description of strategies tested. Refer to Table 4.1 for parameter settings used for each strategy.

Maintain follow-ups: Focus is on follow-up clearing in areas previously treated so that gains made through previous clearing efforts and financial investment are not foregone. Areas are primarily selected for treatment if they have been cleared within the last 6 years (50% of total weight) or have had a recent fire (20% of total weight).

Keep-it Clean: Focus is on areas that are currently lightly invaded with the aim preventing these areas from becoming further invaded. Areas are primarily selected for treatment on IAP density (50% of total weight) with emphasis for selection on low to very low IAP densities (89% of IAP sub-factor weight). The second most important factor is topographic position where high lying areas are selected (31% of total weight).

Water production: One of the main aims for the IAP programme is securing water resources. Focal areas for treatment were prioritized based on the river channel topographic type (44% of total weight; 65% of sub-factor weight), considering IAP density (26% of total weight) with emphasis on densely invaded areas (71% of sub-factor weight).

Management consensus: This strategy reflects the view shared by conservation managers on which areas should be selected for treatment. Focus is primarily on post-fire clearing (40% of total weight), IAP density (17% of total weight) with emphasis on lightly infested areas (87% of sub-factor weight) and topographic position (17% of total weight), with high lying area being most important (65% of sub-factor weight).

Triage: A contiguous core conservation area, of high biodiversity value, was delineated. The strategy entailed repeated clearing of this core area. Any remaining resources following clearing of the core area were used to clear areas directly adjacent to the core area.

Random: Management units were selected at random at the beginning of each model year until allocated person days had been depleted with no memory or influence on the units that were selected from year to year.

Table 4.1 Main factors (management objective) (**bold**) and sub-factor (*italic*) weights applied in each of the strategies (modified from Roura-Pascual *et al*. 2010). Main factors for a strategy sum to 1.0, with each sub-factor summing to 1.0. The main aims of each strategy are detailed in Box 4.1.

Management Strategy	Maintain follow-ups	Keep-it-Clean	Water production	Management Consensus	Data source and comments
Recently burnt areas	**0.2**	**0**	**0.04**	**0.4**	
Yes	0.9	0	0.9	0.9	Age <= 3 Years
No	0.1	0	0.1	0.1	Age > 3 Years
Topography	**0.09**	**0.31**	**0.44**	**0.17**	
Planar, flat & pit	0.07	0.07	0.07	0.07	(Wood 1996; Neteler *et al.* 2008)
Channel	0.28	0.28	0.65	0.28	
Pass, ridge & peak	0.65	0.65	0.28	0.65	
Density of IAPs	**0.09**	**0.5**	**0.26**	**0.17**	
Closed	0.03	0.03	0.45	0.03	Density of IAPs within each management unit (Working for Water Program 2003)
Dense	0.04	0.04	0.26	0.04	
Medium	0.06	0.06	0.15	0.06	
Scattered	0.11	0.11	0.07	0.1	
Very scattered	0.2	0.2	0.03	0.2	
Occasional	0.39	0.39	0.02	0.38	
Rare	0.19	0.19	0.02	0.19	
Fire risk	**0.07**	**0.04**	**0.03**	**0.13**	Vegetation type: (Cowling *et al.* 1996) Vegetation Age: (Forsyth & van Wilgen 2008) (Chapter 3)
Low	0.07	0.07	0.07	0.07	
Medium	0.28	0.28	0.28	0.28	
High	0.65	0.65	0.65	0.65	
***IAP Age**	**0.03**	**0.09**	**0.1**	**0.06**	* *Acacia* only
Adult	0.11	0.11	0.74	0.11	Age: >3.0 years
Sapling	0.64	0.64	0.21	0.64	0.5-3.0 years
Seedling	0.26	0.26	0.06	0.26	0-0.5 years

Table 4.1: *Continued*

Management Strategy	Maintain follow-ups	Keep-it-Clean	Water production	Management Consensus	Data source and comments
**** IAP Identity**	**0.03**	**0.06**	**0.1**	**0.05**	
Hakea	0.1	0.1	0.07	0.1	** Only *Acacia* species modelled
Acacia	0.26	0.26	0.65	0.26	
Pinus	0.64	0.64	0.28	0.64	
Last clearing	**0.5**	**0**	**0.04**	**0.03**	
No treatment	0.05	0	0.05	0.05	Never cleared
Initial	0.3	0	0.3	0.3	Previously cleared but not treated for > 6 years
Follow-up	0.55	0	0.55	0.55	Cleared within last 6 years
Maintenance	0.1	0	0.1	0.1	Cleared within last 6 years

4.2.4 Model description

A spatio-temporal, polygon-based, population model was developed for the park using Visual Basic in MS Excel (2013 v15.0) (Sup. Mat. Figure 1, Chapter 3). The model simulates *Acacia* population size, age structure and area invaded, within each of the 809 management units, based on two key drivers of *Acacia* persistence, namely fire dynamics and plant population dynamics (growth and seedbank dynamics) (Le Maitre *et al.* 1996; Krug *et al.* 2010). Fire dynamics were based on the fire history of TMNP in combination with vegetation age characteristics and fire intensity as determined by the Fire Danger Index based on daily weather recordings, while seed dynamics were based on current literature that assessed seed accumulation rates, vertical movements of seed in the soil, germination rates and dispersal in the landscape (see Chapter 3 for details on model parameters). The purpose of the model is to test the performance of each strategy against its potential future outcomes at different levels of clearing efficacy.

Starting population data for the model (year 0) were based on fine-scale data collected from a systematic survey in-field from 10,057 plots that covered all management units (Cheney *et al.* 2018; Chapter 2). The *Acacia* species included in the model were grouped based on their response to management i.e. those that, i) readily coppice if not treated correctly (e.g. through the incorrect clearing method or application of herbicides), such as *Acacia saligna*, *A. mearnsii*, *A. melanoxylon* and ii) species that do not readily coppice, namely *Acacia cyclops* and *A. longifolia*. The model was run for the equivalent of 50 simulation years for each management strategy. Within a model simulation year, the model time interval was set to quarterly calendar increments, aligned with current IAP clearing operations (Chapter 3 Figure 3.1). Available resources were divided per quarter until the total available resource allocation for the year was reached. The standard resource unit for alien plant control in the park is based on the number of person days required to treat an invaded area. The TMNP's 2017 allocation of 40,128 person days was used as the available resource with which to undertake clearing each year. Any unused person days in a simulation year were not carried over to the next simulation year.

At the start of each year, the model assessed the value of each factor and sub-factor relevant to each strategy within management units. Management units were prioritised for clearing based on scores for the factors and sub-factors for each of the four scoring strategies (Table 4.1). The scoring was done at the beginning of each simulation year so as to enable the effects of the model variables, such as fire, clearing success, seed germination, to be 'fed-back' into the model and inform the that year's prioritisation scoring. For the Triage strategy, factor weights were ignored and the management units were pre-scored based on biodiversity value and repetitive selection of the same ordered management units occurred. For the Triage strategy this resulted in management resources being directed primarily into the high value conservation areas with secondary areas being treated as resources became available. For purposes of comparison, a Random strategy was introduced as a null strategy where management units were selected at random at the beginning of each model year until allocated person days had been depleted, with factor weights ignored.

Due to the stochastic nature of some of the model variables, the management strategies (see 4.2.5) were run for 15 iterations of each strategy at 20 incremental levels of clearing efficacy from 5-100% for 50 years.

4.2.5 Management strategy comparison

To compare the long-term outcome of the six strategies (five management and one random), specific areas of interest for analysis included of hectares cleared and management units that reach a maintenance state, at different levels of implementation success. Sections 4.2.5.1 - 4.2.5.3 below describe the metrics determined and analysed for each strategy.

4.2.5.1 Hectares and Management Units treated

Firstly, the performance of each management strategy was assessed at 20 efficacy levels between 5-100% effective (also noted as efficacy between 0.05 to 1.0) for the duration of the model between years 10 to 50 in terms of i) the number of hectares and ii) management units that were treated each year, iii) the total hectares and, iv) management units treated by the endpoint of the model in year 50. The first nine years were excluded from the analysis to allow the models to stabilize and reduce the influence of the starting parameters on model performance, especially initial plant population parameters. To simplify reporting, focus was on very high (0.95), high (0.9), medium (0.75), low (0.5) and very low (0.25) levels of implementation efficacy with details of additional efficacy levels supplied as Supplementary Material. The amount of clearing effort (as measured in person days) required by each strategy at each level of efficacy was calculated annually.

4.2.5.2 Hectares and Management Units achieving the management goal

Secondly, management strategy performance was compared using the number of hectares and management units that realised the set management goal of less than 1 plant per hectare at relevant levels of clearing efficacy for each strategy in each year and at the end of 50 years.

4.2.5.3 Hectares and Management Units sustained in maintenance

Third, 161 management units (20%) and 5,646 hectares (25%) were in a maintenance state at the start of the model (year 0), *i.e*. in-field sampling recorded *Acacia* density at <1 plant per hectare. This analysis evaluated the number of these hectares and management units that were sustained in a maintenance state for the duration of the model as well as at the end of the model period. This enabled assessment of the potential shift away from areas currently under maintenance to new maintenance areas for each strategy at varying efficacy levels.

Differences in the outcome of each strategy (hectares and management units cleared, reaching maintenance and sustained in a maintenance state) were compared pairwise using the Wilcox non-parametric test. To reduce the number of comparisons for reporting, we focus on comparisons of each strategy to the random model, with additional results available in the supplementary material. Data analyses were conducted in R (Team 2013), with plots drawn using ggplot2 (Wickham 2016).

4.2.5.4 Strategies frequency histograms

Each strategy was expected to select different management units for clearing at a specified level of efficacy. Over time, some management units may be selected more frequently under one strategy, but less frequently or not at all under others. Under each strategy, each management unit had 50 opportunities to be selected (one per year). Given 15 iterations per year over 50 years, each management unit could be selected maximum of 750 times (i.e. 50 years x 15 iterations) across model runs. For each of the 809 management units, the total number of treatments received out of the possible 750 was calculated per strategy at a given efficacy level and plotted as a kernel density histogram (Wickham 2016). In addition, a kernel density histogram based on the actual number of times each management unit was treated in the history of the clearing programme was plotted using the parks' clearing database which covers 1998-2017 (20 years of actual treatments) (Working for Water 2017). A normal distribution would be expected under a random strategy, whereas a uniform distribution of treatments would indicate a biased prioritisation where specific areas are constantly selected and others are consistently not selected, while remaining areas receive an even spread of clearing work. A left-skewed distribution would indicate the presence of the majority of management units receiving very few or no treatments, while a right skewed distribution would indicate most management units receiving a high number of treatments. For example, the water strategy is expected to produce a skewed distribution based on repeat selection of management units important for water production. Differences in the mean of the frequency were tested with a Wilcox test at different levels of efficacy.

4.3 Results

4.3.1 Overview of results

The output from the simulation models generated a large number of results and comparisons. The key highlights are presented in sections 4.3.1 to 4.3.4, with additional detail provided in supplementary tables. The core results relate to three aspects of model output, *i.e.* i) the number of hectares and management units treated, ii) the number of hectares and management units that achieved a maintenance level and iii) the number of hectares and management units that were sustained in a maintenance state. A summary of the 'best' and 'worst' performing management strategies for each of these indicators is provided in Table 4.2. Although there is a fair degree of variation in the performance of management strategies, there are a few consistent trends. Firstly, the Keep-it-Clean strategy was able to treat the most hectares, while the Water production strategy was largely the worst performer across indicators in terms of the number of hectares treated. The Follow-up strategy performed best in relation to achieving the management goal of reducing areas to a maintenance state, while the Keep-it-Clean strategy was largely the worst in this regard, despite its hectare coverage. The strategy that sustained the most current maintenance hectares in a maintenance state was the Triage strategy, while the Keep-it-Clean strategy sustained the least. The Management Consensus strategy consistently fared well across most indicators.

4.3.2 Management units and ha treated

4.3.2.1 Overall strategy performance

Strategy performance was assessed by averaging model results across clearing efficacy levels between 0.05-0.90 over the combined model period of 10 to 50 years (Fig 4.1, Table 4.3). The Keep-it-Clean strategy (*i.e.* the strategy focussed on maintaining the currently large areas of very low *Acacia* density in this state, Box 4.1) treated the highest mean number of hectares (16,135 ± 4,428SD, Table 4.3) and management units (593 ±136SD, Table 4.3) per year followed by the Triage strategy (14,471ha ± 4,910SD, 354MU ±253SD) with both strategies performing significantly better than the Random strategy in this regard (p<0.001).

Table 4.2: Management strategies that performed best and worst in terms of hectare-based outcomes. The random strategy is not considered as a contender for best or worst strategy and strategies performing better than random are denoted (+) and worse than random (-). Significant differences (in comparison with the random model as tested with a Wilcox test) appear in bold with a double symbol (++ or - -). Detailed comparisons are presented in Tables 4.3 to 4.5 and Supplementary Material Tables 4.1 to 4.6 as indicated in [square brackets].

		Clearing efficacy averaged over 0.05-0.9	0.95 Clearing efficacy	0.9 Clearing efficacy	0.75 Clearing efficacy	0.5 Clearing efficacy	0.25 Clearing efficacy
Hectares **Treated** over model years 10-50 [Table 4.3, Sup. Mat. Table 4.1]	Best	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**
Hectares **Treated** in year 50 [Table 4.3, Sup. Mat. Table 4.2]	Best	Keep-it-Clean +	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**	Keep-it-Clean **++**
Hectares **Maintained** over model years 10-50 [Table 4.4, Sup. Mat. Table 4.3]	Best	Follow-up **++**	Follow-up **++**	Follow-up **++**	Consensus **++**	Triage **++**	Water **++**
Hectares **Maintained** at year 50 [Table 4.4, Sup. Mat. Table 4.4]	Best	Follow-up **++**	Triage +	Follow-up **++**	Consensus **++**	Follow-up **++**	Follow-up **++**
Hectares **Sustained** over model years 10-50 [Table 4.5, Sup. Mat. Table 4.5]	Best	Triage **++**	Triage **++**	Follow-up **++**	Triage **++**	Triage **++**	Triage **++**
Hectares **Sustained** in year 50 [Table 4.5, Sup. Mat. Table 4.6]	Best	Follow-up **++**	Triage +	Triage +	Consensus **++**	Consensus **++**	Follow-up **++**
Hectares **Treated** over model years 10-50 [Table 4.3, Sup. Mat. Table 4.1]	Worst	Water **- -**	Follow-up +	Water **- -**	Water **- -**	Water **- -**	Water **- -**
Hectares **Treated** in year 50 [Table 4.3, Sup. Mat. Table 4.2]	Worst	Consensus -	Water **- -**	Water **- -**	Water **- -**	Water **- -**	Water **- -**
Hectares **Maintained** over model years 10-50 [Table 4.4, Sup. Mat. Table 4.3]	Worst	Keep-it-Clean **++**	Keep-it-Clean **- -**	Keep-it-Clean **- -**	Keep-it-Clean **- -**	Keep-it-Clean -	Triage **++**
Hectares **Maintained** at year 50 [Table 4.4, Sup. Mat. Table 4.4]	Worst	Keep-it-Clean **++**	Keep-it-Clean +	Water **- -**	Water **- -**	Keep-it-Clean +	Triage **++**

Hectares **Sustained** over model years 10-50 [Table 4.5, Sup. Mat. Table 4.5]		Keep-it-Clean - -	Keep-it-Clean - -	Keep-it-Clean - -	Keep-it-Clean - -	Keep-it-Clean -	Keep-it-Clean ++
Hectares **Sustained** in year 50 [Table 4.5, Sup. Mat. Table 4.6]		Keep-it-Clean -	Keep-it-Clean -	Water - -	Keep-it-Clean - -	Water +	Keep-it-Clean +

All the other management strategies treated significantly less hectares and management units per year than the Random strategy (Random strategy: mean 10,802ha, ±4,928SD, and mean 397 MU ±173SD; *p*<0.001), with the Water production strategy (*i.e.* prioritizing clearing of riparian zones and wetlands, Box 4.1) treating the least mean hectares (4,549 ±4,869SD) and management units (256, ±160SD) annually. Annually, the Consensus and Follow-up strategies treated about half the hectares and management units compared to the Keep-it-Clean strategy (Consensus: mean 8,912 ha ±7,655SD and 342 ±262SD management units; Follow-up: mean 7,942 ha ±6,047SD and 327 ±208SD management units). At the end of the model run at year 50, a similar outcome was observed with the Keep-it clear strategy clearing significantly more hectares and management units (mean 15,529ha, ±4,537SD, and 575 MU, ±143SD; *p*<0.001, Table 4.3) than the other management strategies.

Table 4.3. The number of hectares (ha) and management units (MU) treated per year averaged over clearing efficacies of 0.05-0.9 and 15 model runs, for model years 10 to 50 and for year 50.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.05-0.90	10-50	8912	7655	830	22669	*p*<0.001	342	262	29	809	*p*<0.001
Follow-up	0.05-0.90	10-50	7942	6047	836	22669	*p*<0.001	327	208	30	809	*p*<0.001
Keep-it-Clean	0.05-0.90	10-50	16135	4428	5606	22668	*p*<0.001	593	136	254	809	*p*<0.001
Random	0.05-0.90	10-50	10802	4928	1861	22668	N.A.	397	173	67	809	N.A.
Water	0.05-0.90	10-50	4549	4869	972	22669	*p*<0.001	256	160	68	809	*p*<0.001
Triage	0.05-0.90	10-50	14471	4910	2076	22669	*p*<0.001	354	253	24	809	*p*<0.001
Consensus	0.05-0.90	50	7719	7249	984	22667	*p*<0.001	302	249	45	809	*p*<0.001
Follow-up	0.05-0.90	50	6606	5453	1125	22668	*p*<0.001	285	189	50	809	*p*<0.001
Keep-it-Clean	0.05-0.90	50	15529	4537	6050	22667	*p*<0.001	575	143	270	809	*p*<0.001
Random	0.05-0.90	50	9877	4434	2035	22665	*p*<0.001	365	156	74	809	*p*<0.001
Water	0.05-0.90	50	3518	3719	1095	22665	*p*<0.001	223	127	88	809	*p*<0.001
Triage	0.05-0.90	50	13041	5138	2076	22666	*p*<0.001	294	244	24	809	*p*<0.001

4.3.2.2 The impact of clearing efficacy on hectares and management units treated

Clearing efficacy had a significant effect on the mean hectares and management units that could be treated, for all strategies tested (Fig. 4.1, Sup. Mat. Table 4.1). At 100% efficacy all management strategies were able to clear all hectares, indicating that the choice of a specific strategy becomes irrelevant at this level of efficacy. At very high efficacy levels (0.95), all management strategies were able to treat a mean of >21,200 ha (94%) and 760 (94%) management units (Sup. Mat. Table 4.1) each year, from years 10-50, with no significant difference between the management strategies and the Random strategy (p>0.05). The general trend for all management strategies was a sharp decline in the number of hectares and management units being cleared annually as efficacy levels decreased. For example the mean number of hectares treated by the Consensus strategy (*i.e.* the shared view of conservation managers, Box 4.1) decreased to a mean of 18,069ha ±6,629SD at 0.90 clearing efficacy, 11,931ha ±7,928SD at 0.75, 8,882ha ±7354SD at 0.50 and 5,347ha ±5056SD at 0.25 clearing efficacy (Sup. Mat. Table 4.1). Only the Keep-it-Clean and Triage strategies treated significantly more hectares (p<0.001, Fig 4.2, Sup. Mat. Table 4.1) than the Random strategy at all efficacy levels, while all the other strategies consistently treated significantly less hectares (p<0.001, Fig 4.2, Sup. Mat. Table 4.1).

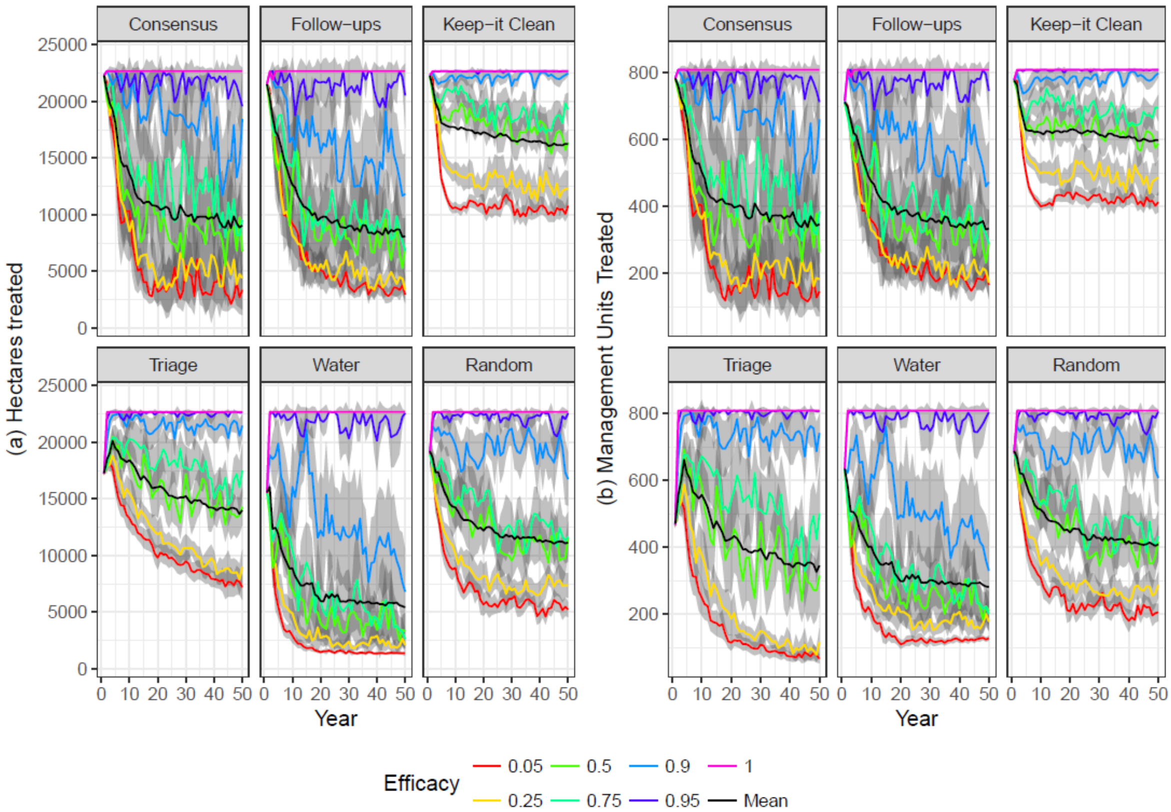

Fig. 4.1 : Effect of clearing efficacy on the number of hectares (a) and management units (b) treated per year over 50 years for each of the management strategies. Mean and 95 %

confidence over 15 model runs are shown for selected levels of clearing efficacy. Supplementary Material Fig. 4.3 shows all 20 tested levels of efficacy.

4.3.2.3 Strategy outcomes

At model endpoints (year 50), the overall trend was for the Keep-it-Clean and Triage strategies to treat significantly more hectares (p<0.001, Fig 4.2, Sup. Mat. Table 4.2) than the Random strategy. The other management strategies constantly treated significantly less hectares (p<0.001, Sup. Mat. Table 4.2) than the Random strategy, expect for the Consensus strategy which was not significantly different to the Random strategy at 0.90 and 0.75 clearing efficacy levels. In terms of the management strategies, the Water production strategy treated the least number of hectares at all efficacy levels.

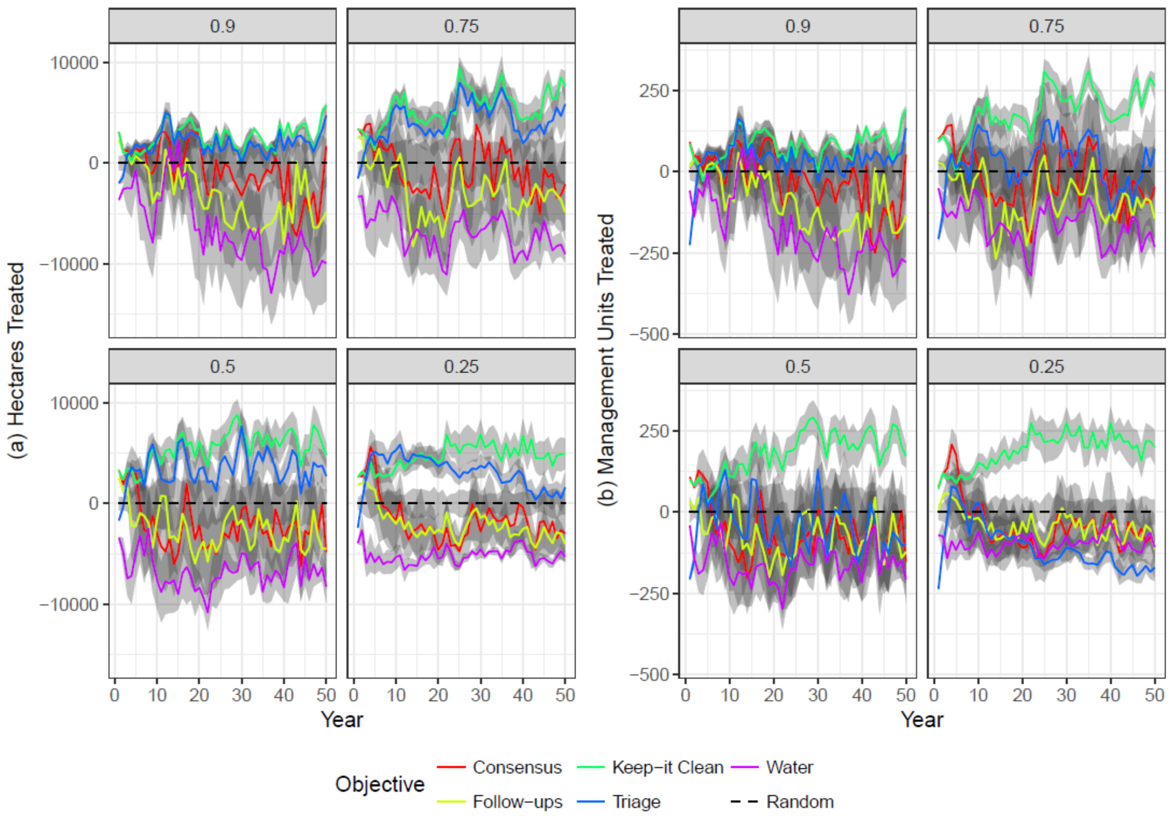

Fig. 4.2 Relative performance of the strategies in the number of hectares (a) and management units (b) treated per ha per year over 50 years for each of the management strategies in comparison to the random strategy at four management efficacy levels (0.25, 0.50, 0.75 and 0.90), represented by the mean 95% CI of 15 model runs per efficacy level.

4.3.2.4 Resource effort used

The number of person days required by all management strategies was similar. At 100% efficacy the number of person days required declined to below 10,000 from year 20 onwards (Fig. 4.3). As clearing efficacy decreased, the number of person days utilised annually remained high and near the maximum possible allocation. The Consensus and Follow-up strategies required around 38,000 person days for clearing efficacy levels between 0.75 and 0.90. For the Water production and Keep-it-Clean strategies, the full person days were utilised in all years where clearing efficacy levels dropped below 0.9 (Fig. 4.3). The impact of efficacy had a much greater effect on cumulative costs than the particular strategy applied selected (Fig. 4.3b). For example the cumulative mean person days used after 50 years at 0.95 efficacy for all strategies was 1.4 million person days, compared to 2.0 million person days at efficacy levels of 0.50. This difference amounts to the equivalent person days of 15 years of clearing, which in current project budgets amounts to ZAR300 million.

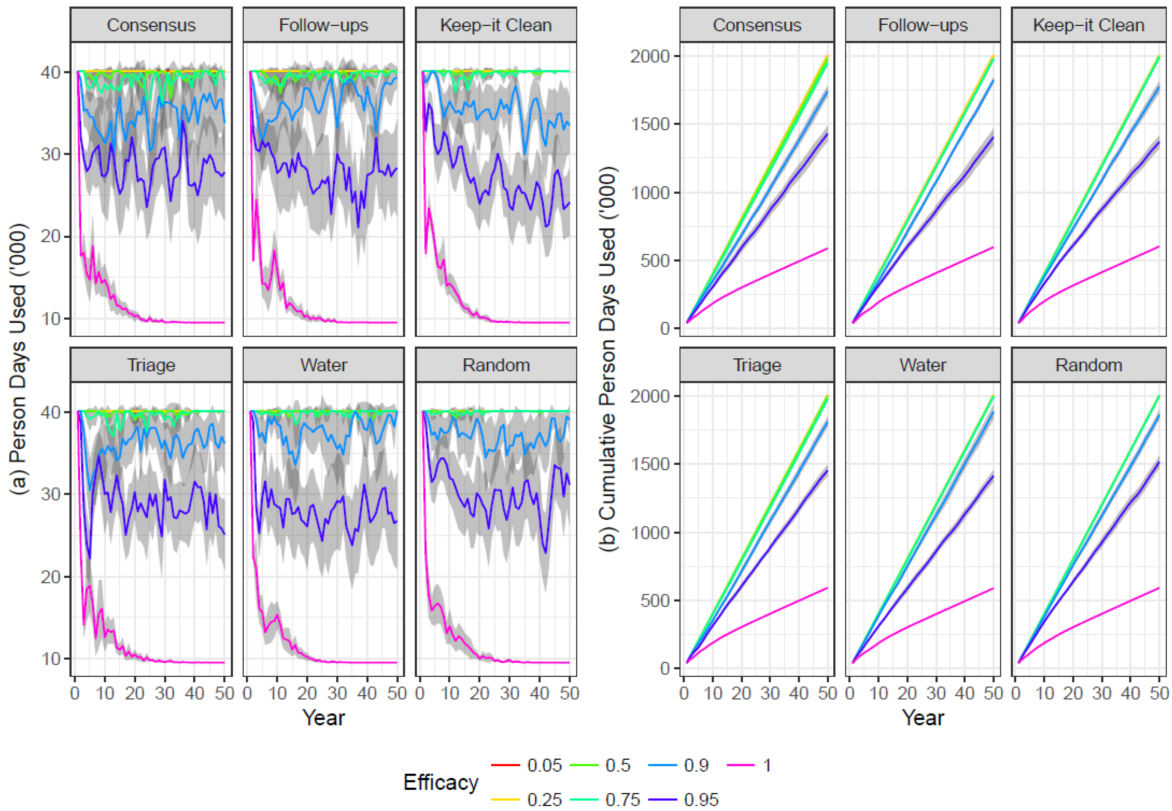

Fig. 4.3: The number of person days used annually (a) and the cumulative person days used over 50 years (b) for each of the management strategies at given levels of efficacy, represented by the mean 95% CI of 15 model runs per efficacy level.

4.3.3 Achieving management goal

The management goal set was to achieve an *Acacia* density of lower than 1 plant/ha in a given management unit, with the area thus being considered in a maintenance state. All management strategies achieved a minimum average of 8400 ha (37%) and 100 (12%) management units in a maintenance state from year 10 onwards at averaged levels of efficacy (Fig. 4.4, Table 4.4). Although the Keep-it-Clean strategy treated the most hectares (Table

4.3), this management strategy achieved the lowest number of hectares per year in a maintenance state across all years and efficacy levels (mean= 8,462ha ±3064SD, Table 4.4, Fig. 4.4). All management strategies realised significantly more hectares in a maintenance state than the Random strategy (p<0.001, Table 4.4, Fig 4.4). The Follow-up strategy realised the greatest mean number of hectares (10,296 ±3708SD; p<0.001, Table 4.4) in a maintenance state, which was significant more than all the other management strategies. The trend remained the same at the model end (following 50 years of implementation) with the Follow-up strategy attaining more mean hectares in a maintenance state (10,707 ±3381SD, Table 4.4) across all levels of clearing efficacy. All the management strategies performing better than the Random strategy (p<0.05). In addition, all strategies were able to increase the total number of hectares in a maintenance state from the starting value of 5,646 hectares to at least 8,000ha under averaged efficacy (Table 4.4).

Table 4.4. The number of hectares (ha) and management units (MU) that reached a maintenance state of < 1 plant/ha, per averaged over years 10 to 50, all levels of clearing efficacy, and 15 model runs. The starting value for the number of hectares in a maintenance state was 5,646 hectares and 161 management units.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.05-0.90	10-50	10026	3834	1911	20092	p<0.001	224	158	34	699	p<0.001
Follow-up	0.05-0.90	10-50	10296	3708	2508	20317	p<0.001	232	158	37	673	p<0.001
Keep-it Clean	0.05-0.90	10-50	8462	3064	1601	18608	p<0.001	164	105	23	579	p<0.001
Random	0.05-0.90	10-50	8333	4149	440	20061	NA	185	139	14	673	NA
Water	0.05-0.90	10-50	9442	2830	3440	20192	p<0.001	162	124	41	690	p<0.001
Triage	0.05-0.90	10-50	9513	4398	1382	20572	p<0.001	223	158	28	709	p<0.001
Consensus	0.05-0.90	50	10161	3598	3857	20092	p<0.001	216	156	34	664	p<0.001
Follow-up	0.05-0.90	50	10707	3381	5474	19335	p<0.001	235	162	50	659	p<0.001
Keep-it Clean	0.05-0.90	50	8091	3336	1601	17608	p<0.05	150	111	23	527	NS
Random	0.05-0.90	50	7581	4512	844	19161	NA	170	144	16	611	NA
Water	0.05-0.90	50	9501	2359	5193	18433	p<0.001	155	106	50	592	NS
Triage	0.05-0.90	50	9314	4395	2416	19989	p<0.001	216	158	36	677	p<0.001

At 95% efficacy levels, over the model period 10 to 50 years, all the management strategies achieved a mean of at least 18,200ha (88%) and 590 (73%) management units in a maintenance state from a starting point of 5,646ha and 161 management units (Sup. Mat. Table 4.3). Again, the Keep-it-Clean strategy achieved significantly less hectares in a maintenance state (p<0.001, Sup. Mat. Table 4.3) than the Random strategy, while the remaining management strategies achieved significantly more (p<0.001, Sup. Mat. Table 4.3). The Follow-up strategy attained the highest mean number of hectares annually in a maintenance state at high efficacy levels, maintaining significantly more area (19,633ha ±894SD) than all strategies besides the Water production strategy (Sup. Mat. Table 4.3).

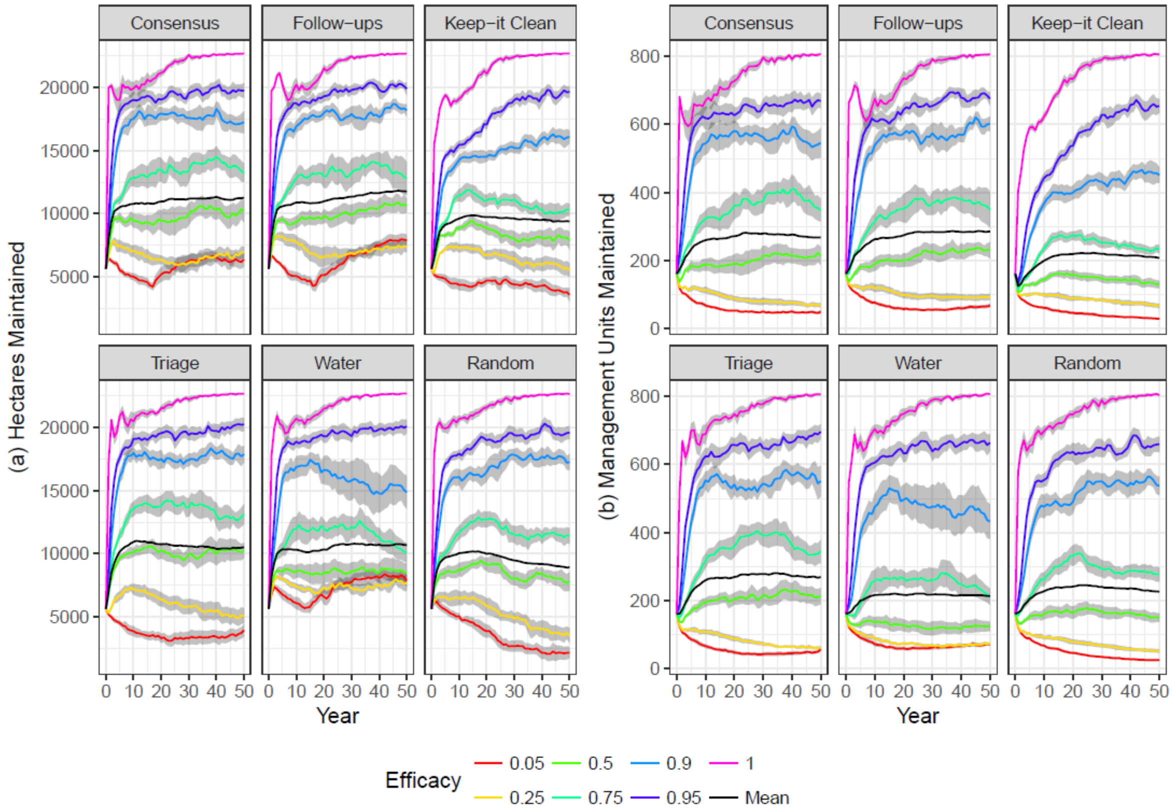

Figure 4.4: Effect of clearing efficacy on the number of hectares (a) and management units (b) that reached a maintenance state of 1 plant per ha over 50 years for each of the management strategies. Mean and 95 % confidence over 15 model runs are shown for selected levels of clearing efficacy. Supplementary Material Fig. 4.4 shows all 20 levels of efficacy tested.

The general trend observed at lower clearing efficacies was a sharp decline in the annual achievement of the management goal (Fig. 4.4). For example, at a 90% clearing efficacy, the Consensus strategy maintained a mean of 17,629 ha (±1,204SD) annually, compared to 13,575ha (±1,544SD) at 0.75, 9,826ha (±1,492SD) at 0.50 and 6,488ha (±1,005SD) at 0.25 clearing efficacy level (Fig. 4.4, Sup. Mat. Table 4.3), with a similar trend for the management units. The Keep-it-Clean strategy only outperformed the Random strategy at low (0.50) to very low (0.25) clearing efficacy levels (Fig. 4.4, Sup. Mat. Table 4.3). By year 50, all management strategies achieved a similar high number of hectares in a maintenance state at very high clearing efficacies (0.95) (Sup. Mat. Table 4.4). Results were however variable at lower levels of clearing efficacy. The Follow-up strategy was able to achieve significantly more hectares (mean=18,169ha ±886SD; p<0.05, Sup. Mat. Table 4.4, Fig 4.5) in a maintenance state than the Random strategy at 90% clearing efficacy after 50 years of implementation. There was no significant difference between the Consensus and the Random strategies. However, at a 75% clearing efficacy, the Consensus strategy maintained significantly more hectares (mean=13,230ha ±1,333SD; p<0.01, Sup. Mat. Table 4.4, Fig 4.5) than the Random strategy, while there was no significant difference between the Follow-up and the Random strategies. The Keep-it-Clean and Water production strategies only maintained significantly more (p<0.001) hectares than the Random strategy at low levels of clearing efficacy, otherwise achieving significantly less than a random application (Fig. 4.5, Sup. Mat. Table 4.4).

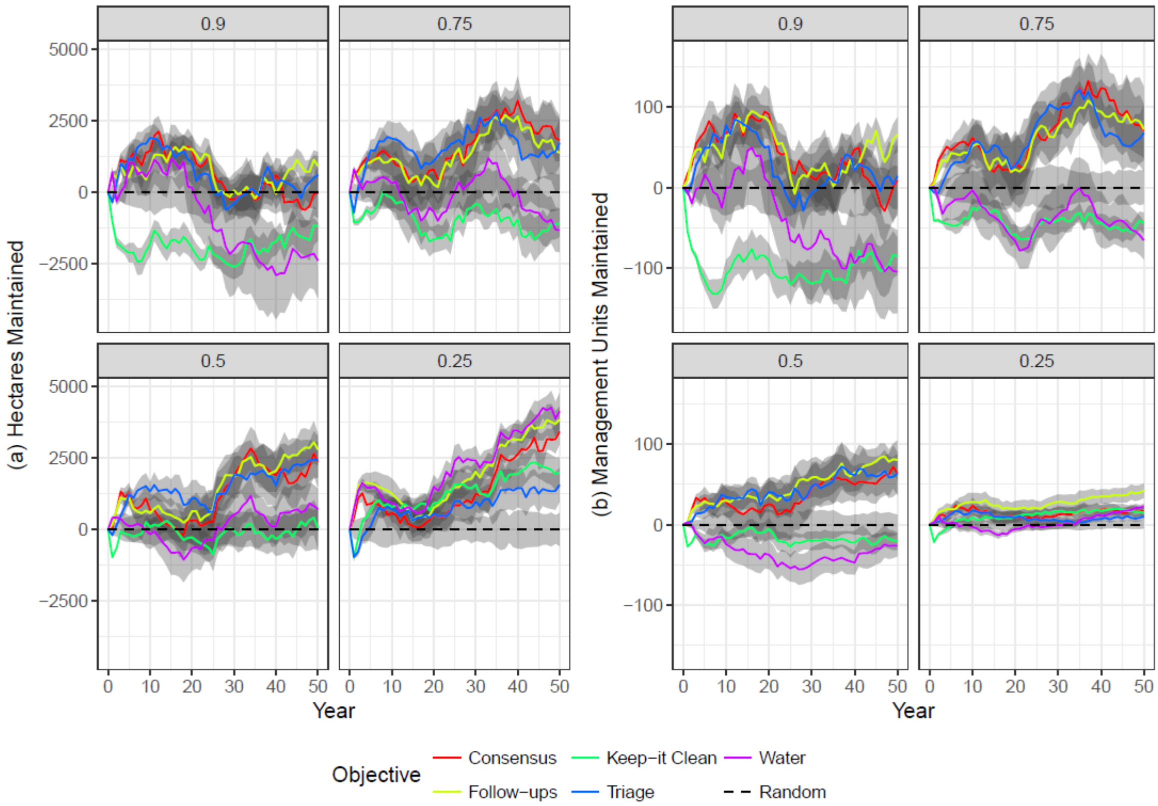

Fig. 4.5 Relative performance of the strategies in the number of hectares (a) and management units (b) that reached a maintenance state of 1 plant per ha per year over 50 years for each of the management strategies in comparison to the random strategy at four management efficacy levels (0.25, 0.50, 0.75 and 0.90), represented by the mean 95% CI of 15 model runs per efficacy level.

4.3.4 Maintenance areas sustained

The park had 5,646 hectares (25%) and 161 (20%) management units in a maintenance state at the start of the model (i.e. year 0). At 100% clearing efficacy, these areas remain in this maintenance state under all management strategies. When clearing efficacy decreased below this level, there was a shift away from the current areas under maintenance to new areas, for all management strategies. Overall, management strategies retained a mean of 2,700 (48%) hectares and 44 (27%) of the managements units in a continued maintenance state across all levels of clearing efficacy and years (Fig. 4.6, Table 4.5). Of the management strategies, the Triage and then Follow-up strategies sustained the largest portion of the starting maintenance areas in a continued maintenance state per year over the model years 10 to 50 (Triage 58%, mean = 3,275ha ±795SD; Follow-up 57%, mean = 3,208ha ±753SD, Table 4.5, Fig. 4.6). The Keep-it-Clean and Water production strategies both kept significantly fewer of the starting maintenance hectares in a continual maintenance state than the Random strategy (p<0.001, Table 4.5, Fig. 4.6).

Table 4.5. The number of hectares (ha) and management units (MU) that were sustained in a maintenance state of < 1 plant/ha, per year during the model run between years 10 to 50 and efficacy 0.05-0.9 (n=15), based on the starting 5,646 hectares and 161 management units that were in a maintenance state at the start of the model.

Strategy	Clearing efficacy	Model Yr	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.05-0.90	10-50	3184	762	740	5405	p<0.001	55	25	13	55	p<0.001
Follow-up	0.05-0.90	10-50	3208	753	520	5320	p<0.001	56	25	13	56	p<0.001
Keep-it Clean	0.05-0.90	10-50	2773	620	598	4963	p<0.001	44	19	11	44	p<0.001
Random	0.05-0.90	10-50	2819	982	99	5353	NA	49	24	7	49	NA
Water	0.05-0.90	10-50	3125	644	792	5411	p<0.001	47	23	12	47	p<0.001
Triage	0.05-0.90	10-50	3275	795	518	5351	p<0.001	54	24	12	141	p<0.001
Consensus	0.05-0.90	50	2989	818	844	5244	p<0.001	44	25	13	44	p<0.001
Follow-up	0.05-0.90	50	3078	750	1173	4879	p<0.001	47	26	14	47	p<0.001
Keep-it Clean	0.05-0.90	50	2551	737	638	4681	NS	35	20	11	35	NS
Random	0.05-0.90	50	2415	1139	237	4770	NA	38	24	8	38	NA
Water	0.05-0.90	50	2904	633	792	5095	p<0.001	35	18	12	35	NS
Triage	0.05-0.90	50	2991	885	853	5195	p<0.001	43	25	14	139	p<0.001

By year 50, all management strategies sustained more than 2,500 (44%) hectares and 35 (22%) of the managements units in a continued maintenance state (Fig. 4.6, Table 4.5) across efficacy levels. All but the Keep-it-clean management strategy sustained significantly more hectares in a continued maintenance state than the Random strategy (Fig. 4.6, Table 4.5). The Follow-up and then Triage strategy scored highest in continued maintenance of areas at year 50 (Follow-up 55%, mean = 3,078±750SD, Triage 53%, mean = 2,991ha ±885SD, Fig. 4.6, Table 4.5).

As clearing efficacy levels decreased, there was a steady decline in continued maintenance of areas at the start of the model from all management strategies (Fig. 4.6, Sup. Mat. Table

4.5). At 90% clearing efficacy levels the Follow-up and Triage strategy continually maintained starting maintenance areas at higher levels than the Random strategy (Follow-up 80%, mean= 4,533ha ±350SD; Triage 80%, mean= 4,528 ±342SD, *p*>0.001), while the other management strategies performed no different or significantly worse than the Random strategy (Fig. 4.7, Sup. Mat. Table 4.5). Only at 25% clearing efficacy levels did all the management strategies perform better than the Random strategy (Fig. 4.7, Sup. Mat. Table 4.5) in retaining hectares in a maintenance state.

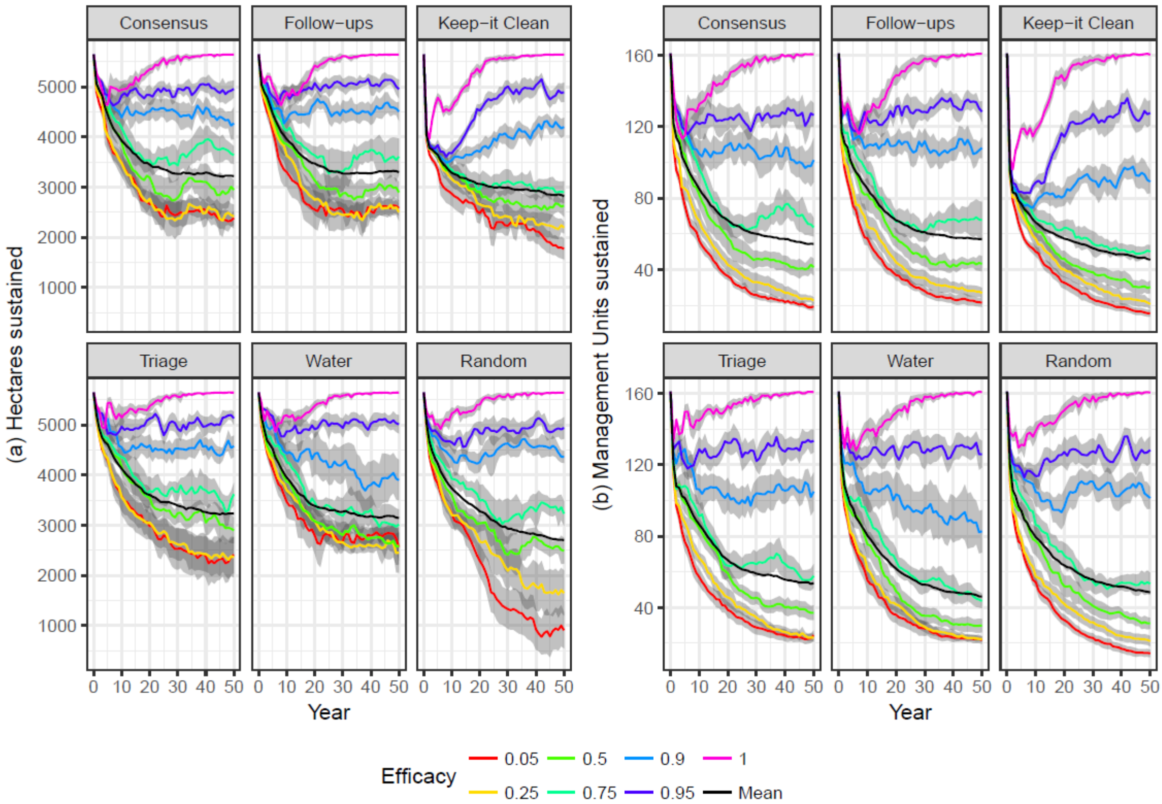

Figure 4.6 Effect of clearing efficacy on the number of hectares (a) and management units (b) that were sustained in a maintenance state of 1 plant per ha over 50 years for each of the management strategies. Mean and 95 % confidence over 15 model runs are shown for selected levels of clearing efficacy. Supplementary Material Fig. 4.5 shows all 20 levels of efficacy tested.

In areas maintained at the end of the model (year 50), at 95% clearing efficacy there was no significant difference between the management and the Random strategies for both hectares and management units (Sup. Mat. Table 4.6). At 90% efficacy levels only the Water production strategy had significantly less hectares continually maintained than the Random strategy (69%, mean= 3,898ha ±731SD, *p*<0.05) while the other management strategies showed no significant difference from the Random strategy (Fig. 4.7, Sup. Mat. Table 4.6). The strategies showed a mixed performance at 75% and 50% clearing efficacy levels. The Consensus and Triage strategies performed significantly better in terms of the hectares sustained than the

Random strategy at medium clearing efficacy levels (p<0.05, Sup. Mat. Table 4.6, Fig. 4.7), while the Consensus and Follow-up strategies showed significantly better results than the Random strategy at low clearing efficacy levels (p<0.05, Sup. Mat. Table 4.6, Fig. 4.7).

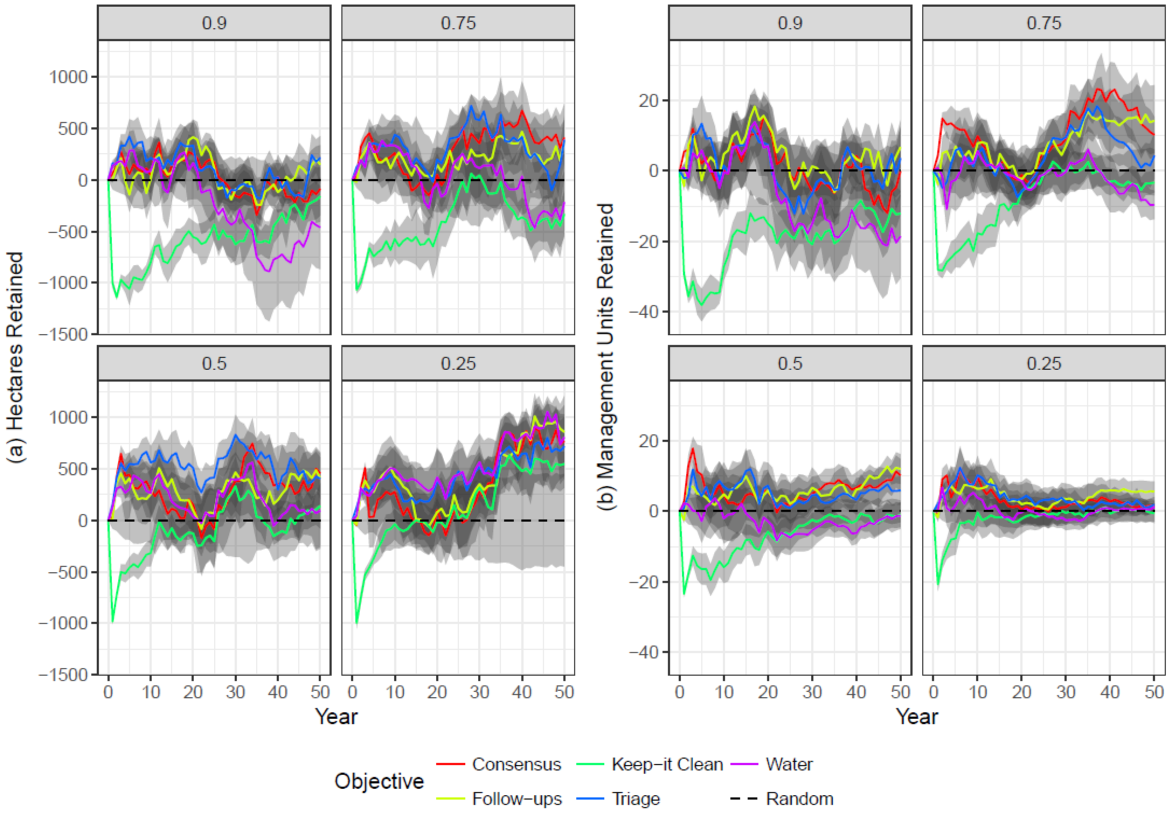

Fig. 4.7 Relative performance of the strategies in the number of hectares (a) and management units (b) sustained in a maintenance state of 1 plant per ha per year over 50 years for each of the management strategies in comparison to the random strategy at four management efficacy levels (0.25, 0.50, 0.75 and 0.90), represented by the mean 95% CI of 15 model runs per efficacy level.

4.3.5 Treatment frequency distribution under different strategies

Treatment frequency per management unit (i.e. the number of times a particular management unit is selected for treatment over the full model implementation) declined for all strategies with a reduction in clearing efficacy, as indicated by a left-shift in peak kernel density of treatment frequency (Fig. 4.8, Sup. Mat. Figure 4.6). In other words, a smaller number of management units were repeatedly selected over the model period at lower clearing efficacy (Fig 4.8). For example, the Consensus strategy had its highest kernel density at a treatment frequency of 0.7 when clearing efficacy was 0.75, whereas the peak frequency decreased to 0.55 and 0.35 at clearing efficacies of 0.5 and 0.25 respectively. Historical clearing implementation has its peak treatment frequency at roughly 0.45 which was found to be a significantly lower repeat frequency (p<0.001) than was achieved by all the models expect the

Water production model (*p*=NS) at an efficacy comparable to that estimated for historical implementation (~0.75). At 50% clearing efficacy levels, the Management consensus, Follow-up clearing and Keep-it-Clean strategies still maintained the peak cluster densities at a treatment frequency of >0.50, implying that the majority of the management units would receive a treatment at least once every two years. This treatment frequency was still significantly ($p<0.01$) better than the current observed park treatment frequency of 0.45.

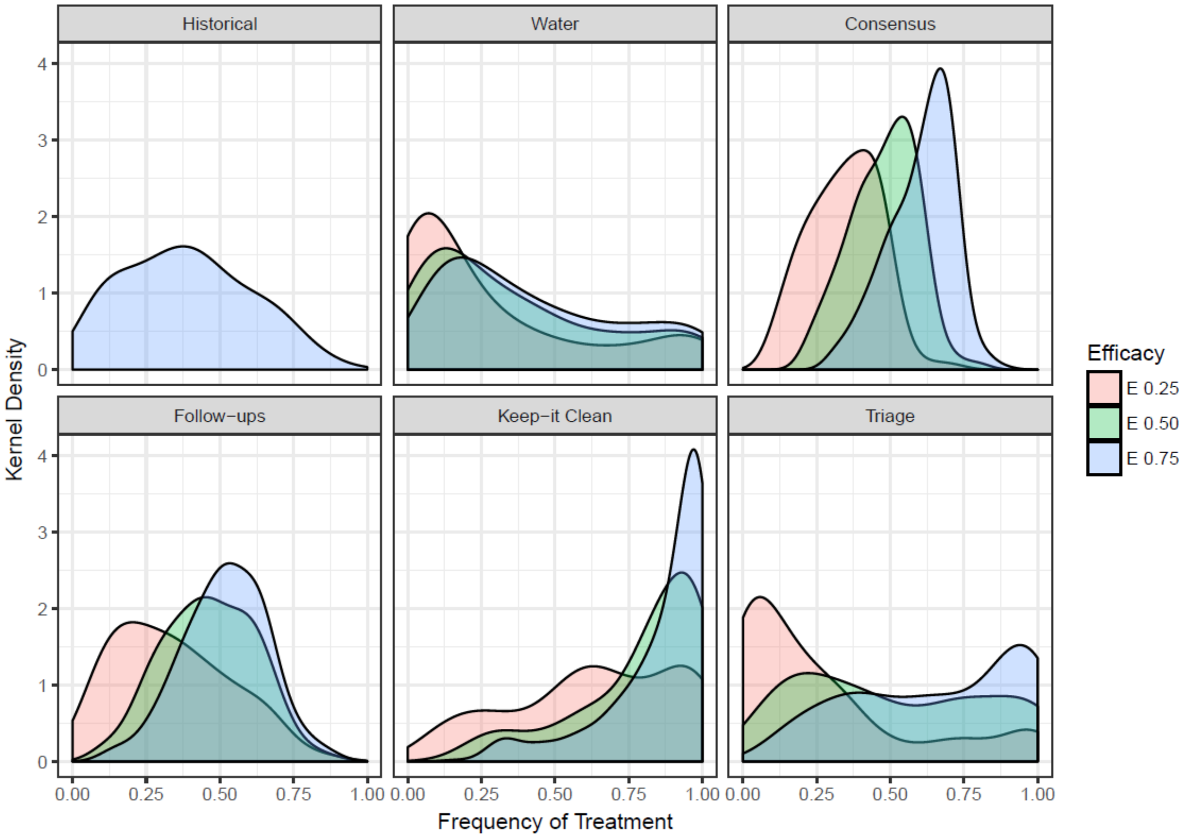

Fig. 4.8. Kernel density of treatment frequency per management unit for each management strategy over 50 years and 15 model runs, as well as the actual frequency of treatments received per unit in the park to between 1998 and 2017(Historical park data). Management strategies are shown for three efficacy levels (0.25, 0.50 and 0.75).

4.4 Discussion

The long-term performance and outcomes of five strategies that have been suggested and applied to alien invasive plant management were tested over a 50 year simulation based on data for *Acacia* species in Table Mountain National Park. The assessment focused on the interaction between strategy performance and clearing efficacy in achieving the management goal of reducing *Acacia* density to below 1 plant per hectare. At near perfect levels of clearing efficacy, all strategies converged towards reaching the management goal for the entire protected area. At lower efficacy levels, the strategies diverged from each other in their ability to achieve desired outcomes. The Keep-it-Clean strategy (focusing on large areas of very low *Acacia* density) was able to treat the greatest number of hectares and management units at all efficacy levels. However, the models showed that treating large areas did not necessarily translate into the achievement of low IAP density across the PA, predominantly as this strategy focused on sites of already low alien density. So, while the Keep-it-Clean strategy covered the widest area, it produced the least hectares in a maintenance state across strategies for the PA. The Consensus strategy achieved the highest number of hectares in a maintenance state and the highest retention of current hectares in a maintenance state at efficacy levels approximating those of current WfW programme implementation (~75% efficacy, Chapter 3). While this finding suggests that the Consensus is strategy the most fitting for the observed levels of efficacy, the models also indicate that a Follow-up strategy becomes more appropriate at higher implementation efficacy. The Triage strategy was the most effective strategy at retaining area of high biodiversity value in a maintenance state, while overall, across all efficacy levels, the Water Production strategy performed consistently poorly.

To assist conservation managers with complex decision making, Structured Decision Making processes are able to present a range of objectives for alien plant clearing programmes (Bower *et al.* 2017; Schwartz *et al.* 2018). Although the range of objectives can allow for stakeholder insight and buy-in, the formulation of too many objectives may not benefit or support the underlying desired conservation outcome. That is, the proliferation of objective setting may actually obscure, undermine or conflict with the real conservation objective (Carrigan 2018; Roper *et al.* 2018). Despite IAP strategies and objectives having been in place for more than 30 years (Macdonald *et al.* 1985), formal assessment of their shortcomings has not been undertaken even though these assessments can provide significant insights for managers. Some of the limitations identified here to potentially relevant to particular objectives are unpacked below.

Not all objectives deliver the desired conservation outcome.

Modelling showed that over time, strategies were divergent in the areas that were selected for clearing. This finding was consistent with previous work that tested management strategies for sensitivity in area selection (Roura-Pascual *et al.* 2010). Divergent area selection results in each strategy setting a different management trajectory which did not converge over the 50 years modelled. For example, the Water production strategy achieved the least number of hectares maintenance in across the PA. While the important and direct ecosystem services benefit of water security is enhanced, following this objective alone puts the programme on a different trajectory, ultimately not serving the overall conservation goal. Over time, this undermines the sustainability of the strategy as eventually the surrounding landscape would be lost to invasion, while the waterways are kept clear.

Not all objectives are good objectives.

Conservation agencies recognise that ecosystems are in a constant state of flux and management is often implemented via a learning approach for example through adaptive management (Biggs *et al.* 2003; Roux & Foxcroft 2011). In the adaptive management approach, learning from management action via monitoring the outcomes is emphasised (Shea *et al.* 2002; Levendal *et al.* 2008; Downey 2013). However, at least for the WfW programme, the monitoring of outcomes is largely absent (Blossey 1999; Marais *et al.* 2004; McConnachie *et al.* 2012; van Wilgen *et al.* 2012b; van Wilgen & Wannenburgh 2016; Fill *et al.* 2017), with the implementation focus of expedited delivery on employment targets and areas treated. Without, the formal monitoring of the programme's outcomes, the programme objectives have been adopted and have become entrenched as plausible solutions to the complex problem without systematic review. Without monitoring, there is a break in the management process where the much needed forward planning is compromised. The reduction in sound forward planning in favour of increased focus on management action can change the maxim 'Ready, Aim, Fire' to 'Ready, Fire, Aim, Fire, Aim, Fire…' (Game *et al.* 2014). The associated lack of monitoring and focus on management action has two major drawbacks.

First, resources and effort are committed and spent on management actions, with no guarantee that the actions will result in tangible progress towards desired objective. The model analysis showed that a set of management actions can perform worse than a random selection of actions in achieving management goals. For example, the Keep-it-Clean strategy performed significantly worse than a Random strategy in terms of the number of hectares that achieved maintenance. Second, the models showed that a random prioritization of actions can fare reasonably well under certain conditions. This advocates that unless actions are rigorously implemented within the adaptive learning framework, it will be almost impossible to learn and move in the correct management direction (Biggs *et al.* 2003; Roux & Foxcroft 2011).

Not all objectives are complimentary.

A challenge that may stem from collective objective setting that aims to accommodate differences' in stakeholder views (Reed 2008), is that the resulting objectives may not be complementary. This could hinder implementation, resulting in no resolution of the original stakeholder divergence. For example, at 75% efficacy levels the Management consensus strategy achieved the highest hectares in a maintenance state while utilising the least number of person days. Although lower resource requirements may be seen as a positive, diminishing workloads is in direct conflict with the job creation objective of the programme, which seeks to maximise employment (Koenig 2009; van Wilgen *et al.* 2017). In contrast, less efficient strategies that maximise resource requirements such as the Keep-it-Clean strategy would better realize the employment objective, while failing to achieve the desired conservation outcome. As such, there is a need to constantly engage with funders to ensure that conservation objectives are not compromised by funder-driven objectives.

Not all objectives are popular and so may not be adopted.

Conservation triage has been proposed to focus management on core areas of high importance in times of limited resources (Bottrill *et al.* 2008, 2009; van Wilgen *et al.* 2016). Although conservation triage has drawn both positive and negative views as a viable conservation strategy, the strategy of 'abandoning' lower priority sites sits uneasy as a plausible management approach (Jachowski & Kesler 2009; Parr *et al.* 2009; Gerber 2016). In the range of simulation models tested, a Triage strategy that focused primarily on repeatedly treating a core conservation area and, when possible, treating additional secondary areas was tested. This strategy performed very well in terms of retaining current areas in a maintenance state as well as being the second best preforming strategy in achievement of additional hectares in a maintenance state. However, adoption of a Triage strategy would be met with resistance by conservation managers as it conflicts directly with the park's mandate for managing all biodiversity and not smaller sub-sections (SANParks 2016).

When adopting new or changing management approaches, conservation managers have been resistant to change (Cook *et al.* 2009; Cook *et al.* 2012; McConnachie & Cowling 2013). Simulation models indicated that there would be a shift away from areas that were currently in a maintenance state if an alternate management strategy were to be rigorously adopted. As decades of management time and resources have been invested into the maintenance state of these areas, there would be a natural tendency by management to 'maintain gains' of these areas and not permit them to become re-invaded.

A single IAP objective that allows for efficacy improvement.

In IAP management there has been emphasis on management objectives that reduce impact and risks or securing ecosystem services for protected areas. As such, protected areas as important biodiversity that can deliver ecosystem services have already been prioritised as requiring immediate conservation action. A further prioritisation with additional objectives could be seen as self-defeating (Game *et al.* 2013). From the variation in model results between strategies, it would be prudent for conservation managers to adopt a single IAP objective for the PA and then focus on improving efficacy. Although widely debated, there are very few proposals for landscape eradication of invasive plants from PAs (Moore *et al.* 2011). The adoption of management strategies that focus only on the short-term impacts and risks, and not long-term solutions are by default conceding that conservation managers will be controlling IAP in PAs for perpetuity. None of the current management strategies tested achieved a total reduction across the landscape of IAP, indicating that alien Acacias are likely to persist. To some extent this is ironic given that conservation resources are limited and need to be used effectively (Bruner *et al.* 2004; Emerton *et al.* 2006; Ferraro & Pattanayak 2006) The analysis indicated that the quality of the implementation was the principle driver of achieving the management goal, not the individual strategies *per se*. Higher efficacy levels, *i.e.* moving towards high quality and complete treatment of IAP's, not only reduced the required resources, but also the difference in the achieved outcomes between the strategies. Given the persistent nature of Acacias (Richardson *et al.* 2011; Fill *et al.* 2017), there may only be a single objective for IAP's in PA's, that of planning for long-term eradication. Currently all management strategies require repeated and potentially endless cycles of management, without the guarantee of endless supply of funding for the task. By increasing programme quality alone, all current strategies will converge to a point of low cost maintenance.

A way forward

Due to the variability of clearing efficacy levels achieved by the WfW programme annually, the best performing management strategy for implementation will change annually. This, along with the result that strategies have different prospects for achieving the management goal, suggests that allowing flexibility in decision making , as opposed to applying a rigid strategy, is likely more appropriate (Knight *et al.* 2011; Cook *et al.* 2012). In the case of Acacias, placing the emphasis on prevention of reseeding, through timely follow-up, rather than strategy *per se*, the management actions required annually could be adapted as necessary. However, this flexibility of management actions would require active and regular monitoring as the models have shown that implementation of the incorrect actions, at the low efficacy levels, would be costly.

The intended purpose of monitoring in IAP programmes is to measure the progress towards management objectives (Dewey & Andersen 2004). Without monitoring there is no way to determine if the conservation actions were effective or if the set objective was reached. Although IAP programmes are designed with intended feedback loops (Foxcroft & McGeoch 2011), monitoring appears to be inadequately implemented (van Wilgen *et al.* 2012b; Fill *et al.* 2017; van Wilgen *et al.* 2017). The lack of feedback monitoring may be a contributing factor to landscape-wide poor implementation in some IAP programmes (McConnachie *et al.* 2012;

van Wilgen & Wannenburgh 2016; Kraaij *et al.* 2017). Given that the monitoring requirements for adaptive learning are inadequate in terms of IAP management, there could be an argument for rationalising IAP objectives in-line with the core intent of PA management. That is, setting a simple and unchanging goal (e.g. the eradication of species, or reduction below key thresholds that minimize impact). With a single goal in mind, the programme could shift focus towards improved implementation efficacy.

The task of improving programme quality would have to be implemented over a period of time as there needs to be additional awareness and training of WfW staff to meet the required quality levels. Due to the reality that there will be varying levels of efficacy in programme implementation, it would be reasonable that current management approach would require modification. The model outputs suggest a pragmatic management approach that could be adopted that provides managers with a group of strategies which can be implemented at different sites over the PA rather than a single one fits all approach. This flexibility could be proactivity implemented, for example in important water areas, the water production strategy could be applied locally, while post-fire sites are grouped for the Follow-up or Consensus strategy. This flexible implementation would consider the most appropriate strategy for an area based on the population and spatial parameters of the site with the single long-term aim of IAP eradication as opposed to a ‘stale-mate’ of only reducing IAP impact, while the invasive species persist in the PA landscape.

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4.6 Supplementary material

The following supplementary Information may be found in the supplementary section accompanying this thesis:

Sup. Mat. Figure 4.1 Overview of the modules in the spatio-temporal simulation model that the management strategy and units (MU) were modelled and the calendar quarter within a simulation year in which they are called.

Sup. Mat. Figure 4.2 Link between protected area (PA) vision, objectives and management actions flowing to 1 of 4 management strategies. Weightings (Wt) for each objective/factor that determine a strategy was determined through the Analytical Hierarchy process (Roura-Pascual *et al*. 2010).

Sup. Mat. Figure 4.3 The number of hectares (a) and management units (b) treated per year over 50 years for each of the management strategies tested at 20 management efficacy levels between 0.05 and 1.0, represented by the mean and 95% CI, over 15 model runs.

Sup. Mat. Figure 4.4 The number of hectares (a) and management units (b) that reached a maintenance state of 1 plant per ha over 50 years for each of the management strategies at given levels of efficacy, represented by the mean and 95% CI over 15 model runs per efficacy level.

Sup. Mat. Figure 4.5 The number of hectares (a) and management units (b) that were sustained in a maintenance state of 1 plant per ha over 50 years for each of the management strategies at given levels of efficacy, represented by the mean and 95% CI over 15 model runs per efficacy level.

Sup. Mat. Figure 4.6 The frequency that management units were selected by different management strategies at three levels of clearing efficacy. Areas with a frequency of treatment > 50% approximates to a treatment frequency of < 2 years.

Sup. Mat. Table 4.1. The number of hectares (ha) and management units (MU) treated per year averaged over model years 10 to 50 and 15 model runs, at set levels of clearing efficacy.

Sup. Mat. Table 4.2. The number of hectares (ha) and management units (MU) treated in year 50 averaged over 15 model runs

Sup. Mat. Table 4.3. The number of hectares (ha) and management units (MU) that attained the management goal of < 1 plant/ha, per year, averaged over model years 10 to 50 and 15 model runs, at set various efficacy levels.

Sup. Mat. Table 4.4. The number of hectares (ha) and management units (MU) that attained the management goal of < 1 plant/ha, per year, averaged in year 50 and 15 model runs, at set various efficacy levels.

Sup. Mat. Table 4.5. The number of hectares (ha) and management units (MU) that were sustained in a maintenance state of <1 plant/ha, per year for years 10 to 50 and efficacy at various levels (n=15), with a starting maintenance state of 5,646 hectares and 161 management units.

Sup. Mat. Table 4.6. The number of hectares (ha) and management units (MU) that were retained in a maintenance state of <1 plant/ha, at the end of the model run at year 50 and efficacy at various levels (n=15), with a starting maintenance state of 5,646 ha and 161 MU units.

Chapter 5.

Quantifying range structure to inform management in invaded landscapes

Abstract

Invasive alien plants (IAPs) pose a current and future potential threat in many Protected Areas (PAs). To mitigate the impacts of these IAPs, control programmes have been put in place to manage a wide range of invading species in PAs. The implementation of IAP control is mostly undertaken through area-based management where the PA is divided into management units and all the IAPs identified within each management unit are controlled simultaneously. However this approach has several shortfalls including the methods to prioritise management units, spatial grain dependence and spatial interdependence of management units which allow for the continued persistence of IAP's in PAs. Although implemented less frequently, PAs also use a species-based approach to target a single or few invasive species where ongoing focussed efforts can result in the eradication of the target species. Here I propose using a Commonness framework, to reconcile the dichotomy between area-based and species-based management approaches. Biological invasions can be viewed as invading species on a trajectory from being uncommon to becoming common. The Commonness framework comprises eight commonness types based on three species characteristics of local population size (small or large), geographic range (wide or narrow) and spatial pattern (even or clumped). Comprehensive fine-scale alien plant species dataset from Table Mountain National Park is used for a case study to test if the Commonness typology can be employed to align alien species management strategies across IAP invasion phases within a PA. When IAPs were mapped to the commonness framework, most species fell into the Newly Established commonness type at fine spatial grains. At coarser grains, the overall trend was for species to be classed within wide occupancy ranges, but with small population sizes as mainly Dispersed and Sparse types. The most appropriate management strategies for all species at fine grains were a rapid response, reconnaissance or sweeping approach. This showed misalignment with the current IAP Control strategy which was aligned to the Incipient or Constrained commonness types. Use of a 'phylo-tree' is made to map the spatial hierarchy of areas at six spatial grains, which allows for visual interpretation of sites that require species-specific goals (for example eradication though rapid response), while allowing other sites to have a more conventional area-based goals. The continued collection of presence-absence data and range data is essential to support the goal to manage and reverse the negative impacts on IAPs.

5.1 Introduction

Movement of plant species by trade, forestry and a variety of other human endeavours has resulted in novel distribution ranges for numerous species (Hulme 2009; Lockwood *et al.* 2013). Many of these species thrive in their new ranges, and expand populations to cover large areas. Known as invasive alien plants (IAP), these species are characterised by range expansion properties and increased local population densities (Blackburn *et al.* 2011). These expansion and densification processes, where species move from being uncommon to becoming common in the landscape, do materialise in the same manner for all species and involve a number of interacting mechanisms. Some species follow slow diffusive dispersal, while others have both diffusive and long range dispersal characteristics (Pauchard & Shea 2006; Wilson *et al.* 2009). The range occupancy and the local population densities within invaded landscapes will therefore likely differ for different range expanding species, and this information is key for informing invasive species management. For example, the relative position of a species on a commonness trajectory can inform the potential risk it poses, while intraspecific comparisons of populations over different parts of their range may provide early warning of emerging range expansion (Veldtman *et al.* 2010; Donaldson *et al.* 2014).

Invasive alien plants pose a current and future potential threat in many areas, including those designated for the protection of biodiversity (Foxcroft *et al.* 2013; Foxcroft *et al.* 2017). Frequently these protected areas (PAs) have had long histories of invasion by multiple species (Spear *et al.* 2011) that have resulted in significant negative impacts on native biodiversity and ecosystem structure and function (Richardson *et al.* 2007; Gaertner *et al.* 2009; Le Maitre *et al.* 2011; Blackburn *et al.* 2014). To mitigate the impacts of IAP, control programmes have been established to deal with a wide range of invading species in PAs (van Wilgen *et al.* 2012b). Despite substantial investment, long-term control of IAP has been varying and generally limited in success (Gardener *et al.* 2010; Vince 2011; McConnachie *et al.* 2012; Kraaij *et al.* 2017), with the outlook for control requiring increased funding and resources.

The implementation of IAP control programmes is typically undertaken through area-based management where an area is divided into management units and all the identified IAPs within each management unit are controlled simultaneously (Wittenberg & Cock 2001; Working for Water 2003; Tu 2009). The overall aim of the area-based approach is to achieve ecological integrity or restoration goals at particular sites. However, the area-based approach has several shortcomings that limit its intended outcome. First is related to the implicit attribute of spatial grain (Dungan *et al.* 2002; Pauchard & Shea 2006; Hui *et al.* 2010). Management strategies and objectives are based on grain-dependent range characteristics of population extent and abundance as well as management attributes such as treatment success. For example, the selection of rapid response versus a control strategy is determined by both the abundance of the species and the area that it occupies (Wittenberg & Cock 2001; Tu 2009). Range characteristics such as population density and extent are typically measured at the single grain of the management units to be treated. However, these measures are likely to change at different grains and the relative change in value of these attributes, in terms of a hierarchy of grains, is often overlooked. For example, a species with high abundance at a fine grain may have relatively low abundance at a coarser grain sizes and vice versa. Similarly species occupancy can also vary widely over a number of grains where occupancy can have varying rates of increase depending on the patchiness of the distribution and the grain of measurement (He & Gaston 2000; Veldtman *et al.* 2010). Understanding variation in occupancy values can give insight into the overall population dynamics of a species (areas of saturation and possible expansion) from a site to a landscape and even a regional level (Kunin 1998; Wilson *et al.* 2004; Donaldson *et al.* 2014). The use of a single grain for deriving and implementing management strategies is a limitation for strategy and objective setting as the true picture can be obscured (like looking at a 3 dimensional object in 1 dimensional space), potentially resulting in inappropriate application of clearing strategies.

A second constraint of area-based management is that due to finite budgets for PA management (Frazee *et al.* 2003; Bruner *et al.* 2004), management units that require treatment have to be prioritised. A number of Structured Decision Making frameworks have been employed to assist prioritisation of conservation actions in PAs (Bower *et al.* 2017; Schwartz *et al.* 2018). These include, for example, Analytical Hierarchy Process (Forsyth *et al.* 2012), Adaptive Management objective setting (Foxcroft & McGeoch 2011) and Risk and Threat Analysis (Downey 2010; McGeoch *et al.* 2016). In each approach, the perceived ecological function or management focus is determined through the setting of specific management objectives that seek to retain or restore natural ecosystem structure and functions (Bower *et al.* 2017). Management focal areas often include river systems, wetlands, high fire risk areas, or areas where endangered or keystone species are found (Roura-Pascual *et al.* 2009). Irrespective of the prioritisation methodology, certain areas are ranked above or below others, meaning some areas would not be treated or only receive treatment as budgets become available. The outcome of not treating the target IAPs, at all sites in a management area, results in a decreased probability of species being eradicated, allowing for the persistence of IAP in the landscape.

A third limitation of the area-based approach is the frequent failure to consider spatial interdependence of management units in the range of the IAPs, in other words, what is happening in directly adjacent areas. This occurs as a result of the prioritisation process that scores treatment areas independently of one-another based on pre-set objectives (Forsyth *et al.* 2012). For example, river systems may receive a particular priority score, which is different to post-fire areas, yet these areas are ecologically interdependent: for many wattle species (*Acacia* spp.), waterways are an important dispersal pathway, while post-fire areas are important recruitment sites. Although there is a clear ecological link, failure to consider spatial interdependence could result in areas being selected and prioritised very differently depending on management priorities, allowing for the invasion process to perpetuate in the landscape.

Although implemented less frequently, species-based approaches to IAP control have also been implemented (Nel *et al.* 2004; Blackburn *et al.* 2014). A species-based approach is typically applied where single or few invasive species are present, over a narrow or restricted geographic range, with a short invasion history that have high potential impacts (Downey *et al.* 2010). The management approach is to deal primarily with the target species and ignore non-target species. Target species may be selected on the basis of particular traits, impacts or opportunity for a rapid response approach (Wittenberg & Cock 2001; Hulme 2006; Simberloff *et al.* 2013) with the primary aim in these types of programmes being the eradication of the target species. Budget requirements are less onerous than area-based management, and continual focussed effort can result in the eradication of the target species. The drawback of this approach is that the ecological integrity of an area or landscape may still remain degraded due to the presence of other non-target alien species.

The dichotomy between area-based and species-based management approaches can be reconciled by viewing species invasions as a continual process of invasion at different stages at varying landscape (Hobbs & Humphries 1995; Tu 2009; Blackburn *et al.* 2014, DEA 2014). As a species moves through the stages of arrival, establishment, range expansion and domination of the landscape (which can occur simultaneously in different parts of the PA), it moves along a trajectory from being uncommon to becoming common in the landscape (McGeoch & Latombe 2016). Where management pressure is employed, the trajectory applies in the opposite direction, seeking to move invading species from being common to uncommon and if possible, to remove them from the landscape. Depending on the species position on an invasion trajectory, the species can be classed into one of eight commonness types. This classification is based on the species range properties of population size, area occupied and time since establishment into a commonness type (McGeoch & Latombe 2016). The classification of invading species into a commonness type can provide a useful basis to understand observed range and population expansions and contractions within managed areas.

At each stage of invasion there are a variety of management strategies available to treat IAPs which differ substantially in terms of the time, costs, resource requirements and implementation methods (Simberloff *et al.* 2013). Strategies include i) area reconnaissance, ii) rapid response, iii) low density sweeping, iv) control, and v) containment (Table 5.1) (Wittenberg & Cock 2001; Tu 2009; Simberloff 2014). As species range properties are inherently scale dependent (Hartley & Kunin 2003; Hartley *et al.* 2004), the relationship between IAP range properties and the spatial grain of measurement has to be considered when aligning species range structure with management alternatives.

In this chapter the approach used to discern multiple types of 'commonness' is extended by aligning IAP management strategies with the commonness framework (*sensu* McGeoch & Latombe, 2016, Fig. 5.1). Fine-scale, spatially explicit alien species presence-absence data on the extent, occupancy, aggregation and abundance of several species (Cheney *et al.* 2018, Chapter 2) are used to assign species to one of nine commonness types at six hierarchical spatial grains. The usefulness of this classification for understanding how species commonness changes across spatial grains in different parts of the landscape and how this informs the most appropriate management clearing strategy, integrating both species-specific and area-based management approaches is assessed.

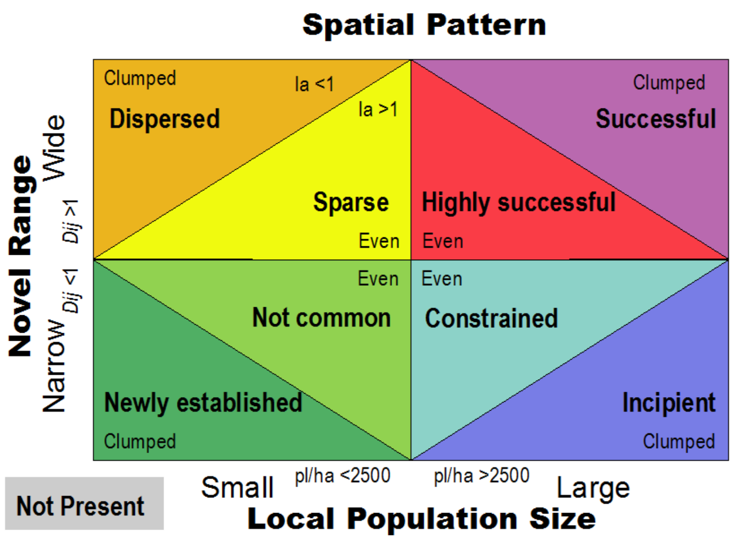

Fig. 5.1 Commonness framework (modified from McGeoch & Latombe 2016) based on three population properties; novel geographic range (wide or narrow), local population size (small or large) and spatial pattern. Population size is measured in absolute terms, with a cut-off of 2500 plants per hectare; range is measured with the box counting fractal D where the cut-off is determined by D*ij* <1 or D*ij* > 1; and spatial pattern is measure by the distance to regularity *Ia* with the cut-off as *Ia* <1 or *Ia* >1. The ninth category, 'not present', is used for where a species is absent from a site.

Table 5.1 Potential scale-relevant management strategies for invasive alien species based on properties associated with range structure categorizations (sensu McGeoch & Latombe 2016). The primary determinants of a management clearing strategy is determined by local population size (plants/ha) and the extent of the population (AOO or D). The local spatial aggregation is seen as 'chance of management success' where the likelihood of successful treatment increase where species are more aggregated.

Commonness Type	Range (Narrow / Wide)	Local Population (Small / Large)	Spatial patterns (Clumped / dispersed)	Management Strategy (Goal)	Definition	Comment on required resources
*Not present	NA	0	0	Reconnaissance Goal: prevent establishment of new populations	Looking for individuals in areas where they have yet to occur or have been previously removed	Very high search cost, very low treatment cost
Newly established	Narrow	Small	Clumped	Rapid Response (EDRR) Goal: Eradication	Total removal of very small populations that have been detected	Requires relatively high search effort, high cost per individual and low cost per ha
Not common	Narrow	Small	Dispersed			
Incipient	Narrow	Large	Clumped	Control[1] Goal: Reduce population size	Clearing medium size areas of medium-density IAP	Requires relatively low search and low per individual cost, but medium cost per ha
Constrained	Narrow	Large	Dispersed			
Dispersed	Wide	Small	Clumped	Maintenance / Sweeping Goal: Reduce geographic range	Clearing large areas of low-density IAP	Requires high search and high cost per individual and very low cost per ha
Sparse	Wide	Small	Dispersed			
Highly successful	Wide	Large	Clumped	Containment Goal: Limit expansion.	Preventing further spread of IAP in areas of the landscape where they dominate	Requires low search cost, medium cost per individual, very high cost per ha
Successful	Wide	Large	Dispersed			

[1] Control has been the core management focus in the PA

5.2 Materials and methods

5.2.1 Study area

Table Mountain National Park (TMNP) is located on the Cape Peninsula, South Africa, and covers approximately 25,000 ha. The PA is a well-known biodiversity 'Hot Spot' in the Cape Floristic Region (Cowling *et al.* 1996), with 158 endemic plant species occurring on the peninsula (Helme & Trinder-Smith 2006). However, the region also has a long history of plant invasion, with the dominant taxa comprising woody alien species from the genera *Acacia*, *Pinus* and *Hakea* (Shaughnessy 1980; Spear *et al.* 2013). A national response in the form of the Working for Water (WfW) programme was set up in 1996 to control IAPs, with the aim of restoring and maintaining habitat structure and function to mitigate the loss of ecosystem services, especially water production (van Wilgen *et al.* 2012a). Working for Water has historically invested (1995 – 2015) approximately ZAR 564 million (1 US$ ~ 16 ZAR in 2017) in South Africa's PA's (van Wilgen *et al.* 2012a; van Wilgen *et al.* 2016). Despite the TMNP having a well-established IAP control strategy as part of the WfW programme, with over 20 years of continuous clearing, and supported by extensive resources, the TMNP still requires substantive annual budgets of around ZAR 20 million for the implementation of the control strategy (Chapter 1).

5.2.2 Sampling and analysis grids

The commonness framework proposed by McGeoch & Latombe (2016) has eight commonness types based on three species population characteristics of i) local population size (small or large), ii) geographic range (wide or narrow) and iii) time since establishment (long or short). For this study spatial pattern of invasion (aggregation) is substituted in place of time since invasion, as data on spatially explicit invasion trends are seldom available and current range structure may be used to infer future range dynamics. A ninth type 'not present / absent' is introduced for a site where a species is absent or has not been recorded after the site was surveyed.

To quantify each of these three characteristics, a fine-grain 150m sampling grid was established over the PA, resulting in 10,057 sample cells. At the centroid of each sample cell, a 500m^2 plot was established and the number of individuals of each alien species present was counted (Cheney *et al.* 2018, Chapter 2). To analyse the relationship between grain and species commonness characteristics, data were aggregated for each alien species using fractal analysis grids (constructed in ArcGIS 10.x, ESRI) at grains of 150m (n = 10,057), 300m (n = 2,841), 600m (n = 845), 1200m (n = 258), 2400m (n = 84) and 4800m (n = 30) (Fig. 5.2a).

To account for population variation across the PA, the grid cells were grouped into analysis units based on topography, vegetation type, fire history and invasive species clearing history (Fig. 5.2b). Starting with the 30 cells at the 4800m grain, these were grouped into a single park level analysis unit, while the 84 cells at the 2400m grain were grouped into two analysis units, the 258 cells at the 1200m grain into eight analysis units, until the 10,057 cells at the 150m grain were grouped into 127 analysis units.

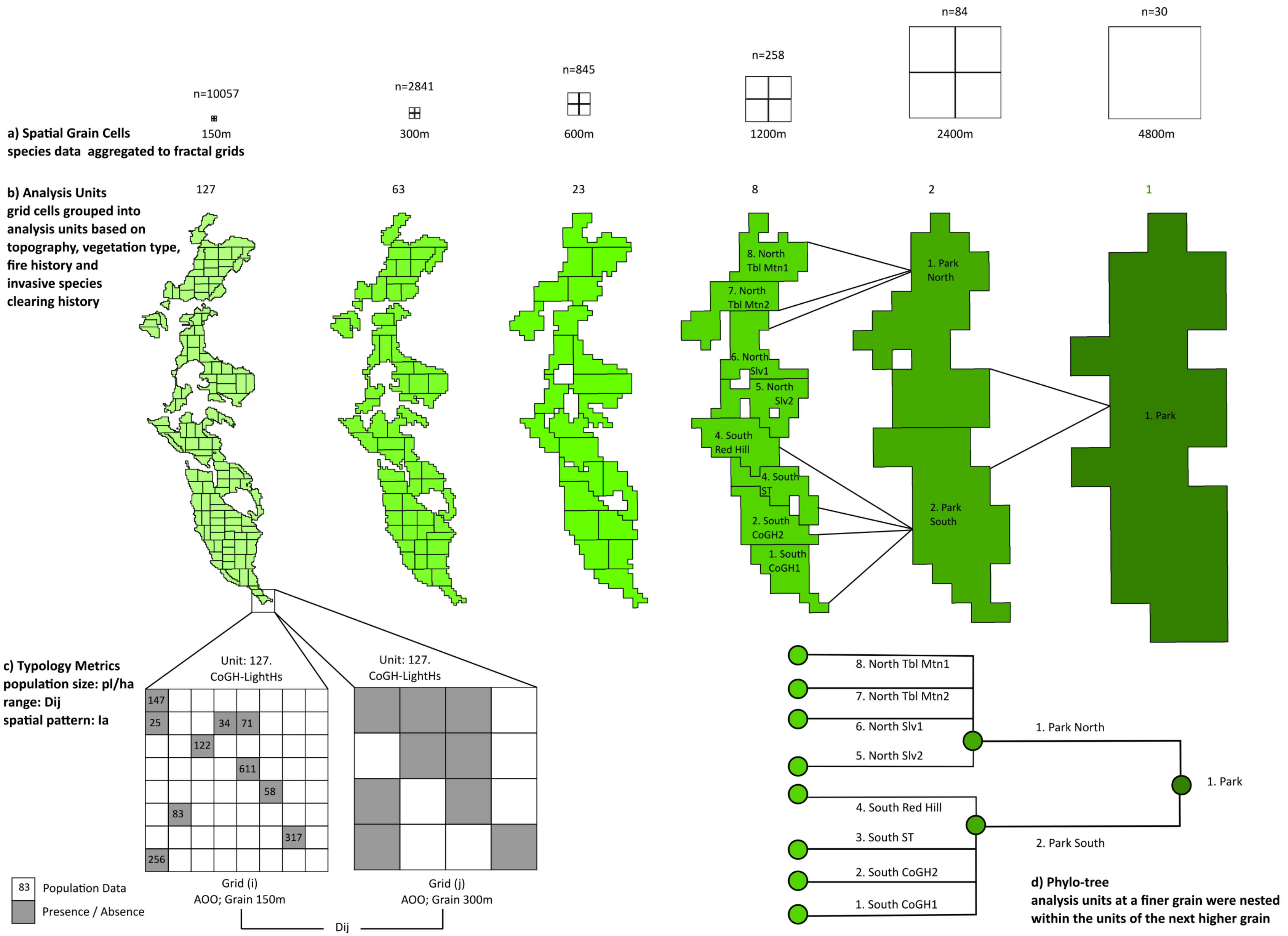

Fig. 5.2 Precursor steps for data analysis.
a) Fine scale occurrence data (plot size – 500m^2) was aggregated fractal grid cells with dimensions 150m, 300m, 600m, 1200m, 2400m and 4800m.
b) Grid cells were clustered into analysis units based on topography, vegetation type, fire history and invasive species clearing history.
c) The commonness type was calculated from the following three metrics: population size (plants per hectare), geographic range (D*ij*) and aggregation (SADIE *Ia*) for each analysis unit.
d) The analysis units were created to nest within each other at each grain to form a hierarchy.

To view how the relationship between commonness types and grain changed between two grains (for example the 150m and 300m grids), the analysis units followed a nested layout where units at a finer grain were nested within the units of the next higher grain to form a non-overlapping hierarchy relationship (Fig. 5.2d). For example, analysis units 1, 2 and 3 at grain 150m, were nested into analysis unit 1 at grain 300m. Similarly analysis units 1 and 2 at scale 300m were nested within analysis unit 1 of scale 600m, until there was only one analysis unit the PA with a grain of 4800m. This non-overlapping hierarchical nesting is required to undertake range analysis and compose the commonness phylo-tree for spatial analysis (Section 5.2.6).

5.2.3 Selection of species and species groups for analysis

Invasive species and taxa that had a long history of invasion and that were the current focus of the alien plant control programme were selected for analysis. These included seven species (*Acacia cyclops*, *Acacia longifolia*, *Acacia saligna*, *Leptospermum laevigatum*, *Paraserianthes lophantha*, *Pinus pinaster* and *Pinus radiata*). Patterns at genus levels for four genera (all *Acacia* species, all *Eucalyptus* species, all *Hakea* species and all *Pinus* species) were analysed.

5.2.4 Species mapping to the commonness framework

Species could be classified within one of nine commonness types based on their geographic range, local population size and time since establishment within a defined geographic area and spatial grain (Fig. 5.1). In the context of this study ‘time since establishment’ (McGeoch & Latombe 2016) was replaced as the PA has a long-history of invasion by all the species of interest. In addition, the continued management control of IAP would have altered species invasion patterns. Therefore ‘time since invasion’ is substituted with a metric of spatial aggregation pattern. This is important for management because species with different spatial aggregations have different management success prospects, in that clumped populations are much easier to treat (similar to a newly established populations), while populations that are dispersed in the landscape (similar to a long-established population) are more difficult manage. For the purposes of this study, a ninth type ‘not present / absent’ is also considered in the analysis as a site where a species is not recorded.

The three metrics for local population size, geographic range and spatial pattern (all described below), were calculated for each analysis unit, for each species at each of the six fractal grid grains. For each species, the three metrics were used in conjunction to assign each analysis unit to one of the nine commonness types at each of six spatial scales (Fig. 5.1, Table 5.1). It was therefore possible to calculate the total number and spatial distribution of analysis units with each commonness type at each spatial scale.

5.2.4.1 Local population size

Local abundance as measured by the number of plants/ha was chosen as the metric for local population size. For each analysis unit, the total number of individuals counted within the grid cells was divided by the size (in hectares) of the grid cells to produce the number of plants/ha (Fig. 5.2c). For purposes of commonness framework, populations are considered as either small (<2,500 plants/ha) or large (≥2,500 plants/ha). This classification cut-off value of 2,500 plants/ha was chosen as it is equivalent to the WfW mapping standard of 15% plant cover (Neethling & Shuttleworth 2013) and the IUCN guideline for population size of endangered plant species criteria (Mace *et al.* 2008; IUCN 2012).

5.2.4.2 Geographic range

The geographic range of a species is typically measured by either or both its Area of Occupancy (AoO, the actual area in which the species is found) or Extent of Occurrence (EoO) (Gaston 1991, 1994). The relationship between EoO and AoO describes the degree to which space within the extent is filled and can be measured using D, the box counting fractal dimension. AoO is inherently scale dependant as it entails multiplying the number of occupied grid cells by the size of the cell (Hartley *et al.* 2004). As a starting point to determining the geographic metric for the commonness topology, the AoO (km^2) for each species was calculated at each of the six spatial grains from the fine scale presence-absence data (Cheney *et al.* 2018, Chapter 2). The emerging statistic D was calculated by comparing AoO (km^2) and linear resolution (km) between two grains (Wilson *et al.* 2004; Veldtman *et al.* 2010; Donaldson *et al.* 2014) for each incremental reduction in grain resolution, thus describing the 'space-filling property' of each species (Fig. 5.2c). The statistic is calculated by using the equation $D_{ij} = 2 - b_{ij}$ where b_{ij} is the slope of the regression between log area occupancy (km^2) and log linear dimension (km). D_{ij} values can range from 0 to 2 where a value of 0 indicates the occupancy of a coarse-grain cell by a single occupied fine-grain cell, corresponding to a very narrow geographic distribution range, while a value of 2 indicates that all fine-grain cells within a coarser-scale cell are occupied, indicating a wide range of distribution (Kunin 1998). When categorising species having a wide or narrow distribution for the commonness framework, species with D_{ij} <1 were considered as having a narrow distribution and those with D_{ij} ≥1 as having wide distributions. The direct relationship between AoO at different spatial grains is plotted for each species (Sup. Mat. Fig. 5.1).

5.2.4.3 Spatial aggregation

Species spatial aggregation patterns were determined using the SADIE (spatial analysis by distance indices) aggregation index (Perry 1998; Perry *et al.* 1999). This method uses count-based data and compares the spatial arrangement of the observed distance to regularity (the total number of moves which individuals in each grid cell must move so that all grid cells have the same number of individuals) with the permuted distances to regularity derived from a randomization procedure. The index of aggregation (*Ia*) and associated randomization test is calculated with *Ia* =1 indicating a random distribution, *Ia* >1 an aggregated distribution, and *Ia* <1, a regular/uniform distribution. It follows that grid cells with *Ia* >1 were classed as clumped and in terms of the commonness framework and *Ia* <1, as even.

5.2.5 Clearing strategies

Five broad clearing strategies are available to managers depending on the stage of invasion (Wittenberg & Cock 2001; Hulme 2006; Tu 2009; Simberloff 2014) (Table 5.1). These clearing strategies range from i) site reconnaissance, i.e. checking that an area has not been invaded or a previously cleared area has not been reinvaded, ii) to a rapid response approach, where new or very small populations have been detected, iii) sweeping, which entails continual treatment of large area of low density, iv) control, using a variety of methods on medium to dense infestations and v) containment, where IAP dominate the landscape and the most pragmatic approach is to stop further spread in the landscape. Each commonness type has a best approach management strategy related to clearing. The expected strategy was calculated based on the proportion of analysis units that fell into the associated commonness type (Table 5.1). The primary determinants of which management clearing strategy to deploy is determined by local population size (plants/ha) and the extent of the population (AoO or D). The local spatial aggregation of a species is seen as a ‘chance of management success’ where chances of successful treatment increase where species are more aggregated.

5.2.6 Spatial hierarchy analysis

The metric values calculated for the commonness framework were expected to change with spatial grain (Hui *et al.* 2010). The extent to which they changed and the impact on the appropriate management strategy was unknown. The spatial relationship between each analysis unit was therefore mapped to a phylo-tree (Yu *et al.* 2017) where the analysis units at grain 150m were considered as the tree tips and the other grains as tree nodes and the single analysis unit of the PA as the first node (Fig. 5.2d). The commonness type of a given species or species group, as measured at the relevant spatial grain, was plotted using one of the specified nine colours at each node or tip (Fig. 5.1). This allowed for visual interpretation of changes in commonness across scales and identification of areas requiring particular strategies, as well as the influence of specific invaded sites at successively courser or finer spatial grains.

5.3 Results

5.3.1 Local population size

At fine grains (150m and 300m), *Acacia* species showed wide variation in local population size, where *Acacia cyclops* density ranged from 0 to 8111 plants/ha; *Acacia longifolia* ranged from 0 to 21,846; and *Acacia saligna* ranged from 0 to 67,572 plants/ha (Fig. 5.3). Of the other species, only *Paraserianthes lophantha* had density ranges comparable to *Acacia* species with local population sizes from 0 to 8602 plants/ha. Although species showed wide ranges of local population density, mean local population size at fine grains (150m and 300m) was much lower with *Acacia cyclops* at 510 plants/ha across all analysis units; *Acacia longifolia*, 584 plants/ha); and *Acacia saligna*, 2490 plants/ha. For the majority of species, for example *Leptospermum laevigatum*, *Hakea* species and *Pinus* species, mean plant density was <100 plants/ha. At courser scales (2400m and 4800m) the mean plant density decreased further (e.g. *Acacia cyclops*: 160 plants/ha; *Acacia longifolia*: 197 plants/ha; and *Acacia saligna*: 788 plants/ha). For the majority of species, for example *Leptospermum laevigatum*, *Hakea* species and *Pinus* species, mean plant density was <50 plants/ha.

5.3.2 Geographic range

As expected the 'raw' AoO values were very scale dependant with AoO (km^2) varying from $0km^2$ (totally absent) at fine grains (150m and 300m) up to $691km^2$ at the coarsest grain (4800m) for species (Sup. Mat. Fig. 5.1). *Leptospermum laevigatum* had the smallest mean AoO at fine grain of 150m (0.03 km^2; ±0.04SD) with a total AoO across the PA of 3.67 km^2 (Sup. Mat. Table 5.1). *Acacia cyclops* had the highest mean AoO at the 150m grain (0.41 km^2; ±0.37SD) with a total AoO of 51.91 km^2 across the PA.

The general trend was for taxa to have narrow geographic ranges at fine grains (150m and 300m), with the box counting fractal dimension (D*ij*) <1 (Fig. 5.4). As the spatial grain increased to above 1200m, there was a general increase to higher D*ij* values of between 1 and 1.5, indicating wide geographic ranges, except for *Leptospermum laevigatum* (Fig. 5.4) which only showed an increase to D*ij* >1 at scales of 2400m and above. At the largest scale analysed (4800m), only *Pinus radiata* measured D*ij* values <1, indicating that even at the scale of the entire PA, this species had a fairly narrow geographic distribution (Fig. 5.4).

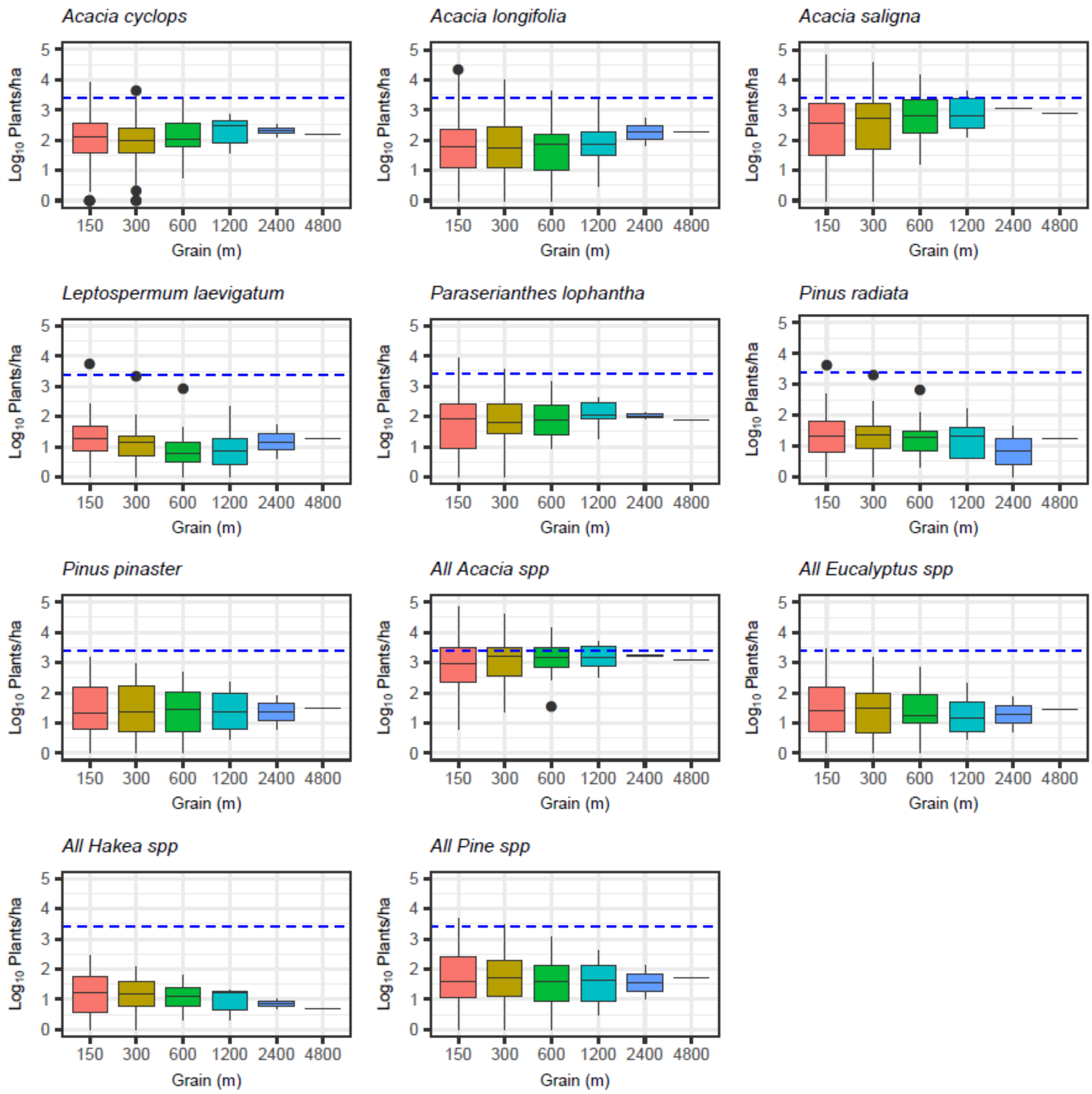

Fig. 5.3 Population density (Log_{10} plants per ha) of species and species groups. Population density is used as the metric for Local Population Size in the Commonness Typology (Fig. 5.1) where plants/ha <2500 indicate small local populations and plants/ha ≥2500 indicate large local populations denoted by the blue dashed line. Boxes represent the 25th and 75th quantiles, while the whiskers values 1.5 times the inter quartile range. Solid dots represent outliers beyond this range.

5.3.3 Species spatial aggregation

Taxa spatial patterning in terms of the SADIE *Ia* tended to be random (*Ia* ≈1) to clumped (*Ia* >1) at all grains (Fig. 5.5). All the *Acacia* species, *Pinus* species and *Leptospermum* laevigatum also had outlier populations with highly clumped distributions (SADIE *Ia* >2) at fine grains of 150m and 300m. At the Park scale, only *Pinus* species and *Eucalyptus* species had very clumped distributions with *Ia* >2.

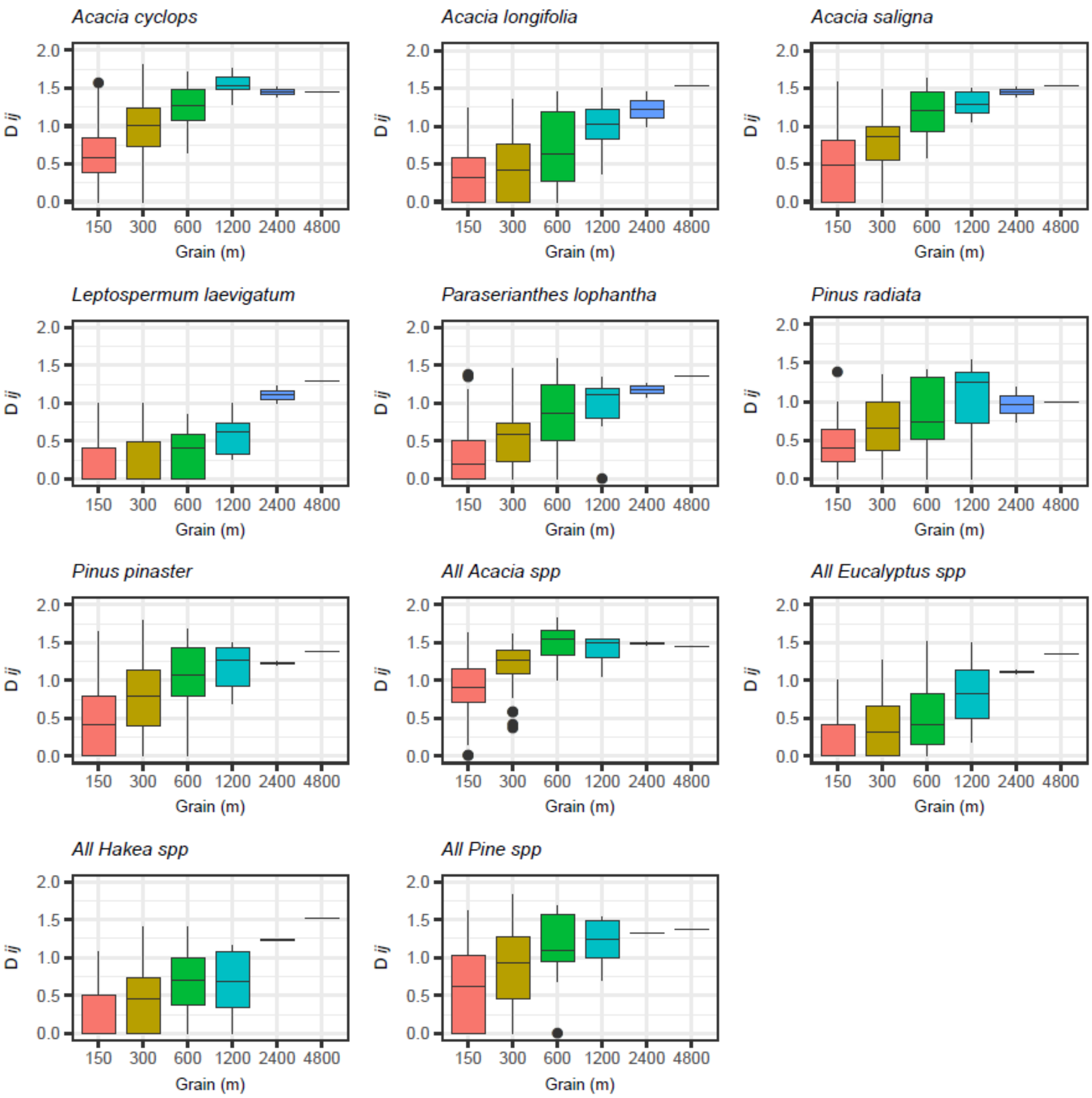

Fig. 5.4 Spatially semi-explicit range structure (measured using Box counting fractal D*ij* of species and species groups). D*ij* is used as the metric for Local Population Size in the Commonness Typology (Fig. 5.1) with D*ij* <1 indicating narrow novel range and >1 wide novel range.

5.3.4 Management strategies and influence of scale on commonness

At fine grains, the majority of analysis units for all species fell into the 'Newly Established' commonness type, except for *Leptospermum laevigatum*, which was classified as being 'Not Common' (Sup. Mat. Fig. 5.2a and b). The commonness type with the second highest frequency was 'Not Common' for all species, indicating that species had small, but evenly spaced, populations in the landscape. For example *Acacia saligna* and *Acacia longifolia* had 59 (46%) and 47 (37%) of the analysis units falling into the 'Newly Established' commonness type, respectively (Fig. 5.6a and c). At the medium grain of 600m, only *Acacia saligna* and

Acacia longifolia had more than one analysis unit in the large population typologies of either 'Constrained', 'Insipient' or 'Successful' (Fig. 5.6b and d, Sup. Mat. Fig. 5.2d-e). At courser grains, the overall trend was for sites to be classed within the wide occupancy ranges, but with small population sizes as mainly 'Dispersed' and 'Sparse' typologies. At the scale of the PA (4800m grain) all species fell into the 'Sparse' commonness type, except for *Acacia longifolia* and *Leptospermum laevigatum*, which classed as 'Dispersed' and *Pinus radiata* which was classed as 'Newly Established' (Sup. Mat. Fig. 5.2f-g).

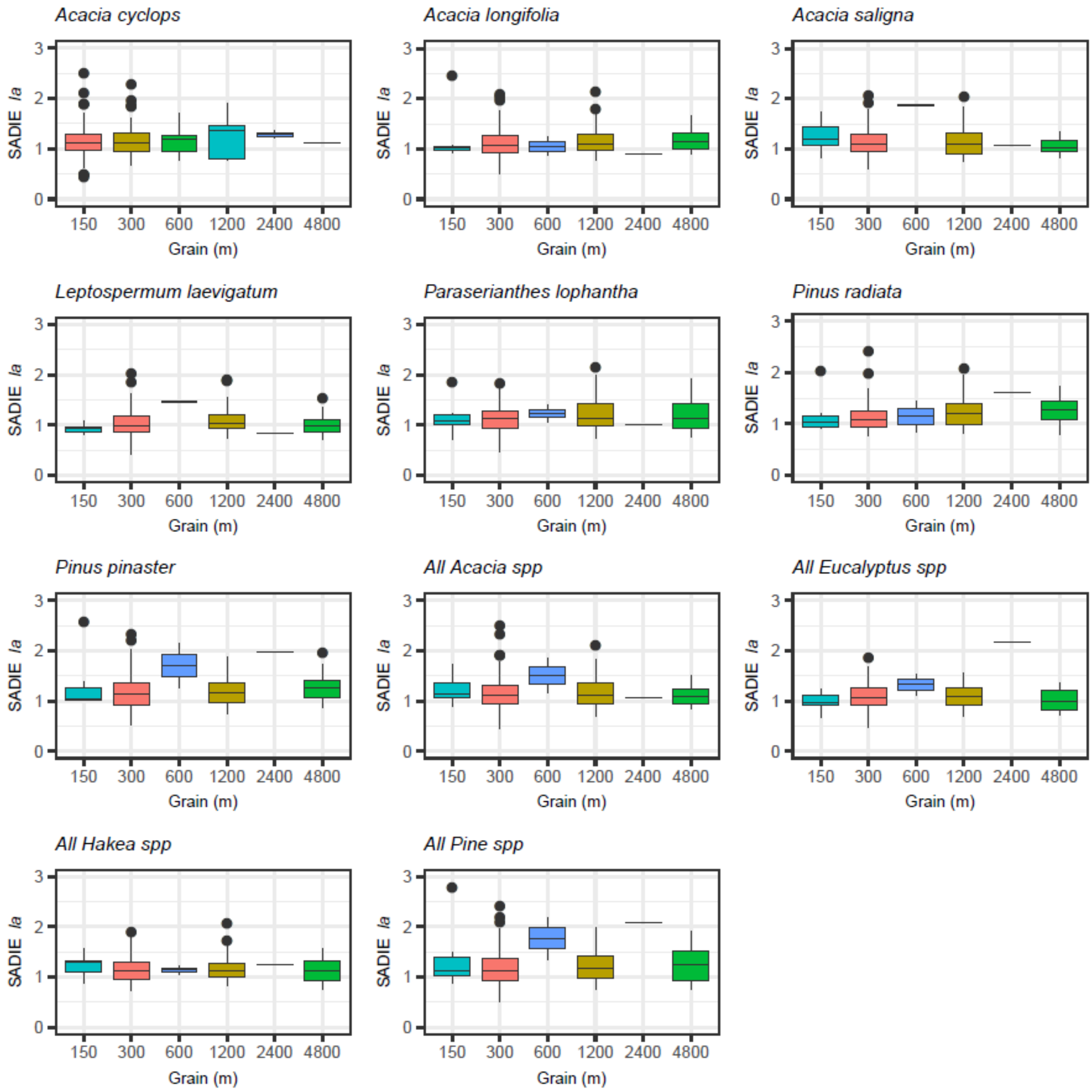

Fig. 5.5 Spatially explicit metric used to quantify range structure (summary statics shown here, Spatial analysis by distance indices (SADIE, Cluster index (*Ia*)) for species and species groups, Ia < 1 indicated even spatial pattern and > 1 clumped spatial pattern.

Due to the high frequency of analysis units falling within the 'Newly Established' and 'Not Common' categories at fine grain (150m) for all species, a rapid response or reconnaissance management strategy would be the most appropriate strategy to deal with them. For example *Acacia saligna* and *Acacia longifolia* have 93 (73%) and 80 (63%) of the analysis units best suited a rapid response approach respectively (Fig. 5.6e and g, Sup. Mat. Fig. 5.3a-b). At this fine scale, very few analysis units fell into the commonness type of 'Incipient' or 'Constrained', which are implicit to the management strategy that is currently implemented in the PA, namely 'Control'. At medium grains (600-1200m), the trend was for species either to remain predominantly in the rapid response strategy for example *Acacia longifolia* (Fig. 5.6h) or a combination of rapid response and sweeping strategies, for example *Acacia saligna* (Fig. 5.6f, Sup. Mat. Fig. 5.3c-d). At the overall PA level (grain 4800m), a sweeping strategy would be appropriate for all species except for *Pinus radiata*, for which a rapid response strategy would be optimal (Sup. Mat. Fig. 5.3e-g).

5.3.5 Spatial hierarchy analysis

Visual inspection of the 'commonness phylo-trees' showed a range of species invasion stages occur in very close proximity to each other at a given spatial grain (Fig. 5.6 i-l, Sup. Mat. Fig. 5.4). Visual inspection of the trees allowed for the identification of three important patterns of potential management relevance. This includes instances of isolated populations of 'Newly Established' or 'Not Common' type (where a single analysis unit is adjacent to management units that do not have the species present. For example *Paraserianthes lophantha*, (Fig. 5.7a, highlighting a portion of the phylo-tree) has two management units classed as 'Newly Established' adjacent to a number of sites where the species was not recorded. Other species that have braches with only a single invaded unit, surrounded by several analysis units with no alien presence include: *Hakea* species, *Pinus radiata*, and *Leptospermum laevigatum*. A second pattern was the occurrence of areas with very high density invasions adjacent to very low density sites *Acacia cyclops*, *Acacia longifolia* and *Paraserianthes lophantha* have branch tips (grain 150m) that were classed as 'Successful' and 'Highly Successful', adjacent to areas that were classed as 'Newly Established' (Fig. 5.7b). The third significant pattern was identified in species for which medium-grain areas require heterogeneous management interventions at a finer scale, i.e. species have a wide range of very different commonness types in close proximity. For example *Acacia saligna* and to a lesser degree *Acacia longifolia* and *Acacia cyclops* have up to six of the commonness types as branch tips, on the same branch (Fig. 5.7b and c).

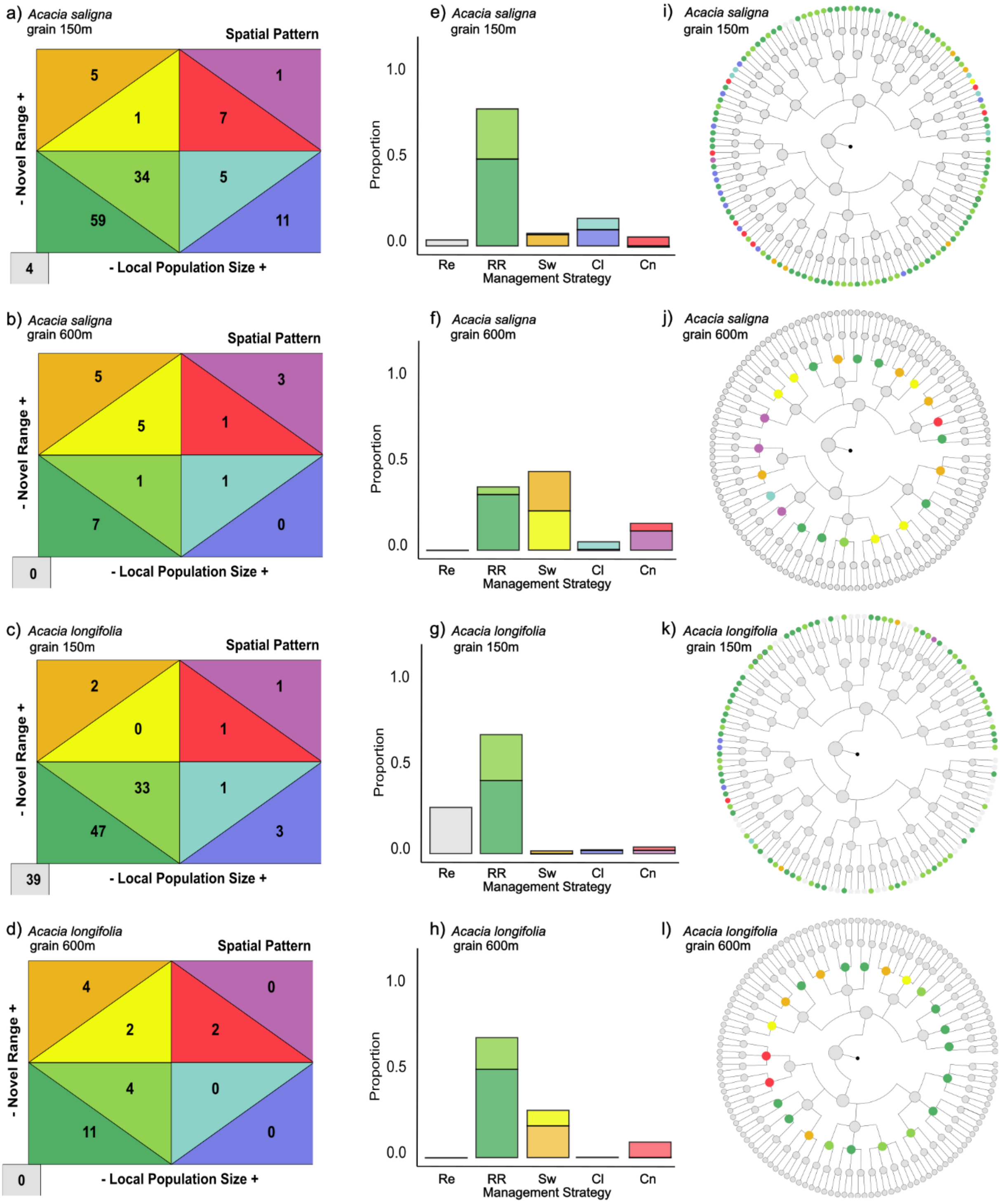

Fig. 5.6 (a-d) The number of analysis units with a particular commonness type (see Fig. 5.1.), and (e-h) the associated proportion of analysis units requiring a particular management strategy (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment) and (i-l) the hierarchical mapping at 150m and 600m spatial grains for *Acacia saligna* and *Acacia longifolia*. The nine colours specified in a-d are replotted for e-h and each phylo-tree node at the specified grain. The detailed information for all species at all grains is available in supplementary material figures 5.2, 5.3 and 5.4.

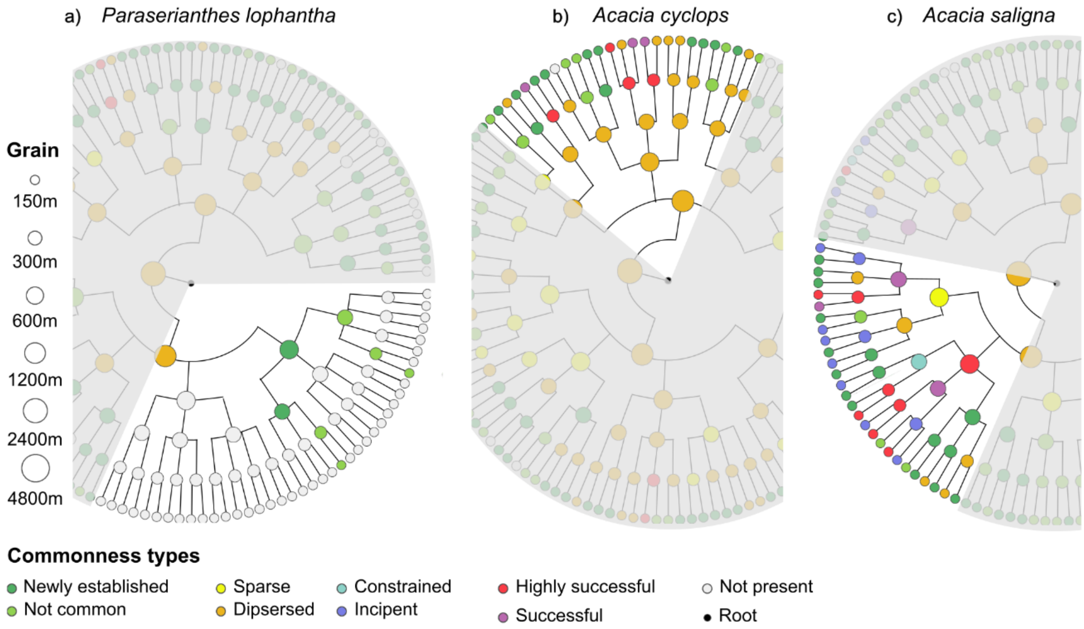

Fig. 5.7 Tree segments showing various types of invasion where there are (a) isolated populations of Newly Established or Not Common types, (b) Successful and Highly Successful typologies adjacent to very low density sites of Newly Established, Not Common and Not Present, (c) a number of very different typologies in close proximity. The nine colours specified are the commonness types as per Fig. 5.1.

5.4 Discussion

Aligning IAP management strategies with their range characteristics, through the use of a commonness framework, represents a novel approach to planning and implementation of IAP programmes. This is achieved by viewing invading species as being on a trajectory from being uncommon to becoming common (McGeoch & Latombe 2016), resulting in the same IAP having a variety of commonness types, at multiple sites within the landscape. The recognition that invasive species can be at different invasion stages, as measured by a variety of scales, in a landscape is important for the correct application for treatment strategies or conservation objectives (Crooks 2005; Panetta *et al.* 2011; Pluess *et al.* 2012). The analysis conducted in this study emphasises that management of IAPs should account for site variability at multi-scales. The approach presented here can be used to reconcile differences in species-based and area-based approaches to IAP management.

Analysis of fine-grain IAP data in terms of a commonness framework showed that the same species can have a variety of commonness types at multiple sites in the PA. This can be interpreted as the same species being in different invasion stages across the landscape. The most frequent commonness type for taxa at fine grain (150m) was 'Newly Established' and

'Not Common'. This indicates that species historically considered as highly invasive and problematic species such as the *Acacias* (Le Maitre *et al.* 2011; Richardson *et al.* 2011) are under relatively good management control. For example, *Acacia saligna*, which is a potential ecosystem transformer (Holmes & Cowling 1997), currently had 73% of the analysis units falling within either the 'Newly Established' or 'Not Common' commonness types indicating that the control programme over the past 20 years has made good progress for this species.

The finding of such highly invasive species in the low population (<2500 plants/ha) and narrow geographic range commonness types is important for future invasion trajectories as three future trajectory possibilities exist. Firstly, optimistically, management pressure will continue and local extinction of IAP from the sites will occur (Simberloff 2009). Secondly, management pressure is weakened allowing the increase in local IAP population density and/or local range resulting in a reinvasion (Gardener *et al.* 2010; McGeoch & Latombe 2016). The third option is for the species is remain in their observed commonness type as the management pressure is not enough to result in the local removal from the landscape and a continued 'stale-mate' between management control pressure and invasion expansion results (Moore *et al.* 2011; Richardson *et al.* 2011; Souza-Alonso *et al.* 2017). This third option currently seems the most likely outcome as the required Rapid Response strategy, that necessitates higher search time cost and more flexible treatment methods, is not undertaken as part of the clearing programme for common species like the *Acacias*.

The incorporation of multi-scale approach to the control programmes is important. For example understanding the underlying drivers of invasion at different scale, for example dispersal mechanisms (Lockwood *et al.* 2005; Wilson *et al.* 2009) can determine management success. These drivers can be different at various scales and addressing the management of an IAP at a single scale alone may only reveal a sub-set of required actions. Unfortunately most strategies for controlling IAP in PAs are developed from information collected at the scale of the management units to be treated (Working for Water 2003). As the size of the management units fall within the medium grains of analysis (600m-1200m), population parameters are likely to be over-estimated. For example, as AoO is inherently scale dependant where the relationship between AoO and grain usually approximates a power law, abundance values in the management units are likely to be over-estimated (He & Gaston 2000; He & Gaston 2003).

Although the over estimation of population parameters can be seen as a precautionary management approach, it has disadvantages, notably the choice of a correct treatment strategy. For example *Acacia cyclops* had more than 75% of the sites suited to a Rapid

Response approach at a fine grain (150m) while at the grain on the management units (600m) more than 90% of the sites would require a Sweeping strategy. A further strategy mismatch is the under-use of the Reconnaissance strategy. Although invasion prevention is widely accepted as the most cost effective and efficient approach to manage IAP (Pluess *et al.* 2012; Souza-Alonso *et al.* 2017), the potential use of Reconnaissance strategy diminishes with increasing grain size. For example, *Acacia longifolia* had 31% of the sites suited to a Reconnaissance strategy, while at courser grains, this strategy was absent.

Categorisation of the commonness types with spatial scales into 'commonness phylo-trees' showed a range of species invasion stages occurring in very close proximity to each other at a given grain. This emphasises that the invasion landscape to be managed is relatively complex because of possible multiple invasion events and a series of historical management actions. However these management complexities in invasion processes, invasability and management history are not readily integrated into current management strategies and approaches. This is due to emphasis of management being an area-based approach. The focus of the IAP programme in the PA is fixed on a Control strategy, which aligns with the commonness typologies Incipient and Constrained, however these two typologies had the lowest frequency in the PA. These low frequencies could be an indication that the Control strategy has been well implemented over the past 20 years, showing success. However in this study, the Control strategy was, found not to be the most appropriate strategy to deal with the current state or future states of invasion in the PA.

Implications for management

IAP management approaches are primarily area-based (treating all IAPs in a defined area) and to a lesser extent species-based (targeting specific IAPs or group of plants). Through the application of a commonness framework, and realising that species are on a trajectory from being uncommon to becoming common, a third 'invasion-based' approach is warranted. This approach accounts for the same species being in different stages of invasion in sometimes distant locations in the landscape. As single management strategy (either area or species based) is limiting, a combination of strategies, informed by the range properties of the species at the site, is be more applicable. Through an appreciation of the dynamic range properties of IAPs, managers would be able to move away from area-based strategies or species-based strategies to a choice of invasion-state strategies (Table 5.1).

Benefit of the approach

The application of the commonness framework to IAP data clearly shows the underlying invasion stage in which a species finds itself at a particular site. The commonness framework is useful to identify the particular management strategy required for a species at a site. For example, *Pinus* species can occur at low to very low population densities, but have very high occupancy rates and therefore require a different management strategy to *Acacia* species that generally have very high site population densities over narrow ranges. Assignment of particular management strategies to sites allows for better site planning and overall a more efficient clearing programme.

The introduction of hierarchical grain analysis showed how commonness types change with grain. For most species analysed there was a shift from narrow occupancy typologies (Newly Established and Not Common) to wide occupancy typologies (Dispersed and Sparse) as grain size increased. As grain size increased, high local population densities were also less common, shifting away from Highly Successful and Successful types to Dispersed and Sparse typologies. These shifts in commonness type have important implications for management priority setting. A high-level overview (course grain) of species invasion at the landscape level, does not indicate fine-grain reality at a site, which can be very different. This can result in both the incorrect conservation objectives being set, as well as the incorrect strategy being applied.

5.5 Conclusion

Through the use of the commonness framework, it has been demonstrated that even for a single species a number of management strategies will be applicable depending on the area to be treated. Measures of range size and population are essential for informing a correct conservation response and management practice for the management of IAPs. Though the use of a commonness framework, there can be refinement and flexible implementation of clearing strategies. This allows for sites to be identified for species-specific goals, for example eradication though rapid response, while allowing for other sites to have to have a more conventional area-based goals to increase clearing and programme effectiveness. The incorporation of range dynamics can assist in the improving management interventions aim to manage and reverse the negative impacts on IAP's.

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5.7 Supplementary material

The following supplementary Information may be found in the supplementary section accompanying this dissertation.

Sup. Mat. Figure 5.1. Area of Occupancy (Log_2 km^2) of species and species groups. Area of Occupancy is used as an intermediate step to calculating D, the box counting fractal dimension.

Sup. Mat. Figure 5.2. The number of analysis units for species and species groups falling within each commonness type at analysis grains of 150m, 300m, 600m, 1200m, 2400m and 4800m.

Sup. Mat. Figure 5.3. The proportion of analysis units for species and species groups falling within each management strategy at analysis grains of 150m, 300m, 600m, 1200m, 2400m and 4800m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).

Sup. Mat. Figure 5.4. Hierarchical mapping of analysis units into a ‘phylo-tree’ at six spatial grains for species and species groups with the commonness type indicates as 1 of 9 colours.

Sup. Mat. Table 5.1 Mean and total area of occupancy (AOO) for selected species and species groups at six grains analysed.

Chapter 6.

Synthesis

6.1. Introduction

The aim of this dissertation was to develop an understanding of how outcomes of invasive alien plant (IAP) clearing programmes could be improved upon, using Table Mountain National Park (TMNP) as a case study. The ideas presented here are intended to strengthen the science-management interface, which is a research area identified as requiring further study (Esler *et al.* 2010; Legge 2015; Abrahams *et al.* 2018). Each chapter in the dissertation focused on providing a scientific rationale for improving management of IAP programmes in terms of data used for management decision making, treatment quality, strategy selection and addressing issues of spatial scale in planning. While the IAP problem in TMNP has not worsened at a course scale over the last 20 years, it has achieved limited tangible success, in terms of reduction of overall alien cover despite a large resource investment (Chapter 1 Fig. 1.3; Table 1.1). As such demonstrating value of money spent and improving management outcomes was important. Complementary studies on management effectiveness of landscape control programmes in the region highlighted that areas were treated sub-optimally, resulting in very long time-frames to treat areas with long-term budget implications (McConnachie *et al.* 2012; van Wilgen *et al.* 2016; Fill *et al.* 2017; Kraaij *et al.* 2017). It therefore became necessary, both from an economic and conservation perspective, to investigate the likely future trajectory of the IAP control programme and to determine the main drivers of management success.

The dissertation considers four management-related aspects of the clearing programme that could potentially be improved. Firstly, as management decisions to treat areas are based on knowledge of IAP species presence and their densities in an area. Chapter 2 set out to test the accuracy of data used in this management decision making process. Secondly, while the quality of treatment of an area is known to be important (McConnachie *et al.* 2012; Fill *et al.* 2017; Kraaij *et al.* 2017), the long-term implications of poor treatment have not been quantified. In Chapter 3 this issue is investigated and the expected levels of future IAP invasion are quantified at 38 levels (between 5%-80% at 5% incremental increases, and between 80% and 100% at 1% incremental increases) of clearing efficacy, where efficacy is defined as the probability that all plants in an area will be treated and killed using the correct chemicals and techniques. Thirdly, although a number of clearing strategies have been proposed by management and documented in literature (Roura-Pascual *et al.* 2009; Roura-Pascual *et al.* 2010; Forsyth *et al.* 2012), the potential outcomes of these strategies had not been formally tested. In Chapter 4, these proposed management strategies are modelled to provide insight into the performance of each management strategy. Lastly, in Chapter 5, a planning approach is presented that re-examines the concepts of area-based and species-based planning. Through the examination of the range metrics of population size, invasion extent and spatial pattern, the invasion stage of a species could be quantified. When coupled with the effect of spatial grain planning methods based on the invasion stage of IAP in an area can be considered.

In this synthesis chapter I draw together the main findings and conclusions of this research, highlight where park management have adopted recommendations and outline the opportunities for future research.

6.2 Data quality underpinning management decisions: what have we learnt?

Conservation managers often rely on several sources of information before decisions can be made and actions taken (Knight *et al.* 2011; Cook *et al.* 2012; Ntshotsho *et al.* 2015). In IAP programmes, key data requirements include a list of known alien plant species, together with their distribution and abundance (Wittenberg & Cock 2001; Tu 2009; McGeoch *et al.* 2012). Given the importance of management data and its use in decision making, an analysis of two management data sets, obtained from conservation managers via workshops and from Working for Water (WfW) programme managers (Chapter 2). In order to compare these datasets, a fine-scale systematic dataset comprising 10,057 sample plots was produced. Within in each sample plot, each individual that was alien was counted give a comprehensive count data was well as a true account of species presents and absents across the study area. Comparing the datasets illustrated the extent of the inaccuracy of the data used in the IAP control programme. Analyses suggested that the data used in the WfW programme to date were collected in a non-standardised and non-rigorous manner. Further analysis revealed that inaccurate data resulted in skewed species distributions and workload quantification that influencing management decision making such as the prioritisation of areas to work (Chapter 2).

6.2.1 Alien species richness and abundance

Variations in alien species datasets are expected due to differences in the purpose for and scales at which data are collected (Foxcroft *et al.* 2009). The fine-scale systematic sampling from this dissertation provided estimates of species richness and abundance that differed by orders of magnitude from the data that are used by managers (Cheney *et al.* 2018). The clearing programme has historically included work on a subset of approximately 25 species, whereas the infield sampling detected 106 species, of which over 70 require control under national legislation. While the alien species was underestimated, the abundance of species was greatly overestimated. For example *Acacia cyclops*, a key targeted species in the clearing programme was estimated by managers to occupy 8.94 km^2 (condensed area), while the ground-truthing in this study suggested an estimate of closer to 0.32 km^2 (condensed area, Chapter 2; Cheney *et al*. 2018). The over-estimation of invasion extent by managers was a key finding that allowed for better understanding the true scope of the invasion problem, thus allowing for direct improvements to the IAP control programme at TNMP

6.2.2 IAP programme improvements from improved data collection

After presenting findings of this PhD work to park management on the differences in species richness and abundance, the WfW programme undertook to adopted the survey methods used in this dissertation to improve the accuracy of field data collected. The adoption of a standardised and repeatable in-field data collection methodology of for planning purposes and implementation purposes allows for three key interventions that will improve the programme. These are i) accurate workload quantification, ii) undertaking early detection and rapid response (EDRR) and, iii) undertaking formalised monitoring, which are outlined below.

Workload quantification

Accurate field data allows for better quantification of the number of species to be treated and the required workload (*i.e.* the number of alien plants to be treated) with the corresponding resource effort (*i.e.* the number of person days required) to undertake the work. As such the in-field measure of species richness and abundance directly impacts on the overall cost of clearing operations and the required budget to undertake the clearing as per the WfW norms and standards (Neethling & Shuttleworth 2013). Through the standardisation of data collection it was possible to provide accurate data for the annual plan of operations (APO) to the WfW programme. The APO comprises a database of management units where the abundance of each alien species can be updated (Fig. 6.1). The standard data collection of alien species richness and abundance results in realistic workload quantification and person day allocation to WfW clearing contracts. By increasing the species listed in the WfW contracts, a complete assessment of required resources for the targeted species to be treated on site can be made. This is seen as a programme improvement as previously, species not listed on the clearing contract were either ignored or had to be cleared by the contractor at their own cost. Contrary to concerns that the reduction in perceived alien plant density would decrease the allocated person days to a clearing contract, and impact on the job creation component of the clearing programme, the contract person days have remained stable due to the more comprehensive listing of alien taxa that need to be treated at a site.

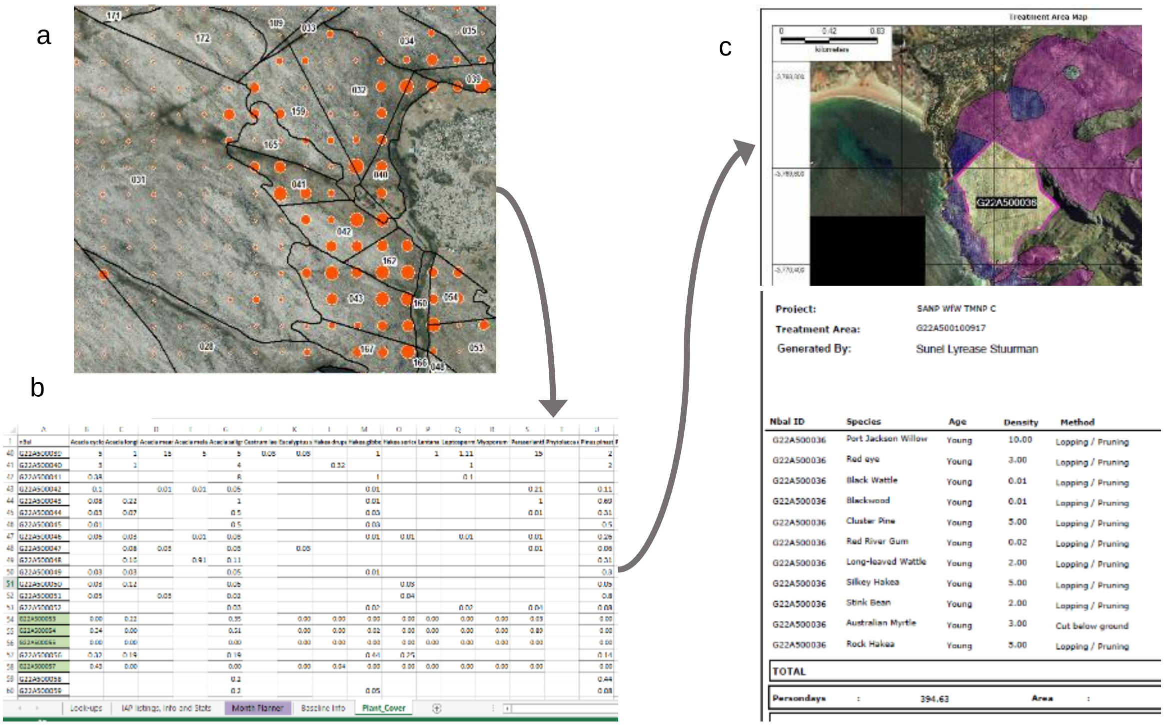

Fig. 6.1 Schematic outline of the process from data collection to implementation. Where data from (a) systematic field surveys (Chapter 2) is used to (b) update species richness and abundance data tables in the Working for Water Information System (WIMS). This data is used (c) to calculate the resource requirements for the WfW clearing contract.

Early detection and rapid response capacity

Although comprehensive lists were readily available through formal (Spear *et al.* 2011; Foxcroft *et al.* 2017) and grey literature for the TMNP, these listings had neither been adopted nor integrated into the IAP programme. Key information for a holistic control programme was therefore absent in that prioritisation of species for the TMNP could not be completed (Pyšek *et al.* 2009; Downey *et al.* 2010a; McGeoch *et al.* 2016). An important function of management prioritisation is the ability to identify new or emerging invasive species within the PA that may need immediate treatment (Foxcroft *et al.* 2011; Jarošík *et al.* 2011). Many of the alien species highlighted by fine-scale mapping were not listed by the park management, however, these species are listed in the National Biodiversity Act (10 of 2004) as alien species requiring direct control. Although treatment of new arriving alien species, with small populations is widely accepted as the most cost effective approach with the highest chance of eradication success (Hobbs & Humphries 1995; Wittenberg & Cock 2001; Tu 2009), this aspect of the WfW programme was absent in the TMNP.

After presenting findings of this PhD work to park management, a specialised Early Detection and Rapid Response (EDRR) component to the clearing programme was approved. The

EDRR teams were piloted in 2016, and the programme was formalised in 2017, with the inclusion of three other National Parks. Due to the success of the teams targeting emerging species that would were not not falling within the main programme, the initial allocation of 1,500 person days in 2016 has more than doubled to 3,987 person days in 2018. The EDRR component of the park's IAP programme is set to increase steadily to around 10,000 person days per year by 2021 with budget of R2.5 million.

Formalised monitoring

The absence of formalised monitoring, within the WfW programme in particular, has been a long-standing and on-going short-coming of programme implementation (Blossey 1999; Marais *et al.* 2004; McConnachie *et al.* 2012; van Wilgen *et al.* 2012; van Wilgen & Wannenburgh 2016; Fill *et al.* 2017). Without a structured monitoring approach there can be only limited evaluation of the effectiveness of the programme, management goals and strategy adjustments. All sound management practices involve learning from the actions implemented (Shea *et al.* 2002; Levendal *et al.* 2008). Comprehensive analysis of trends in indicators or response variables require standardised continuous monitoring. Although comprehensive indicators and thresholds have been formulated for PAs in South Africa (Foxcroft & Downey 2008; Foxcroft 2009; Foxcroft & McGeoch 2011), the formalised monitoring of these has yet to undertaken. The complete fine-scale mapping of the PA enabled a first comprehensive IAP baseline dataset to be complied for the TMNP. The repeat sampling of sites allowed for the establishment of a structured monitoring programme (Dewey & Andersen 2004), which had been lacking for the park. The TMNP is likely to be one of the first places where detailed monitoring for the WfW programme can be applied through the repeat sampling of plots based on cost efficient fine-scale, high quality surveys.

6.3 Primary drivers of long-term outcomes: what have we learnt?

6.3.1 The role of treatment quality

The quality of IAP clearing treatments in field is known to be an important driver of clearing success (McConnachie *et al.* 2012; Fill *et al.* 2017; Kraaij *et al.* 2017). In Chapters 3 and 4 the modelling of *Acacia* population dynamics, demonstrate how dramatic the impacts of work quality can be on IAP programme outcomes. Previous alien plant treatment models implicitly assumed set rates of clearing quality and success that would lead to outputs of achievable programme targets (Le Maitre *et al.* 2002; Krug *et al.* 2010; van Wilgen *et al.* 2016). Through the modelling of 38 levels of clearing efficacy between 5 and 100%, over a 50 year period, the effect on clearing outcomes was illustrated. The models made use of accurate species distribution data (derived in Chapter 2), supported by a collation of published information on for example seed accumulation rates. The models showed large variations in the number of hectares treated, maintained or sustained in a maintenance state as clearing efficacy improved from poor to good. Analysis of the model results showed a non-linear relationship between the level of clearing efficacy and the area that could be treated annually, which has important implications for clearing programmes (Chapter 3). The modelling revealed that small increases in clearing efficacy above 80% result in increasingly large gains in the areas that can be covered for the same amount of resources. Conversely, any decrease in clearing efficacy below the 80% results in rapidly diminishing areas that can be treated annually with the same resources. A key consequence of the efficacy levels currently observed in the clearing programme, is that up to 75% of the future resource costs will be required to treat new infestations resulting from re-seeding of the current standing infestations. With increased efficacy, in particular removing adult plants before they can produce seeds, this future cost can be greatly reduced. A critical insight from Chapter 3 is that IAP programmes can increase the overall areas that can be treated, while reducing the funding requirements, if in-field quality is improved. This is in direct contradiction to the trend of asking for more funding to treat additional areas (Krug *et al.* 2010; van Wilgen *et al.* 2016). In addition the focus on quality provides an alternative management option to the promotion of 'triage' in areas that cannot be reached for clearing due to limited budgets (Bottrill *et al.* 2009; Downey *et al.* 2010b).

After presenting findings of Chapter 3 to WfW project managers, their intervention was to increase allocation of person days for training interventions. The number of allocated training days has more than doubled from 4,174 days in 2016 to 8,670 days for 2018. The focus on training is a step in the right direction to improve the quality of work in-field.

6.3.2 The role of IAP strategy selection

The planning terms 'goal', 'strategy', 'objectives' and 'action' are not used in a standardised manner in the literature and can have many different meanings within the context of conservation and alien species management. Important IAP management strategies that constitute a prioritization of complementary management objectives such as water production, fire management and invasive species type, are defined in the literature (Roura-Pascual *et al.* 2009; Roura-Pascual *et al.* 2010) (Table 4.1). For each IAP management strategy, a range of management objectives had previously been weighted through an interactive Analytical Hierarchy Process based on management and expert opinion (Roura-Pascual *et al.* 2009; Roura-Pascual *et al.* 2010). For example, the management objective to treat areas that had recently burnt would have a different weighting depending on the overall strategy that was chosen for implementation (Table 4.1). Four of these strategies (management consensus, maintain follow-up area, keep areas clean, water production) were tested along with area based triage in a modelling environment to determine which strategy would perform best over time in terms of reducing alien density to below 1 plant per hectare.

The results showed that under the currently-achieved clearing efficacy (~75%), a shared Management Consensus approach attained the highest number of hectares in a maintenance state. However, the results also showed that the choice of strategy is highly dependent on the efficacy level of the clearing. As clearing quality increased or decreased above or below 75%, the best performing strategy changed. An interesting finding was high level of support for the triage strategy which repeatedly cleared aliens from the core conservation area, before clearing other areas. A similarities of this outcome could be drawn between setting priorities for clearing of buffer areas surrounding protected areas (Foxcroft *et al.* 2011; Jarošík *et al.* 2011). Although clearing the buffer areas around PA's is important, the core biodiversity areas should be the priority. A second interesting result was that focussing on lightly infested areas only as a priority proved to be a poor overall strategy and achieved the lowest levels of the desired outcome. Although the debate on the preferred management strategy is likely to continue, the findings of Chapter 4 re-emphasise the results of Chapter 3, highlighting treatment quality as a primary driver of long-term clearing success, while the choice of implementation strategy is a secondary factor.

A key finding from Chapter 4 was that the frequency at which the majority of management units were historically revisited for follow-up treatment is greater than two years. However, as many of the targeted species in the park are able to produce seeds within two years (Marchante *et al.* 2010; Souza-Alonso *et al.* 2017), these species are likely to germinate or coppice and set seed before the area is re-treated. Long periods between follow-up clearing greatly increase the cost and duration of future control, since propagule pressure, which is one of the primary drivers of IAP persistence, is not managed adequately (Lockwood *et al.* 2005; Lockwood *et al.* 2009; Simberloff 2009; Meyerson & Pyšek 2013). This lack of prompt follow-up of sites to treat newly germinated or missed plants has been noted in other studies in the region and suggests a systemic problem for WfW of inadequate forward planning and implementation (McConnachie *et al.* 2012; Fill *et al.* 2017; Kraaij *et al.* 2017). Science management engagement around the results in Chapter 4, reiterated the importance of the frequency of treatment return interval to park management, who endeavoured to improve return time to under two years. The project planning for 2017 and 2018 project years therefore evolved to 100% coverage of the project area within a 21 month return cycle to focus primarily on prevention of adult plants seeding and thus directly reducing current and future propagule pressure. Project feedback reflects that this was achieved, suggesting that decreasing the revisiting time is an achievable target

6.4 Approaches to alien species management

The expected positive outcomes of IAP removal programmes have been questioned (Hobbs *et al.* 2009; Gardener *et al.* 2010; Davis *et al.* 2011). With perceived high management costs and limited successes globally, questions have been raised as to the long-term viability of reversing the current trend of species invasions. Suggestions in the literature have been made to divert limited conservation funds away from alien species management or focus on a few selected areas (Downey *et al.* 2010b; Vince 2011; van Wilgen *et al.* 2016). In Chapter 4, the modelling of expected management outcomes shows that current management strategies and efficacy levels will only achieve a long-term ‘stale-mate’ between management control and IAP invasion, primarily due to constant seedbank replenishment in the case of Acacias.

Studies have, however, shown that eradication is feasible for plant populations, (Moore *et al.* 2011; Panetta *et al.* 2011; Kaplan *et al.* 2012). Where invasive species have been confined to small geographic ranges and can be described as being newly established, successive local eradication (extirpation) has resulted in eradication of invasive species (Simberloff 2013). Chapter 5 builds on a commonness framework which highlights that species are on a trajectory from being uncommon (newly established) to dominating the landscape (successful invasion) (McGeoch & Latombe 2016). Three metrics of population size, invasion extent and spatial pattern were used to determine a species range properties at several grains of analysis. By determining the range properties, a species could be defined in terms of its invasion trajectory.

An important finding in this chapter was that the same species could be at different stages of invasion in different areas of the park. The consequence of this is that a single management approach for a species is not warranted. A second finding is that commonness type changes with spatial grain that can result in different approaches as different grains. By incorporating information on the range properties of occupancy, population density and spatial pattern, IAP populations that fitted the newly established criteria could be readily identified. This opens the way for areas to be identified for local eradication (extirpation) of IAP (Simberloff 2013), importantly with the correct management approach applied. Through the systematic extirpation of identified local populations across the landscape, while controlling areas with higher invasion levels, park-wide eradication of IAP would be possible.

6.5 Opportunities for future research

A logical next step for future research would be to understand the factors affecting in-field productivity of the IAP teams in treating areas. As the task of clearing IAP is very labour intensive (Koenig 2009; van Wilgen & Wannenburgh 2016), both the clearing quality and the productivity of clearing teams needs to be considered, to improve efficacy and meet clearing and biodiversity targets. Understanding in-field productivity of government-led employment programmes is challenging and has many facets including economic (e.g. contractor financial management), technical (e.g. tools and skills), social (e.g. living conditions, job security) and even political ones (Hough & Prozesky 2012).

Working for Water implements a contract based model that sets the maximum price that will be accepted for an area to be cleared. This ceiling price is set primarily via the number of person days allocated to the contract at predetermined wage rates by the Working for Water Information System (WIMS). Chapter 2 showed that a significant over-estimation of species cover allowed for an over allocation of resources, thereby inflating the budgets available per contract. This resulted in a greater number of person days being generated and paid for by the project, compared to the number of person days actually used on site during 2014 and 2015 (Fig. 6.2, Year 2014, 2015). That is, the majority of contracts had too many person days allocated for the amount of work required, with the contractor and teams reaping the direct benefit.

The adoption of more rigorous density estimates in the 2016 project year, via a systematic sampling approach, resulted in a more accurate workload quantification and associated person day allocation (Fig 6.1). However, instead of a perfect balance between person days budgeted and days used in the field, the clearing teams took longer than expected to complete the contracts. In the 2016 project year 38,782 person days were allocated to clearing contracts, while the clearing teams unitised 44,489 person days to complete the work (15% extra person days required) (Fig. 6.2, Year 2016). The trend of clearing teams taking longer than expected to clear sites continued into the 2017 project year. Where WIMS generated 43,541 person days while 63,068 were actually used in-field (44% extra person days required) (Fig.6.2, Year 2017). The shift in 2016 and 2017 to contracts taking longer than expected is currently thought to be linked to the productivity of the clearing teams. With the previous over allocation of person days before 2016, clearing teams had little need to be productive due to an over allocation of person days. However, with better workload quantification, if productivity is below the expected WfW standard, the number of days on-site will overshoot the number of days allocated. Payment however, does not proceed until the work in an area is completed as per the contract. This means that extra un-paid person days are required by the teams to complete the contract, at direct cost to the contractors.

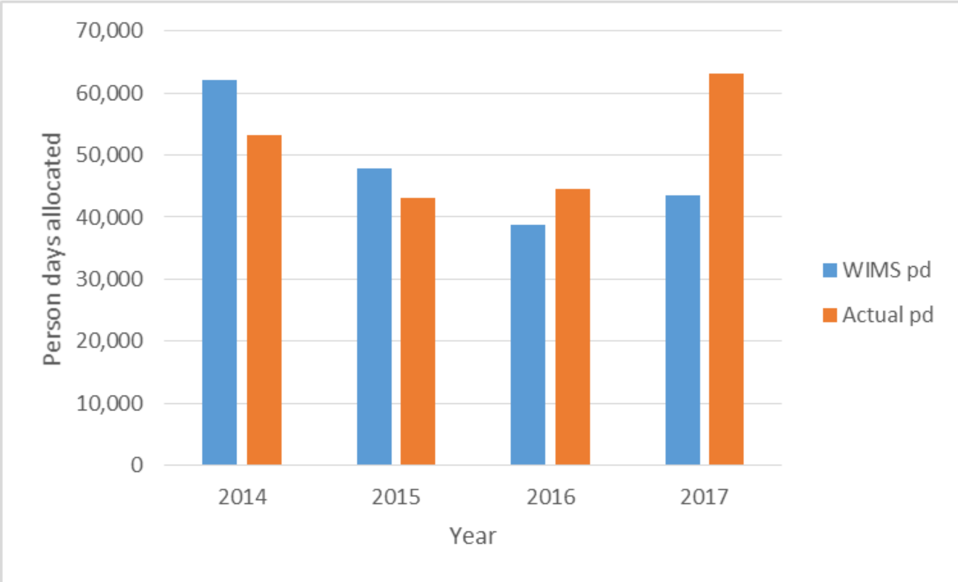

Fig. 6.2 The number of person days generated by the Working for Water Information System (WIMS) and the actual number of person days used by clearing teams. Previous to 2016 methods for collecting data used to generate contracts was ad-hoc and haphazard. From 2016 and 2017 data collected by systematic sampling methodology (Chapter 2).

The situation of improving workload quantification but teams not being able to completed tasks within the allocated is of concern to the WfW project. Initial investigations into possible reasons for the non-achievement of targets pointed to productivity the clearing teams productivity where some teams were less than 50% productive when measured against the WfW norms and standards. The productivity levels of the clearing teams directly impact on the ability of IAP programmes to deliver on required targets which in turn impacts on the organisations' biodiversity management mandate. A frequently cited explanation for the measured low rates of productivity is that WfW targets, set through the norms and standards, are too high. Alternatively the social dimensions, amongst others, financial stability, team dynamics and composition, domestic living conditions, team experience and training, social-protection and relationship with project managers could be important factors. Along with the investigation into what are the causes of low productivity, would be the recommendations to address the issue.

6.6 Conclusion

Through this thesis the demonstrated the cost-effective value of fine-scale data collected in-field. Empirically estimates of the impact of poor clearing quality on long-term prospects of clearing programmes and the implications of this for the choice of clearing strategy have been made. While the clearing programme in Table Mountain has not made many gains despite 20 years of avid application, improvements in species listing, work-load quantification, return-interval for site follow-up, and application of scale-relevant strategies to promote local and broader eradication of targeted species enabled through this thesis have paved the way for improved results in the future. I believe that the application of these results are applicable to other IAP programmes and will go a far way in '*turning the tide*' on invasive plants.

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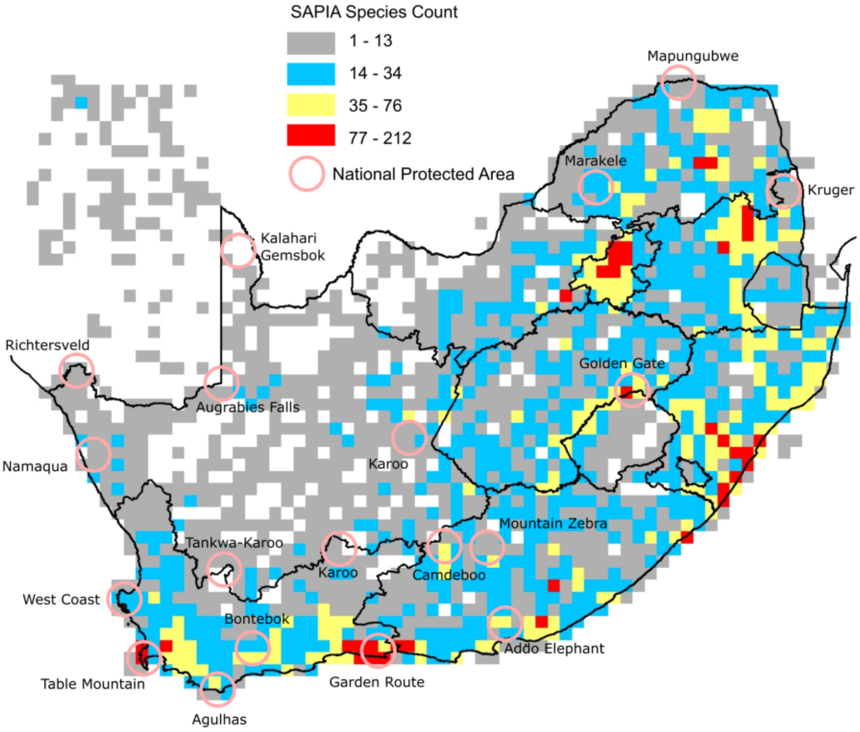
Supplementary Material

Chapter 1.



Supplementary Figure 1.1 Number of alien species across South Africa per Quarter Degree square in relation to the National Protected Areas. Alien species area courtesy of SANBI (2018)

Supplementary Table 1.1. The number of hectares and percentage of the Table Mountain National Park falling into the Working for Water alien plant cover classes. Gains have been made in the denser classes (closed, dense and medium, i.e. the cover of these classes has been reduced), while some losses have occurred in the very low density class (rare, i.e. cover of this class has also been reduced) between 1998 and 2015.

Density Class	1998		2007		2015		Change 1998-2015	
	Hectares	%	Hectares	%	Hectares	%	Hectares	%
closed	1182	4.7	1049	4.1	360	1.4	-1570	-6.2
dense	2260	8.9	1187	4.7	1009	4.0		
medium	1719	6.8	1481	5.8	2222	8.8		
scattered	1262	5.0	1871	7.4	3186	12.6		8.2
very scattered	1716	6.8	1902	7.5	3677	14.5		
occasional	7626	30.1	6467	25.5	5816	22.9	2075	
rare	9602	37.9	11408	45.0	9096	35.9	-505	-2.0
Total	25366	100	25366	100	25366	100		

Chapter 2.

Supplementary Table 2.1. Standardised classes used to group the relative measures of abundance (percentage cover, density and descriptive) for invasive alien plants invasions from the Management, Working for Water (WfW) and Systematic datasets

Standardized Abundance Class	Management: Descriptive	Management, WfW and Systematic: species cover (%)	Management: density (plants/ha)
0	Un-invaded	0	0
1	Rare	> 1%	<6
2	Occasional	1-10%	6 - 800
3	Scattered	11-25%	800 - 2,200
4	Medium	26-50%	2,200 – 7,600
5	Dense	51-75%	7,600 – 10,000
6	Closed	> 75%	> 10,000

Supplementary Table 2.2. Confusion matrix (sensu – (Fielding and Bell 1997)) for comparing presence and absence data from the Management or WfW datasets to the Systematic dataset.

Taxa x	Systematic Dataset		
		Presence	Absence
Management or WfW dataset	Presence	*a*	*b*
	Absence	*c*	*d*

a, is the number of polygons where both datasets recorded a presence value (true presence);
b, is the number of polygons where the Management or WfW datasets did record a presence value (false presence);
c, is the number of polygons where the Management or WfW datasets did not record a presence value (false absence);
d, is the number of polygons where both datasets did not record a presence value (true absence); and
n = a + b + c + d

Supplementary Table 2.3. Confusion matrix measures derived from the confusion matrix for the presence and absence data from the Management or WfW datasets and the Systematic dataset. Notation as per Table 2.

Measures	Formula	Description
Accuracy	(a+d)/n	proportion of correctly predicted polygons
Prevalence	(a+c)/n	proportion of presence records
Sensitivity	a/(a+c)	probability that the Management or WfW datasets will correctly classify a presence
Specificity	d/(b+d)	probability that the Management or WfW datasets will correctly classify an absence
Odds Ratio	ad/cb	ratio of correctly assigned polygons to incorrectly assigned polygons
Kappa (K)	$\frac{(a+d)-\{[(a+c)(a+b)+(b+d)(c+d)]/N\}}{N-\{[(a+c)(a+b)+(b+d)(c+d)]/N\}}$	specific agreement greater that chance (Fielding 2007)
True Skill Statistic (TSS)	(sensitivity + specificity) – 1	specific agreement greater that chance (Allouche et al. 2006)

Supplementary Table 2.4. Comparison of Alien Plant Species presents between the Systematic Mapping, Working For Water and Management Data, where '1' denotes the presents of that species in the data set and '*' is where data at a Genera level was been collected

Species	Systematic Survey Dataset	Working For Water Dataset	Protected Areas Managers Dataset
Acacia cyclops	1	1	1
Acacia longifolia	1	1	1
Acacia mearnsii	1	1	0
Acacia melanoxylon	1	0	0
Acacia pycnantha	1	0	0
Acacia saligna	1	1	1
Agave americana	1	0	0
Agave sisalana	1	0	0
Anagallis arvensis	1	0	0
Arundo donax	1	1	1
Avena fatua	1	0	0
Bidens pilosa	1	0	0
Briza maxima	1	0	0
Briza minor	1	0	0
Bromus diandrus	1	0	0
Callistemon salignus	1	0	0

Species	Systematic Survey Dataset	Working For Water Dataset	Protected Areas Managers Dataset
Centranthus ruber	1	0	0
Cereus jamacaru	1	0	0
Cestrum laevigatum	1	1	0
Chenopodium murale	1	0	0
Cirsium vulgare	1	0	0
Conyza albida	1	0	0
Conyza canadensis	1	0	0
Cortaderia jubata	0	1	0
Cortaderia selloana	1	1	0
Cyperus involucratus	1	0	0
Datura stramonium	1	0	0
Daucus carota	1	0	0
Echium plantagineum	1	0	0
Erodium moschatum	1	0	0
*Eucalyptus spp**	1	1	1
Eucalyptus cladocalyx	1	0	0
Eucalyptus diversicolor	1	0	0
Eucalyptus lehmannii	1	0	0
Euphorbia peplus	1	0	0
Ficus carica	1	0	0
Flaveria bidentis	1	0	0
Fumaria muralis	1	0	0
Fumaria officinalis	1	0	0
Geranium molle	1	0	0
Glechoma hederacea	1	0	0
*Hakea spp**	0	0	1
Hakea drupacea	1	0	0
Hakea gibbosa	1	1	0
Hakea salicifolia	1	1	0
Hakea sericea	1	1	0
Hedera helix	1	0	0
Hypericum perforatum	1	0	0
Hypochaeris radicata	1	0	0
Ipomoea cairica	1	0	0

Species	Systematic Survey Dataset	Working For Water Dataset	Protected Areas Managers Dataset
Lagurus ovatus	1	0	0
Lantana camara	1	1	1
Leptospermum laevigatum	1	1	1
Leucojum vernum	1	0	0
Lupinus angustifolius	1	0	0
Lupinus luteus	1	0	0
Malva parviflora	1	0	0
Medicago polymorpha	1	0	0
Melilotus indicus	1	0	0
Metrosideros excelsa	0	1	0
Myoporum tenuifolium	1	0	1
Oenothera biennis	1	0	0
*Opuntia spp**	0	1	0
Opuntia ficus-indica	1	0	0
Paraserianthes lophantha	1	1	1
Pennisetum clandestinum	1	0	0
Pennisetum purpureum	1	0	0
Pennisetum setaceum	1	1	1
Phoenix canariensis	1	0	0
Phoenix dactylifera	1	0	0
Phormium tenax	1	0	0
Phytolacca octandra	1	0	0
Picris echioides	1	0	0
*Pinus spp**	0	1	1
Pinus canariensis	1	0	0
Pinus halepensis	1	0	0
Pinus pinaster	1	0	0
Pinus pinea	1	0	0
Pinus radiata	1	0	0
Pittosporum undulatum	1	0	0
Plantago lanceolata	1	1	0
Plantago major	1	0	0
Poa annua	1	0	0
Populus x canescens	1	1	0

Species	Systematic Survey Dataset	Working For Water Dataset	Protected Areas Managers Dataset
Quercus robur	1	0	0
Raphanus raphanistrum	1	0	0
Rapistrum rugosum	1	0	0
Ricinus communis	1	0	0
Rubus cuneifolius	1	0	0
Rubus fruticosus	1	0	0
Rumex acetosella	1	0	0
Schinus molle	1	0	0
Sesbania punicea	1	1	0
Solanum incanum	1	0	0
Solanum mauritianum	1	0	0
Solanum nigrum	1	0	0
Sonchus asper	1	0	0
Sonchus oleraceus	1	0	0
Spartium junceum	1	1	0
Taraxacum officinale	1	0	0
Tradescantia fluminensis	1	0	0
Trifolium angustifolium	1	0	0
Tropaeolum majus	1	0	0
Vicia benghalensis	1	0	0
Vicia sativa	1	0	0
Vinca major	1	0	0

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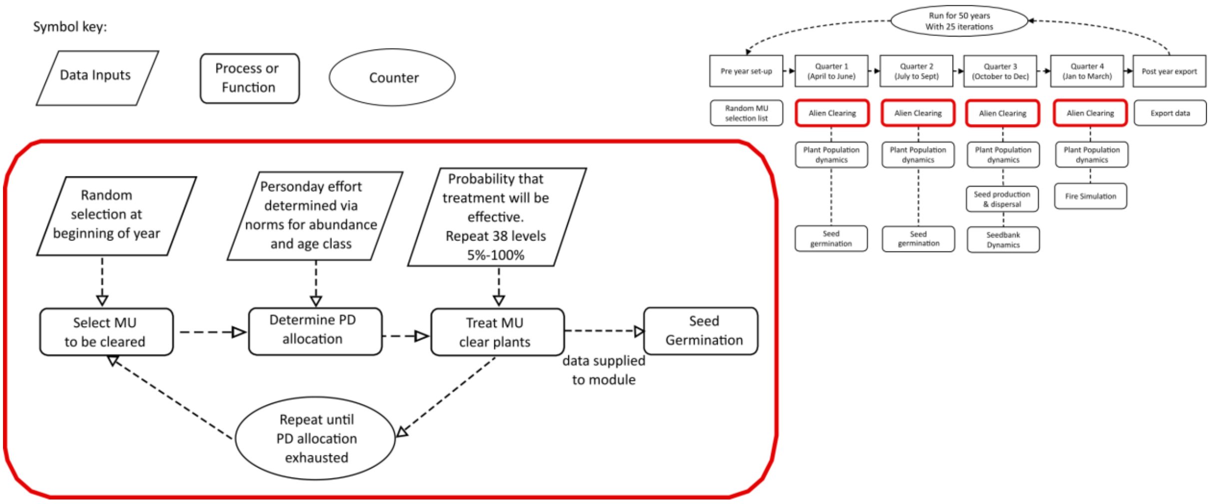
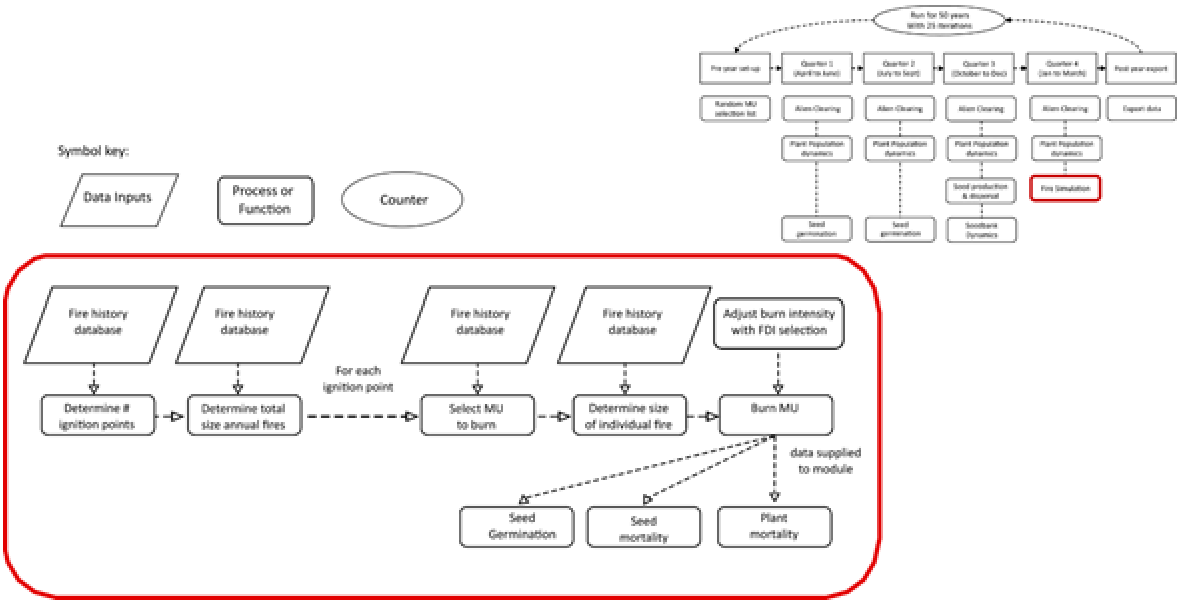
Chapter 3.



Supplementary Figure 3.1 Clearing module where management units (MU) are selected at random and person days (PD) are allocated for treatment based on the abundance and age class of Acacia species where the probability of effective treatment is varied for 1 of 38 efficacy levels. The process is repeated until the allocation of person days are exhausted with output data supplied to other modules, for example Seed Germination.



Supplementary Figure 3.2 Fire module where the number of fire ignition points and the total expected area to be burnt in a year is determined from the 1980-2016 fire database. For each fire ignition point, the management unit to be burnt is selected and if the management unit (MU) is able to be burnt, the expected size of the individual fire is calculated from the fire history database and additional adjacent MUs are burnt until this value is reached. Fire intensity for the burn is varied by use of a Fire Danger Index (FDI) and output data is fed to other modules for example, Seed Mortality.

Supplementary Table 3.1. Assignment of each management unit to a fire ignition class based on the number of ignitions recorded for the management unit in the TMNP fire history database. Ignition classes were then assigned a probability of being an ignition source in the fire module.

Number of ignition points recorded in database* for a Management unit	Fire ignition class	Probability of Management Unit being selected as an ignition source
0	1	0.050
1-6	2	0.125
7-12	3	0.200
13-16	4	0.275
>16	5	0.350
* Database: fire history of the TMNP between 1980 and 2016		

Supplementary Table 3.2. Probability that a Fire Ignition event would result in the entire management unit burning based on vegetation age (Van Wilgen *et al.* 2010). Although ignitions are possible at all vegetation ages, significant portion of the management unit <5 years will not burn given the small fuel loads of young vegetation.

Veld Age (years)	Probability of Management Unit burning
0-4	0.0
5-9	0.2
10-14	0.4
15-19	0.6
20-24	0.8
> 24	1.0

Supplementary Table 3.3. Fire Danger Index (FDI) and Plant mortality where the fire danger rating system is used to provide a measure of the relative seriousness of burning conditions and threat of fire by providing an accurate measure as possible of the relative seriousness of burning conditions by making use of daily maximum temperature, relative humidity, wind speed and recent rainfall (South African Government Gazette 37014 No. 1099 of 2013)

FDI Alert Stage	FDI Calculation	Fire Intensity	Proportion plant mortality
Blue	0-20	Low	0.0-0.20
Green	21-45	Moderate	0.21-0.45
Yellow	46-60	Dangerous	0.46-.60
Orange	61-75	Very Dangerous	0.61-0.75
Red	76-100	Extreme	0.75-1.00

Supplementary Table 3.4. Logistic equations used for annual seed production per m^2 for coppicing and non- coppicing *Acacia* species (Milton & Hall 1981; Holmes *et al.* 1987; Strydom *et al.* 2017) where the general form of the equation is $f(x) = \frac{L}{1+e^{-k(x-x_0)}}$

Annual Seed production	Logistic equations parameters
Non- coppicing < 35 years old	L=360 (rate of annual seed accumulation), k=2, x=age class, x_0=age class '6' (when seed accumulation reaches maximum)
Non- coppicing > 36 years old	L=360 (rate of annual seed accumulation), k=-0.4, x=age class, x_0=age class '42' (when seed accumulation reaches minimum)
Coppicing < 35 years old	L=4250 (rate of annual seed accumulation), k=2, x=age class, x_0=age class '6' (when seed accumulation reaches maximum)
Coppicing > 36 years old	L=4250 (rate of annual seed accumulation), k=-0.4, x=age class, x_0=age class '55' (when seed accumulation reaches minimum)

Supplementary Table 3.5. Fire Intensity as measured by the Fire Danger Index (FDI) effect on proportion of seedbank mortality / seedbank germination. Where cells are blank or '-' indicates no effect by the fire

	Fire FDI Mortality / Post fire germination (mean)									
FDI Alert Stage	Leaf Litter	Depth 1	Depth 2	Depth 3	Depth 4	Depth 5	Depth 6	Depth 7	Depth 8	Deep
Blue	0.0-0.5 / 1	- / 0.9	- / 0.7							
Green	0.5-1.0 / 1	- / 0.9	- / 0.7	- / 0.6						
Yellow	1 / 1	0.0-1.0 / 1	- / 0.9	- / 0.8	- / 0.7	- / 0.6				
Orange	1 / 1	1 / 1	0.0-1.0 / 1	- / 0.9	- / 0.8	- / 0.7	- / 0.6	- / 0.5		
Red	1 / 1	1 / 1	1 / 1	0.0-1.0 / 1	- / 0.9	- / 0.8	- / 0.7	- / 0.6	- / 0.5	- / 0.4

Supplementary Table 3.6. Plant population parameters that bound the population within observed limits

Variable	Parameter	Source
Maximum seed bank density	*Acacia* non-coppice: 2,000 seeds per m^2 *Acacia* coppice: 12,000 seeds per m^2	(Milton & Hall 1981; Holmes *et al.* 1987; Strydom *et al.* 2017)
Maximum seedling density	1,200,000 plants per ha	TMNP Management Records
Density dependent competition	Seedlings (Max) 150,000 per ha Young (Max) 50,000 per ha Adult (Max) 35,000 per ha	(Le Maitre & Versfeld 1994)
Age dependent seed production	*Acacia* non-coppice: 2 – 50 years *Acacia* coppice: 2 - 35 years	
Rates of increasing or decreasing invasion	5% per year	(van Wilgen *et al.* 2016)

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Supplementary Table 3.7. Mean time (Years) and Person Days required to reach a maintenance level (<1 plant per ha) for the 809 management units before or at 50 years based on model 25 iterations. * indicate that a maintenance level for the 809 management units (MU) was not reached by year 50.

Scenario 1: Treating only the current standing Acacia population				
		100% Efficacy	WfW Min Standard (80% Efficacy)	Current Mean Project Efficacy
	# MU	809	809	809
	Hectares	22,671	22,671	22,671
	Years	1.8 (SD=0.4)	19.1 (SD=0.4)	25.2 (SD=0.4)
	Person Days	48,590.4 (SD=5,296.1)	292,369.8 (SD=4,512.4)	377,204.5 (SD= 5,387.9)
Scenario 2: Treatment of current plant population and post-clearing seedling germination				
		100% Efficacy	80% Efficacy	Current Project
	# MU	809	809	809
	Hectares	22,671	22,671	22,671
	Years	24.7 (SD=2.5)	39.0 (SD=1.4)	42.2 (SD= 2.4)
	Person Days	344,462.3 (SD=13,231.1)	645,036.4 (SD=23,606.4)	706,235.3 (SD= 31,152.7)
Scenario 3: Treatment of current plant population, post-clearing and post-fire seedling germination				
		100% Efficacy	80% Efficacy	Current Project
	# MU	809	804.6 (SD=3.5)	798.5 (SD=8.4)
	Hectares	22,671	22,644.8 (SD=18.8)	22,575.7 (SD=74.0)
	Years	36.6 (SD=4.2)	50*	50*
	Person Days	482,496.4 (SD=36,641.8)	894,415.4 (SD= 35,820.7)	957,883.1 (SD= 22,345.5)
Scenario 4: Current standing acacia infestation, post clearing & post fire seed germination, reseeding				
		100% Efficacy	80% Efficacy	Current Project
	# MU	809	344.1 (SD=54.7)	285.4 (SD=53.9)
	Hectares	22,671	13,246.9 (SD= 1,459.1)	11,937.9 (SD=1,451.6)
	Years	37.2 (SD= 5.3)	50*	50*
	Person Days	507,475.1 (SD= 50,162.7)	1,992,947.1 (SD= 16,203.0)	2,000,081.6 (SD= 10,366.2)

Supplementary Table 3.8. The mean number of Management Units (MU), hectares (Ha) that reached a maintenance level (< 1 plant/ha) at Year 50, and the number of Person days required at Year 50, for 36 levels of simulated efficacy. n=25 for 1.00, 0.90 and 0.8, n= 15 for all other.

Efficacy level	MU (mean)	MU (SD)	Ha (mean)	HA (SD)	PD (mean)	PD (SD)
1.00	803.9	6.1	22620.6	79.7	9491.5	7.2
0.99	793.1	10.5	22391.8	199.0	9742.7	356.6
0.98	755.2	25.3	21657.8	445.9	12863.6	3025.2
0.97	725.3	28.9	20981.9	523.8	20781.9	7148.1
0.96	706.6	38.9	20371.4	652.5	23274.7	7156.7
0.95	659.1	34.0	19732.7	876.3	30849.1	8755.5
0.94	663.4	62.3	19704.4	1140.2	28753.3	10820.5
0.93	616.1	60.3	18819.7	1061.5	30397.1	9065.4
0.92	578.1	77.9	17948.5	1422.4	34865.1	7959.8
0.91	570.9	60.9	17697.1	1354.3	35869.3	6691.1
0.90	527.1	53.5	16840.7	1296.3	38582.1	2299.9
0.89	488.5	65.0	16123.9	1289.4	38693.6	3007.8
0.88	485.2	72.3	15600.7	1409.9	39098.7	2188.6
0.87	482.9	50.5	16362.5	1108.6	39799.5	908.5
0.86	420.0	69.0	14857.2	1293.4	40037.2	295.3
0.85	425.1	61.7	14694.2	1409.9	40022.3	328.2
0.84	382.3	63.8	13710.6	1694.6	39157.4	3675.3
0.83	350.9	52.2	13308.0	1072.4	39229.3	3415.2
0.82	358.2	83.0	13119.4	2058.8	40109.7	13.8
0.81	375.3	67.4	13620.0	1771.9	40110.9	17.4
0.80	344.1	54.7	13246.9	1459.1	40112.3	12.0
0.75	293.9	36.7	12050.0	1078.0	40105.9	15.6
0.70	286.3	39.2	11660.5	923.9	40104.3	11.5
0.65	280.5	59.7	11730.1	1065.8	40108.0	14.1
0.60	250.0	51.4	11133.4	1830.6	40107.5	13.3
0.55	217.3	40.1	10809.3	1248.1	40108.6	12.4
0.50	215.3	38.3	10527.1	1489.6	40113.0	12.2
0.45	168.1	25.3	9413.6	691.6	40111.3	16.7
0.40	132.4	23.1	8571.6	1166.7	40110.1	12.3
0.35	98.6	19.6	7097.3	1079.4	40110.7	14.4
0.30	82.2	11.9	7349.7	870.6	40107.0	14.3
0.25	78.9	8.1	7288.8	801.9	40110.5	16.8
0.20	72.2	8.0	7083.8	933.3	40113.9	11.4
0.15	65.3	8.9	7017.5	1376.8	40105.1	15.5
0.10	69.2	5.5	7735.7	869.8	40108.1	12.7
0.05	66.3	7.0	7316.8	417.8	40105.9	13.5

Visual Basic Code Sample, See Appendix 1

```
Attribute VB_Name = "Run_Model_Main"
' Step 4
' Main code block that uses the inputdata formatted in steps 1, 2 & 3
' into the I_Pop_x Sheets as the data that will be used in the model.

' Start  Date : 05-10-2016
' End Development Date : 01-07-2017
' Coded by: Chad Cheney
' To be run from within MS.Excel as part of a workbook set.
```

```
'_____________________________________________==___________________________
__________________________

' Common Variables
Dim mTimeStart As Date
Dim mTimeQStart As Date
Dim mTimeQEnd As Date
Dim iModelSimulate As Integer   'Stores the current model simulation (1-50)
Dim iModelYear As Integer       'Stores the current model Year (0-49)
Dim cQuarter As String          'Stores the current model Quarter (Q1, Q2,
Q3, Q4)
Dim QAvailDays As Double       'Stores the current number of PD available
for a Quarter
Dim mnBal_PdNeed As Single      'Stores the Person Days Needed of the
current nBal
Dim nBal_Ha As Single           'Stores the current Hectares of the treated
nBal
Dim mPlant_Ha As Single         'Stores the current plants per Ha of the
treated nBal
Dim mPlot_Count As Single       'Stores the current plot (row in sheet)
that needs to be carried over between Quarters
Dim mFileLoc As String          'Stores the folder path for the text files
'__________________________________________________________________________
__
'Start Here......
'__________________________________________________________________________
__

Sub Model_Main_1()
    Application.ScreenUpdating = False
    Application.Calculation = xlCalculationManual
    mTimeStart = Now()
    ActiveWorkbook.Save

    mYears = Worksheets("Model Parameters").Range("Model_Years")
    mSimulate = Worksheets("Model Parameters").Range("Model_Simulate")
    iQuater0 True            ' Setup

    For iModelSimulate = 1 To mSimulate   'Model Iterations are by Quarter
over 50 years i.e. 50 x 4
        ' reset the model for the next iteration
        For iModelYear = 0 To mYears - 1
            mTimeQStart = Now
            nBal_ScheduleSort "Systematic"      'Keep It Clean '"Maintain
follow-ups"     '"Water production" '"Random"   '"Consensus" '.... nBals
priorities at beginning of each year
            iQuater1
            iQuater2
            iQuater3
            iQuater4
            mTimeQEnd = Now
            iQuater5
        Next iModelYear
        'Write the dataout
            Write_SimulationData
            If iModelSimulate <> mSimulate Then Model_ResetNextSimulate
'does not delete the last dataset

    Next iModelSimulate
    Application.ScreenUpdating = True
    Application.Calculation = xlCalculationAutomatic
```

```
    MsgBox "Complete"
End Sub
```

References (Supplementary Material Chapter 3)

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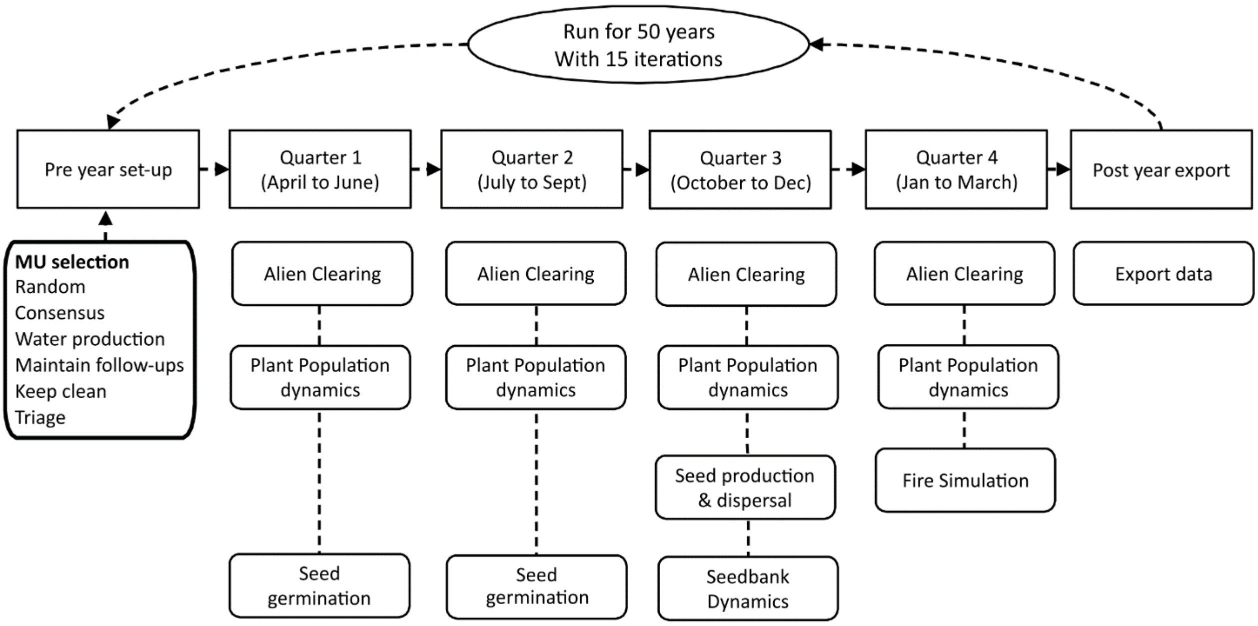
Strydom M., Veldtman R., Ngwenya M.Z. & Esler K.J. (2017). Invasive Australian Acacia seed banks: Size and relationship with stem diameter in the presence of gall-forming biological control agents. *PLOS ONE*, 12, e0181763.

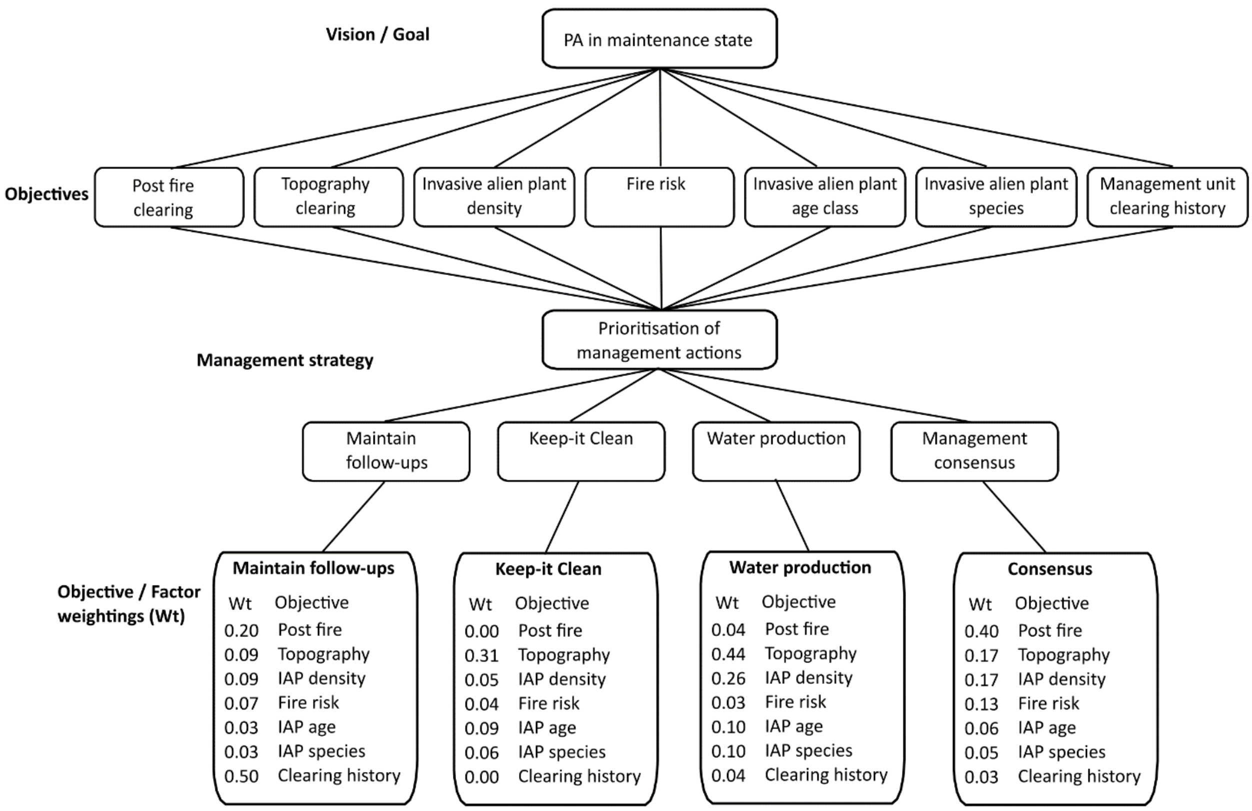
van Wilgen B.W., Fill J.M., Baard J., Cheney C., Forsyth A.T. & Kraaij T. (2016). Historical costs and projected future scenarios for the management of invasive alien plants in protected areas in the Cape Floristic Region. *Biological Conservation*, 200, 168-177.

Van Wilgen B.W., Forsyth G.G., De Klerk H., Das S., Khuluse S. & Schmitz P. (2010). Fire management in Mediterranean-climate shrublands: a case study from the Cape fynbos, South Africa. *Journal of Applied Ecology*, 47, 631-638.

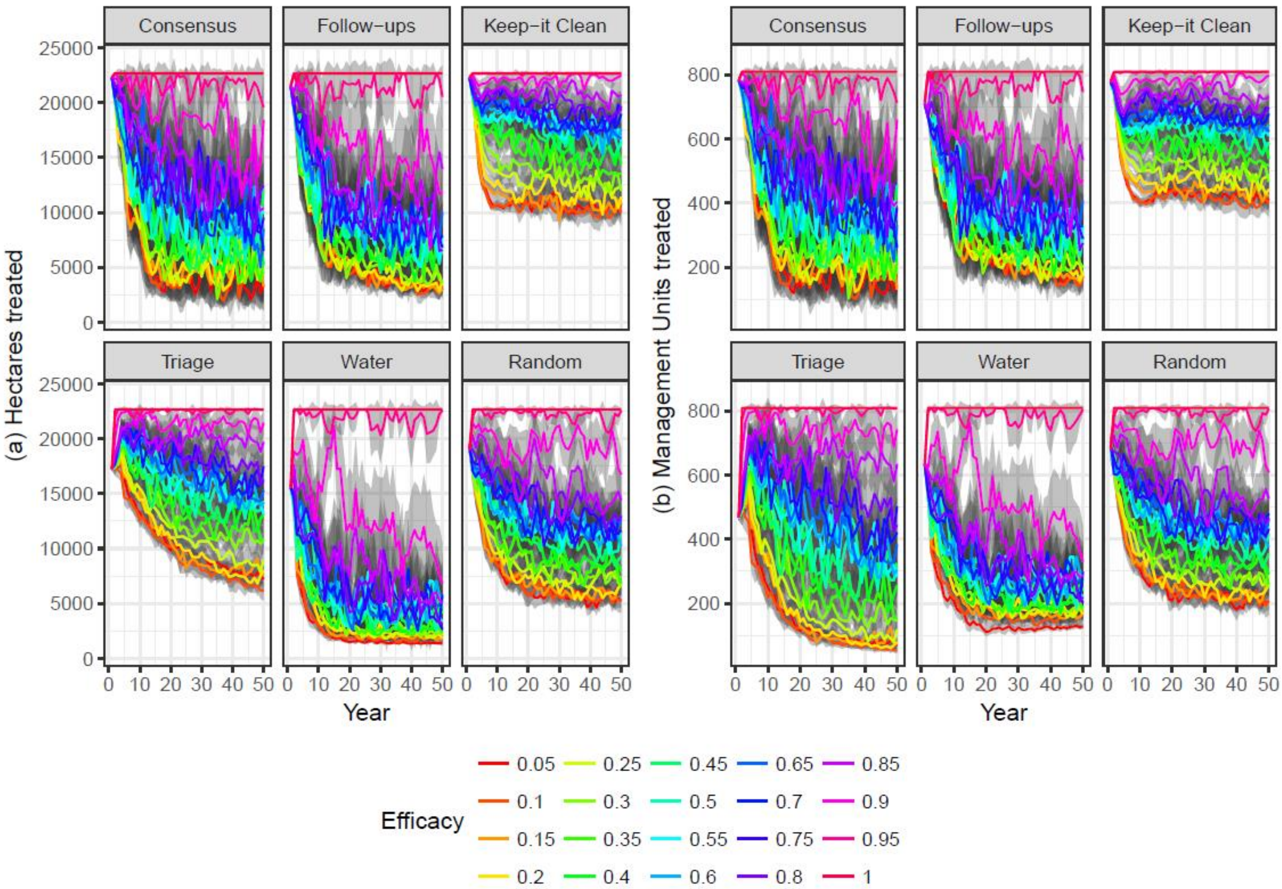
Chapter 4.



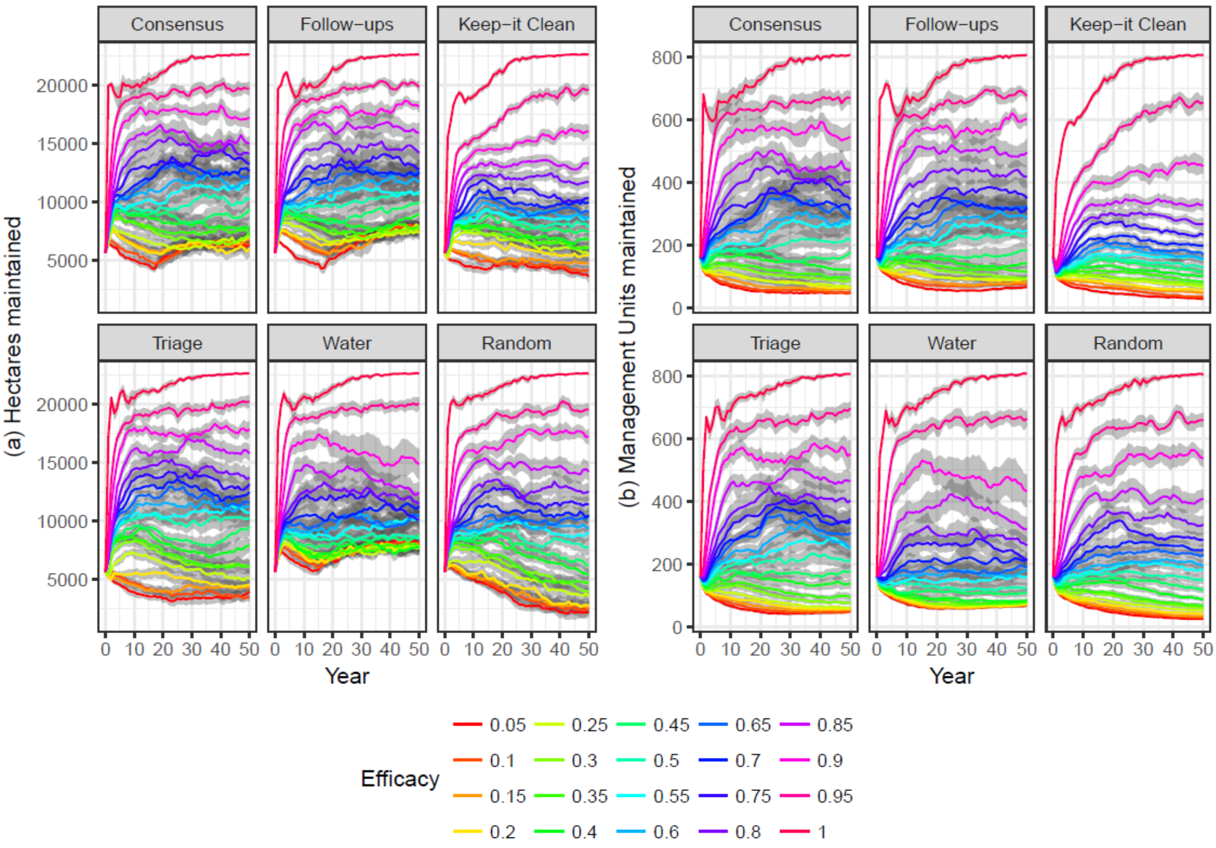
Supplementary Figure 4.1 Overview of the modules in the spatio-temporal simulation model that the management strategy and units (MU) were modelled and the calendar quarter within a simulation year in which they are called.



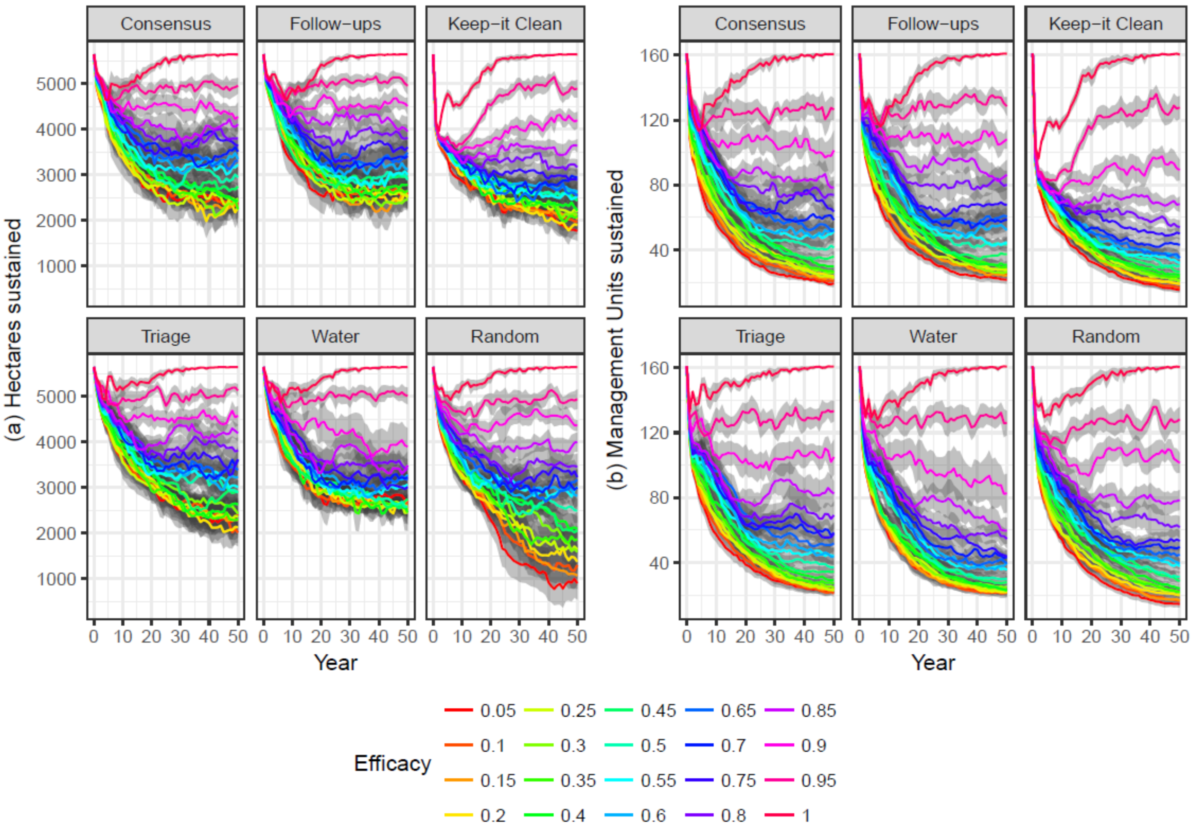
Supplementary Figure 4.2 Link between protected area (PA) vision, objectives and management actions flowing to 1 of 4 management strategies. Weightings (Wt) for each objective/factor that determine a strategy was determined through the Analytical Hierarchy process (Roura-Pascual *et al*. 2010).



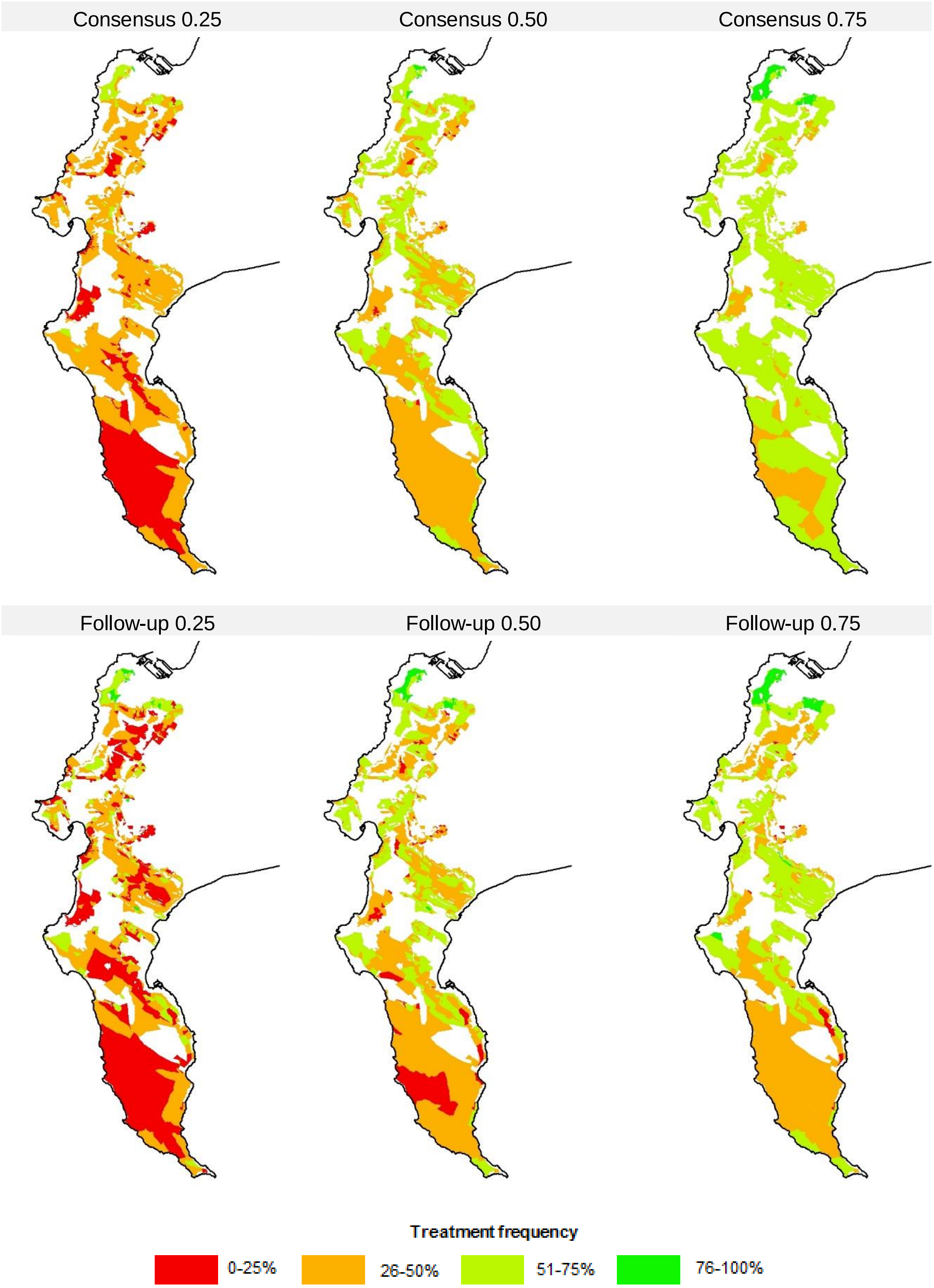
Supplementary Figure. 4.3 The number of hectares (a) and management units (b) treated per year over 50 years for each of the management strategies tested at 20 management efficacy levels between 0.05 and 1.0, represented by the mean and 95% CI, over 15 model runs.



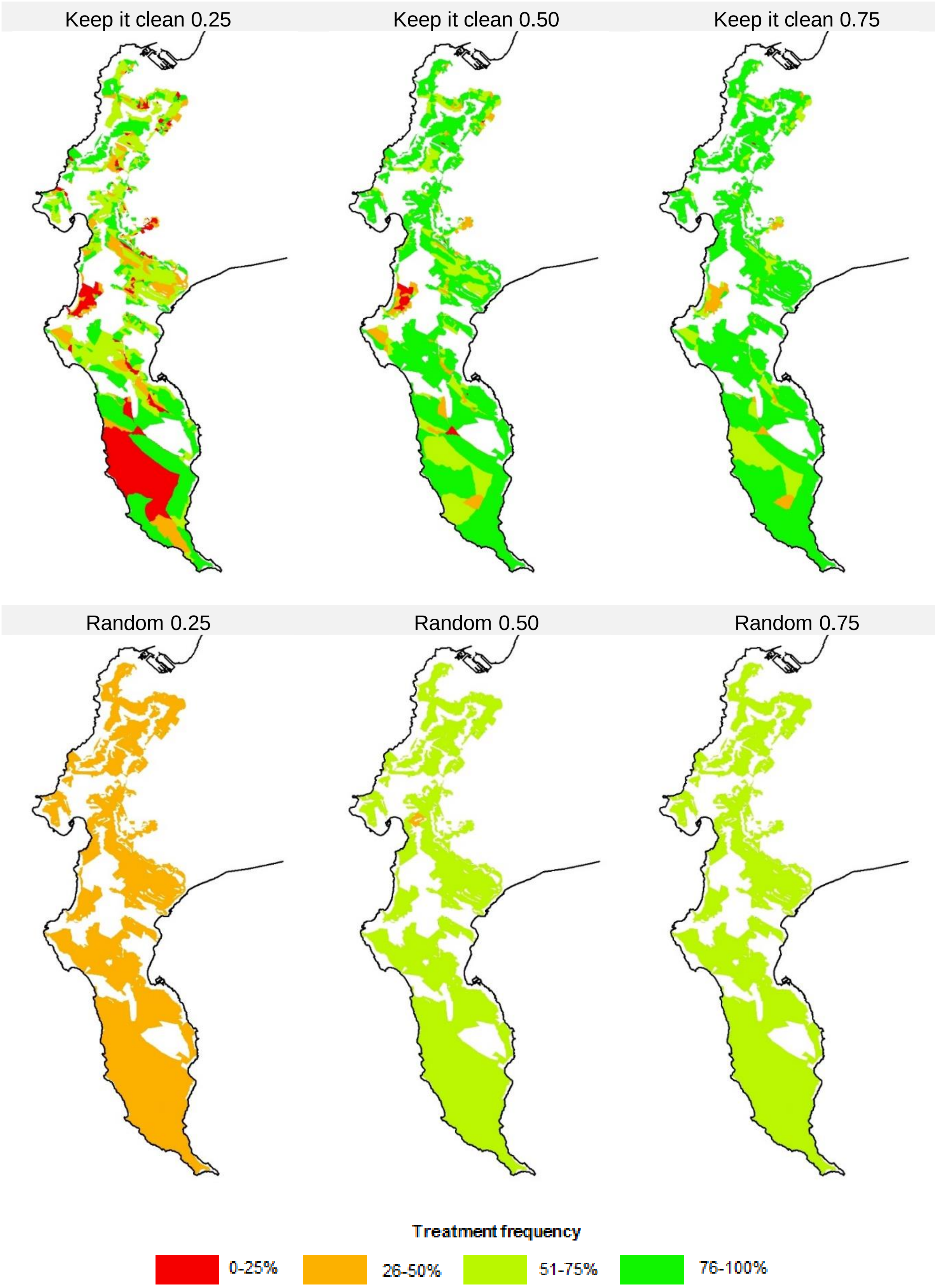
Supplementary Figure 4.4 The number of hectares (a) and management units (b) that reached a maintenance state of 1 plant per ha over 50 years for each of the management strategies at given levels of efficacy, represented by the mean and 95% CI over 15 model runs per efficacy level.



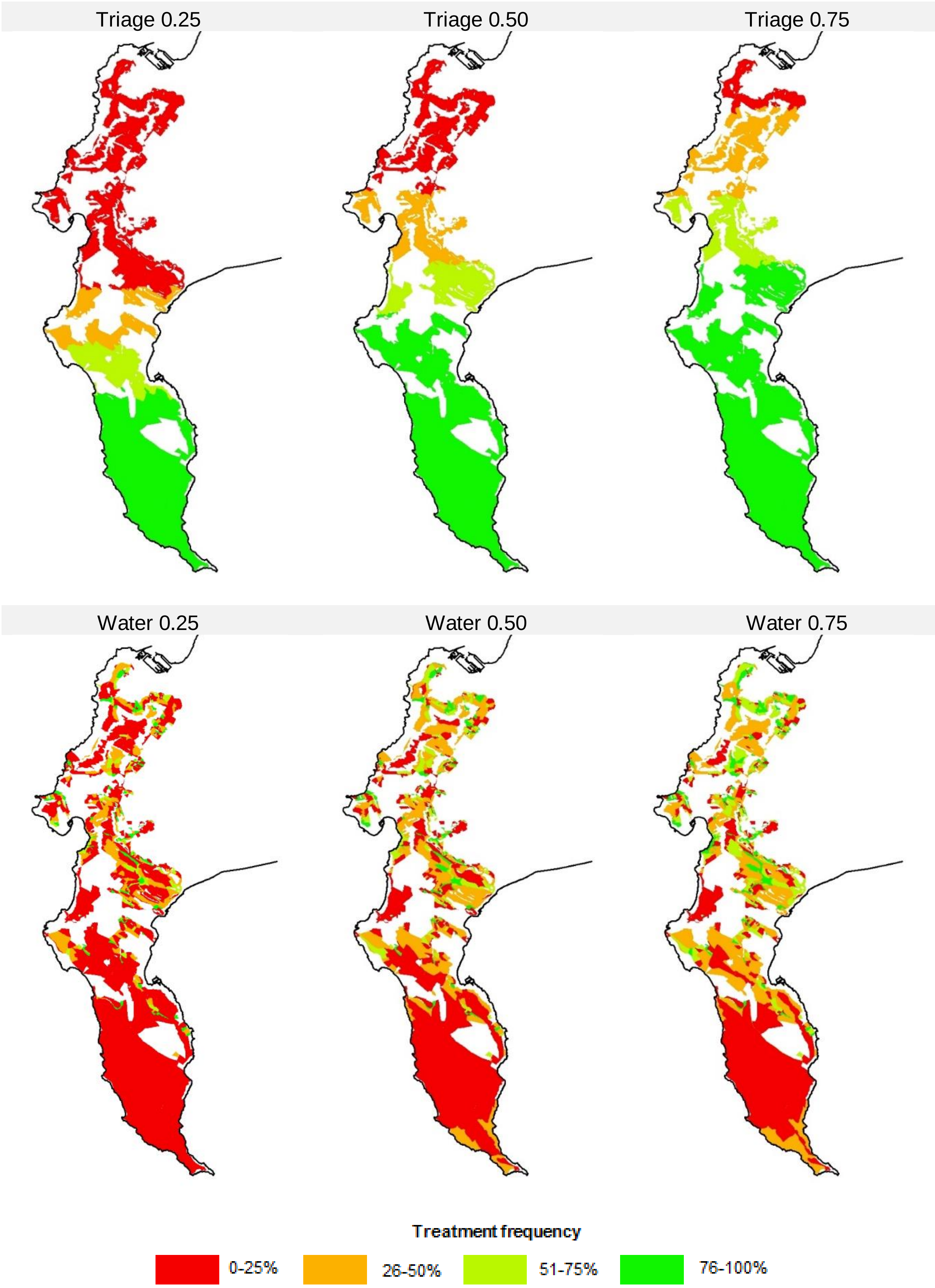
Supplementary Figure 4.5 The number of hectares (a) and management units (b) that were sustained in a maintenance state of 1 plant per ha over 50 years for each of the management strategies at given levels of efficacy, represented by the mean and 95% CI over 15 model runs per efficacy level.



Supplementary Figure 4.6. The frequency that management units were selected by different management strategies at three levels of clearing efficacy. Areas with a frequency of treatment > 50% equates to a treatment frequency of < 2 years.

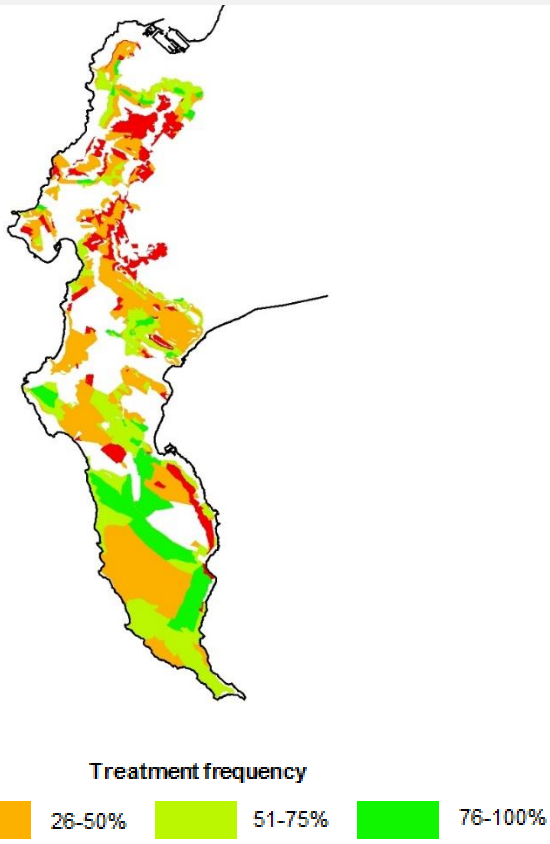


Supplementary Figure 4.6 (cont.). The frequency that management units were selected by different management strategies at three levels of clearing efficacy. Areas with a frequency of treatment > 50% equates to a treatment frequency of < 2 years.



Supplementary Figure 4.6 (cont.). The frequency that management units were selected by different management strategies at three levels of clearing efficacy. Areas with a frequency of treatment > 50% equates to a treatment frequency of < 2 years.

Historical Park Data



Supplementary Figure 4.6 (cont.). The frequency that management units were selected by different management strategies at three levels of clearing efficacy. Areas with a frequency of treatment > 50% equates to a treatment frequency of < 2 years.

Supplementary Table 4.1. The number of hectares (ha) and management units (MU) treated per year averaged over model years 10 to 50 and 15 model runs, at set levels of clearing efficacy.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.95	10-50	21586	3409	2805	22668	NS	774	108	131	809	*p*<0.001
Follow-up	0.95	10-50	21233	4139	3751	22667	NS	765	128	175	809	*p*<0.001
Keep-it Clean	0.95	10-50	22652	150	19324	22666	*p*<0.001	808	6	693	809	*p*<0.001
Random	0.95	10-50	22170	1585	10012	22666	NA	792	54	373	809	NA
Water	0.95	10-50	21694	2914	6891	22667	*p*<0.05	780	83	354	809	*p*<0.001
Triage	0.95	10-50	22547	601	15225	22666	*p*<0.001	803	35	351	809	*p*<0.001
Consensus	0.90	10-50	18069	6629	2088	22667	NS	656	221	76	809	NS
Follow-up	0.90	10-50	15332	7073	2009	22667	*p*<0.001	582	226	87	809	*p*<0.001
Keep-it Clean	0.90	10-50	22149	1163	13825	22666	*p*<0.001	785	45	538	809	*p*<0.001
Random	0.90	10-50	19304	3909	7088	22667	NA	695	134	191	809	NA
Water	0.90	10-50	12445	8063	1401	22667	*p*<0.001	509	242	114	809	*p*<0.001
Triage	0.90	10-50	21461	1936	13855	22668	*p*<0.001	739	116	295	809	*p*<0.001
Consensus	0.75	10-50	11931	7928	1431	22669	*p*<0.05	447	269	50	809	NS
Follow-up	0.75	10-50	9695	6175	1252	22668	*p*<0.001	387	219	59	809	*p*<0.001
Keep-it Clean	0.75	10-50	19057	2744	10690	22667	*p*<0.001	689	78	474	809	*p*<0.001
Random	0.75	10-50	13177	4132	3471	22667	NA	483	146	154	809	NA
Water	0.75	10-50	5835	5182	1242	22667	*p*<0.001	305	165	93	809	*p*<0.001
Triage	0.75	10-50	17790	3542	8673	22668	*p*<0.001	521	210	76	809	*p*<0.001
Consensus	0.50	10-50	8882	7354	1103	22669	*p*<0.001	342	252	54	809	*p*<0.001
Follow-up	0.50	10-50	8721	5940	1202	22666	*p*<0.001	345	208	47	809	*p*<0.001
Keep-it Clean	0.50	10-50	17701	2898	9761	22668	*p*<0.001	628	95	408	809	*p*<0.001
Random	0.50	10-50	11675	4056	2988	22666	NA	426	144	114	809	NA
Water	0.50	10-50	4558	4326	1117	22669	*p*<0.001	259	144	84	809	*p*<0.001
Triage	0.50	10-50	15291	3719	6496	22668	*p*<0.001	378	211	54	809	*p*<0.001
Consensus	0.25	10-50	5347	5056	921	22669	*p*<0.001	219	171	40	809	*p*<0.001
Follow-up	0.25	10-50	5119	3214	994	20599	*p*<0.001	230	117	41	720	*p*<0.001
Keep-it Clean	0.25	10-50	12766	2591	6448	19824	*p*<0.001	493	87	297	755	*p*<0.001
Random	0.25	10-50	7714	2213	2789	15632	NA	285	78	79	564	NA
Water	0.25	10-50	2543	1478	1057	16670	*p*<0.001	190	67	88	588	*p*<0.001
Triage	0.25	10-50	10755	2752	2334	19379	*p*<0.001	161	104	28	651	*p*<0.001

Supplementary Table 4.2. The number of hectares (ha) and management units (MU) treated in year 50 averaged over 15 model runs

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.95	50	19570	6127	2805	22664	NS	712	198	131	809	NS
Follow-up	0.95	50	20517	5124	4314	22664	NS	746	160	218	809	NS
Keep-it Clean	0.95	50	22664	1	22663	22665	NS	809	0	809	809	NS
Random	0.95	50	22553	389	21155	22664	NA	806	10	770	809	NA
Water	0.95	50	22570	283	21600	22666	NS	804	19	737	809	NS
Triage	0.95	50	22626	146	22097	22665	NS	807	7	781	809	NS
Consensus	0.90	50	18445	7353	2610	22665	NS	661	241	128	809	NS
Follow-up	0.90	50	11836	6341	2226	22664	$p<0.05$	473	217	105	809	NS
Keep-it Clean	0.90	50	22469	346	21764	22665	$p<0.01$	799	22	746	809	$p<0.001$
Random	0.90	50	16735	4237	10549	22665	NA	608	155	398	809	NA
Water	0.90	50	6803	6682	1478	21739	$p<0.001$	330	202	125	779	$p<0.001$
Triage	0.90	50	21460	1824	17581	22664	$p<0.01$	742	105	495	809	$p<0.05$
Consensus	0.75	50	9533	8059	1996	22667	NS	386	274	109	809	NS
Follow-up	0.75	50	6803	5198	2480	22298	$p<0.001$	289	185	110	808	$p<0.01$
Keep-it Clean	0.75	50	19284	2682	13903	22667	$p<0.001$	695	72	570	809	$p<0.001$
Random	0.75	50	11647	3943	6713	20262	NA	433	136	223	720	NA
Water	0.75	50	2633	1449	1399	7435	$p<0.001$	201	61	136	378	$p<0.001$
Triage	0.75	50	17500	4131	11403	21839	$p<0.05$	502	247	149	767	NS
Consensus	0.50	50	6757	6666	1544	22667	$p<0.01$	264	234	70	809	$p<0.01$
Follow-up	0.50	50	7096	5215	1942	22664	$p<0.001$	294	174	91	809	$p<0.01$
Keep-it Clean	0.50	50	16386	2074	12897	19671	$p<0.001$	589	64	465	692	$p<0.001$
Random	0.50	50	11584	2587	7552	15918	NA	417	90	234	542	NA
Water	0.50	50	3334	2883	1253	10292	$p<0.001$	210	103	105	432	$p<0.001$
Triage	0.50	50	14307	2936	10693	21298	$p<0.05$	316	166	133	727	$p<0.05$
Consensus	0.25	50	4416	5036	1163	18484	$p<0.01$	183	177	61	682	$p<0.01$
Follow-up	0.25	50	3386	1959	1125	7118	$p<0.001$	173	75	81	311	$p<0.001$
Keep-it Clean	0.25	50	12298	2730	7306	17818	$p<0.001$	487	96	321	657	$p<0.001$
Random	0.25	50	7380	1951	4644	11443	NA	287	70	205	454	NA
Water	0.25	50	2109	943	1163	4803	$p<0.001$	178	52	88	306	$p<0.001$
Triage	0.25	50	8980	2775	3092	12977	NS	117	76	30	278	$p<0.001$

Supplementary Table 4.3. The number of hectares (ha) and management units (MU) that attained the management goal of < 1 plant/ha, per year, averaged over model years 10 to 50 and 15 model runs, at set various efficacy levels.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.95	10-50	19465	952	16549	22075	$p<0.001$	650	48	471	782	$p<0.001$
Follow-up	0.95	10-50	19633	894	16184	21748	$p<0.001$	657	45	517	759	$p<0.001$
Keep-it Clean	0.95	10-50	18210	1569	13598	21668	$p<0.001$	590	77	396	754	$p<0.001$
Random	0.95	10-50	19171	1026	16164	22112	NA	638	48	486	771	NA
Water	0.95	10-50	19553	937	16596	22093	$p<0.001$	650	46	489	775	$p<0.001$
Triage	0.95	10-50	19569	950	15902	21867	$p<0.001$	657	46	503	758	$p<0.001$
Consensus	0.90	10-50	17629	1204	13505	20092	$p<0.001$	563	62	397	699	$p<0.001$
Follow-up	0.90	10-50	17832	1064	12289	20317	$p<0.001$	573	49	345	673	$p<0.001$
Keep-it Clean	0.90	10-50	15243	1044	12558	18608	$p<0.001$	427	49	298	579	$p<0.001$
Random	0.90	10-50	17117	1348	11847	20061	NA	527	60	375	673	NA
Water	0.90	10-50	15917	2429	10397	20192	$p<0.001$	479	97	260	690	$p<0.001$
Triage	0.90	10-50	17651	1016	14040	20572	$p<0.001$	551	55	375	709	$p<0.001$
Consensus	0.75	10-50	13575	1544	8270	17640	$p<0.001$	369	66	189	582	$p<0.001$
Follow-up	0.75	10-50	13351	1742	7465	17423	$p<0.001$	362	67	201	540	$p<0.001$
Keep-it Clean	0.75	10-50	10830	1091	6411	13759	$p<0.001$	252	28	165	325	$p<0.001$
Random	0.75	10-50	11877	1190	8437	14963	NA	296	44	188	421	NA
Water	0.75	10-50	11659	1666	6683	16414	$p<0.01$	257	56	138	467	$p<0.001$
Triage	0.75	10-50	13573	1447	9467	17251	$p<0.001$	366	61	203	586	$p<0.001$
Consensus	0.50	10-50	9826	1492	5125	14157	$p<0.001$	203	48	111	336	$p<0.001$
Follow-up	0.50	10-50	10116	1205	6750	13920	$p<0.001$	218	39	117	335	$p<0.001$
Keep-it Clean	0.50	10-50	8402	1066	4605	10738	NS	147	22	90	208	$p<0.001$
Random	0.50	10-50	8508	1124	5220	11257	NA	164	29	94	259	NA
Water	0.50	10-50	8623	1281	4890	12523	NS	125	32	67	243	$p<0.001$
Triage	0.50	10-50	10121	1260	6671	14756	$p<0.001$	212	42	124	348	$p<0.001$
Consensus	0.25	10-50	6488	1005	2908	9229	$p<0.001$	83	19	44	144	$p<0.001$
Follow-up	0.25	10-50	7050	1025	3651	9638	$p<0.001$	98	19	54	152	$p<0.001$
Keep-it Clean	0.25	10-50	6463	968	3963	8477	$p<0.001$	83	15	44	132	$p<0.001$
Random	0.25	10-50	4988	1402	1391	8098	NA	69	17	34	118	NA
Water	0.25	10-50	7386	760	4459	10224	$p<0.001$	72	9	53	109	$p<0.001$
Triage	0.25	10-50	5929	1226	2275	9067	$p<0.001$	77	18	45	143	$p<0.001$

Supplementary Table 4.4. The number of hectares (ha) and management units (MU) that attained the management goal of < 1 plant/ha, per year, averaged in year 50 and 15 model runs, at set various efficacy levels.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max (MU)	*p* to Random
Consensus	0.95	50	19731	1080	18146	21324	NS	669	37	618	738	NS
Follow-up	0.95	50	19864	948	17927	21189	NS	675	36	593	738	NS
Keep-it Clean	0.95	50	19636	808	18071	20760	NS	654	38	583	714	NS
Random	0.95	50	19565	968	17492	21599	NA	659	41	582	754	NA
Water	0.95	50	20059	966	18704	21369	NS	664	45	570	722	NS
Triage	0.95	50	20220	976	18201	21600	NS	697	40	629	757	NS
Consensus	0.90	50	17234	1578	14536	20092	NS	546	79	400	664	NS
Follow-up	0.90	50	18169	886	16599	19335	p<0.05	602	39	527	659	p<0.001
Keep-it Clean	0.90	50	16067	913	14437	17608	p<0.01	451	42	372	527	p<0.001
Random	0.90	50	17249	1122	15075	19161	NA	537	48	432	611	NA
Water	0.90	50	14856	2360	11855	18433	p<0.01	432	93	303	592	p<0.01
Triage	0.90	50	17867	1171	15861	19989	NS	551	81	427	677	NS
Consensus	0.75	50	13230	1333	11099	15748	p<0.01	347	61	264	461	p<0.01
Follow-up	0.75	50	12788	2335	8797	16734	NS	349	95	210	540	p<0.05
Keep-it Clean	0.75	50	10308	839	8297	11424	p<0.01	233	23	192	271	p<0.001
Random	0.75	50	11401	1107	8941	12898	NA	277	37	194	346	NA
Water	0.75	50	10070	1376	6683	11947	p<0.01	211	42	138	295	p<0.001
Triage	0.75	50	13135	1455	10302	15908	p<0.001	345	62	258	452	p<0.01
Consensus	0.50	50	10196	1603	7651	12659	p<0.001	213	48	117	296	p<0.001
Follow-up	0.50	50	10622	993	8826	12726	p<0.001	230	43	180	328	p<0.001
Keep-it Clean	0.50	50	7875	1272	5169	10099	NS	129	19	96	166	p<0.05
Random	0.50	50	7827	1316	5443	9285	NA	150	22	102	196	NA
Water	0.50	50	8532	1294	6648	10508	NS	124	24	91	166	p<0.05
Triage	0.50	50	10257	1103	8151	11609	p<0.001	214	43	140	284	p<0.001
Consensus	0.25	50	6972	817	5716	8198	p<0.001	68	12	53	101	p<0.001
Follow-up	0.25	50	7391	828	6510	9168	p<0.001	94	16	69	116	p<0.001
Keep-it Clean	0.25	50	5532	954	3963	7167	p<0.001	66	12	44	85	p<0.01
Random	0.25	50	3544	1040	1679	5854	NA	51	9	35	66	NA
Water	0.25	50	7686	1128	5193	9686	p<0.001	74	6	67	84	p<0.001
Triage	0.25	50	5108	1053	2915	6833	p<0.001	62	8	50	73	p<0.01

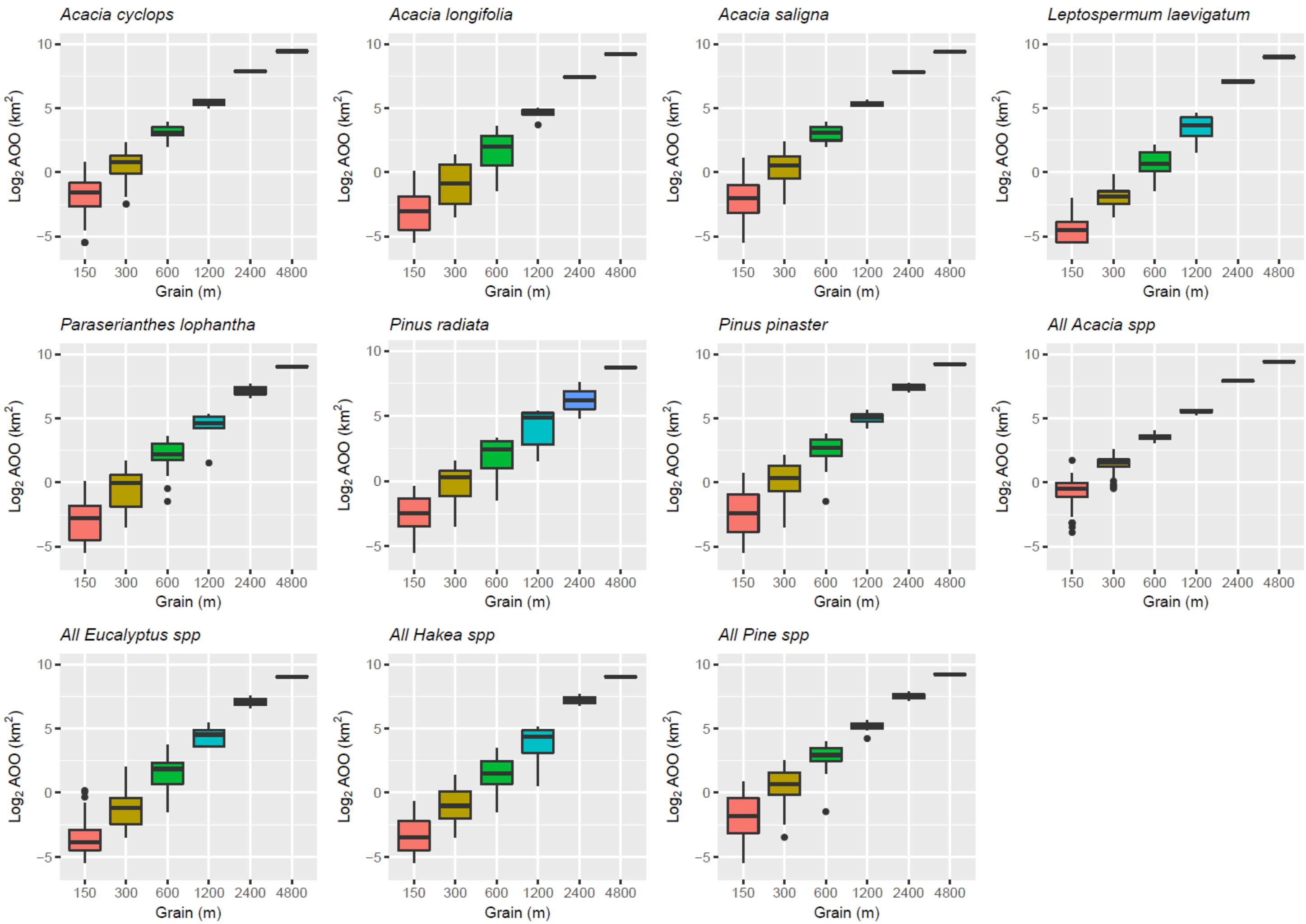
Supplementary Table 4.5. The number of hectares (ha) and management units (MU) that were sustained in a maintenance state of <1 plant/ha, per year for years 10 to 50 and efficacy at various levels (n=15), with a starting maintenance state of 5,646 hectares and 161 management units.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max) (MU	*p* to Random
Consensus	0.95	10-50	4915	300	3722	5610	NS	125	13	87	156	NS
Follow-up	0.95	10-50	5017	276	3783	5570	$p<0.001$	129	11	91	155	$p<0.001$
Keep-it Clean	0.95	10-50	4675	477	2542	5624	$p<0.001$	119	17	66	155	$p<0.001$
Random	0.95	10-50	4874	358	3092	5632	NA	126	13	84	159	NA
Water	0.95	10-50	5003	323	2818	5644	$p<0.001$	128	12	90	160	$p<0.001$
Triage	0.95	10-50	5018	301	3577	5567	$p<0.001$	129	12	87	156	$p<0.001$
Consensus	0.90	10-50	4468	385	2953	5405	NS	105	15	64	146	NS
Follow-up	0.90	10-50	4533	350	2784	5300	$p<0.01$	109	12	58	142	$p<0.001$
Keep-it Clean	0.90	10-50	3960	375	2823	4963	$p<0.001$	88	13	56	130	$p<0.001$
Random	0.90	10-50	4471	392	2249	5353	NA	104	14	66	139	NA
Water	0.90	10-50	4139	735	1957	5411	$p<0.001$	95	23	43	147	$p<0.001$
Triage	0.90	10-50	4528	342	3429	5351	$p<0.01$	104	15	53	141	NS
Consensus	0.75	10-50	3703	490	1549	5025	$p<0.001$	72	15	39	124	$p<0.001$
Follow-up	0.75	10-50	3626	569	1601	4882	$p<0.001$	70	15	35	123	$p<0.001$
Keep-it Clean	0.75	10-50	3059	391	1758	4017	$p<0.001$	57	11	31	83	$p<0.001$
Random	0.75	10-50	3403	553	1211	4440	NA	61	15	32	105	NA
Water	0.75	10-50	3375	630	1312	4847	NS	60	17	29	118	$p<0.05$
Triage	0.75	10-50	3723	537	1967	4962	$p<0.001$	67	15	38	111	$p<0.001$
Consensus	0.50	10-50	3072	624	1045	4609	$p<0.001$	51	15	23	103	$p<0.001$
Follow-up	0.50	10-50	3093	528	952	4542	$p<0.001$	52	15	25	113	$p<0.001$
Keep-it Clean	0.50	10-50	2783	427	1097	3665	NS	41	12	18	76	$p<0.001$
Random	0.50	10-50	2801	550	766	4111	NA	46	16	21	112	NA
Water	0.50	10-50	2991	549	1107	4660	$p<0.001$	42	17	16	106	$p<0.001$
Triage	0.50	10-50	3341	503	1577	4567	$p<0.001$	51	16	26	103	$p<0.001$
Consensus	0.25	10-50	2638	535	864	4356	$p<0.001$	37	14	13	85	$p<0.05$
Follow-up	0.25	10-50	2705	593	863	4581	$p<0.001$	39	14	17	80	$p<0.001$
Keep-it Clean	0.25	10-50	2513	466	598	3519	$p<0.01$	34	12	12	73	NS
Random	0.25	10-50	2274	856	461	3861	NA	34	13	11	73	NA
Water	0.25	10-50	2855	513	792	4318	$p<0.001$	34	13	16	78	NS
Triage	0.25	10-50	2738	689	627	4471	$p<0.001$	38	14	13	78	$p<0.001$

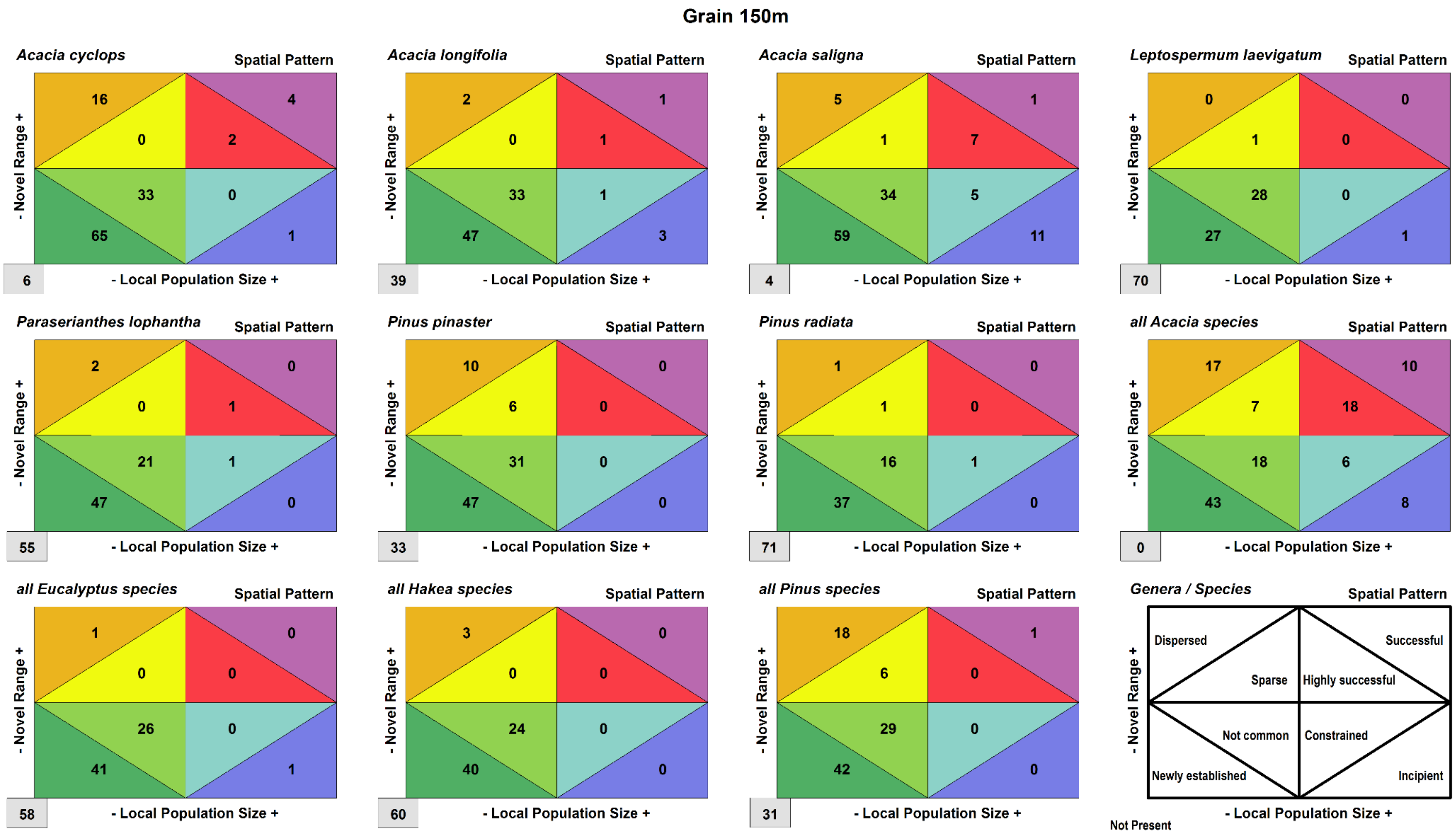
Supplementary Table 4.6. The number of hectares (ha) and management units (MU) that were retained in a maintenance state of <1 plant/ha, at the end of the model run at year 50 and efficacy at various levels (n=15), with a starting maintenance state of 5,646 ha and 161 MU units.

Strategy	Clearing efficacy	Model Year	Mean (ha)	SD	Min (ha)	Max (ha)	*p* to Random	Mean (MU)	SD	Min (MU)	Max) (MU	*p* to Random
Consensus	0.95	50	4957	308	4440	5429	NS	126	12	108	150	NS
Follow-up	0.95	50	4956	339	4404	5444	NS	128	10	115	145	NS
Keep-it Clean	0.95	50	4892	347	4301	5398	NS	128	13	104	146	NS
Random	0.95	50	4940	390	4240	5498	NA	128	14	108	157	NA
Water	0.95	50	5011	332	4406	5501	NS	126	13	100	149	NS
Triage	0.95	50	5130	242	4576	5453	NS	133	11	110	150	NS
Consensus	0.90	50	4274	577	3045	5244	NS	101	22	64	140	NS
Follow-up	0.90	50	4509	341	3882	4874	NS	108	11	83	125	NS
Keep-it Clean	0.90	50	4200	334	3519	4681	NS	89	11	66	108	$p<0.05$
Random	0.90	50	4361	217	4059	4770	NA	101	11	82	115	NA
Water	0.90	50	3898	731	2294	5095	$p<0.05$	83	21	43	114	$p<0.01$
Triage	0.90	50	4576	381	3818	5195	NS	105	19	79	139	NS
Consensus	0.75	50	3641	314	3007	4110	$p<0.01$	64	9	48	75	$p<0.05$
Follow-up	0.75	50	3609	647	2247	4494	NS	68	18	35	94	$p<0.05$
Keep-it Clean	0.75	50	2898	396	2041	3582	$p<0.05$	50	7	42	64	NS
Random	0.75	50	3230	442	2139	3872	NA	53	11	38	76	NA
Water	0.75	50	3014	539	2053	4053	NS	44	7	31	54	$p<0.05$
Triage	0.75	50	3618	410	2890	4386	$p<0.05$	58	12	42	86	NS
Consensus	0.50	50	2946	348	2508	3529	$p<0.05$	41	8	31	64	$p<0.01$
Follow-up	0.50	50	2897	368	2347	3709	$p<0.05$	43	8	36	60	$p<0.001$
Keep-it Clean	0.50	50	2632	400	2226	3665	NS	30	6	23	49	NS
Random	0.50	50	2492	461	974	2904	NA	31	6	23	43	NA
Water	0.50	50	2585	665	1199	3479	NS	30	7	17	41	NS
Triage	0.50	50	2896	461	1780	3630	$p<0.05$	37	7	26	50	$p<0.05$
Consensus	0.25	50	2416	426	1225	3076	$p<0.01$	23	3	18	28	NS
Follow-up	0.25	50	2503	311	1803	2981	$p<0.05$	27	5	21	36	$p<0.01$
Keep-it Clean	0.25	50	2194	210	1836	2715	NS	21	5	12	29	NS
Random	0.25	50	1647	813	461	2670	NA	21	5	12	31	NA
Water	0.25	50	2454	722	792	3262	$p<0.05$	22	2	18	26	NS
Triage	0.25	50	2364	725	883	3168	$p<0.05$	23	4	14	28	NS

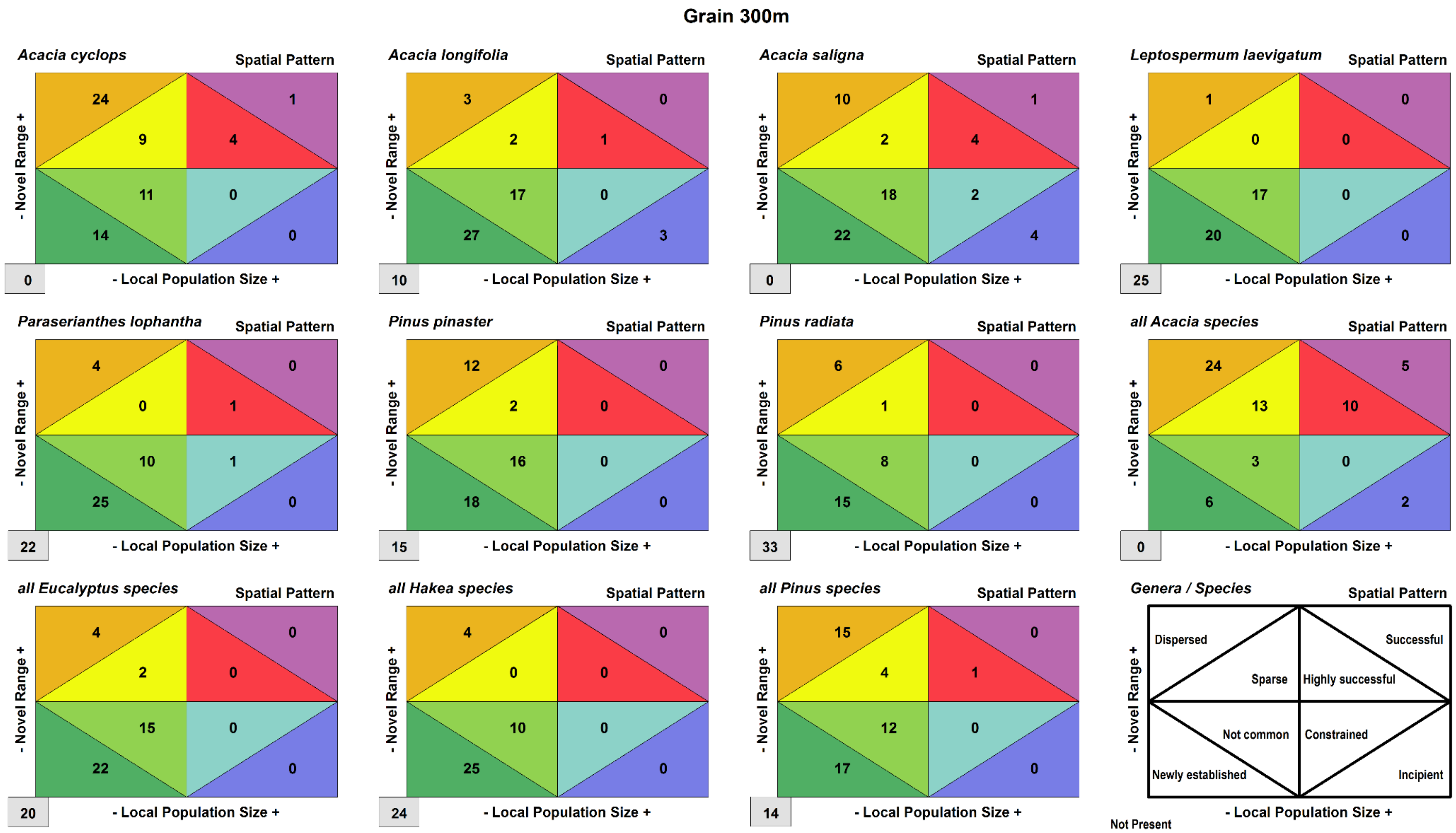
Chapter 5



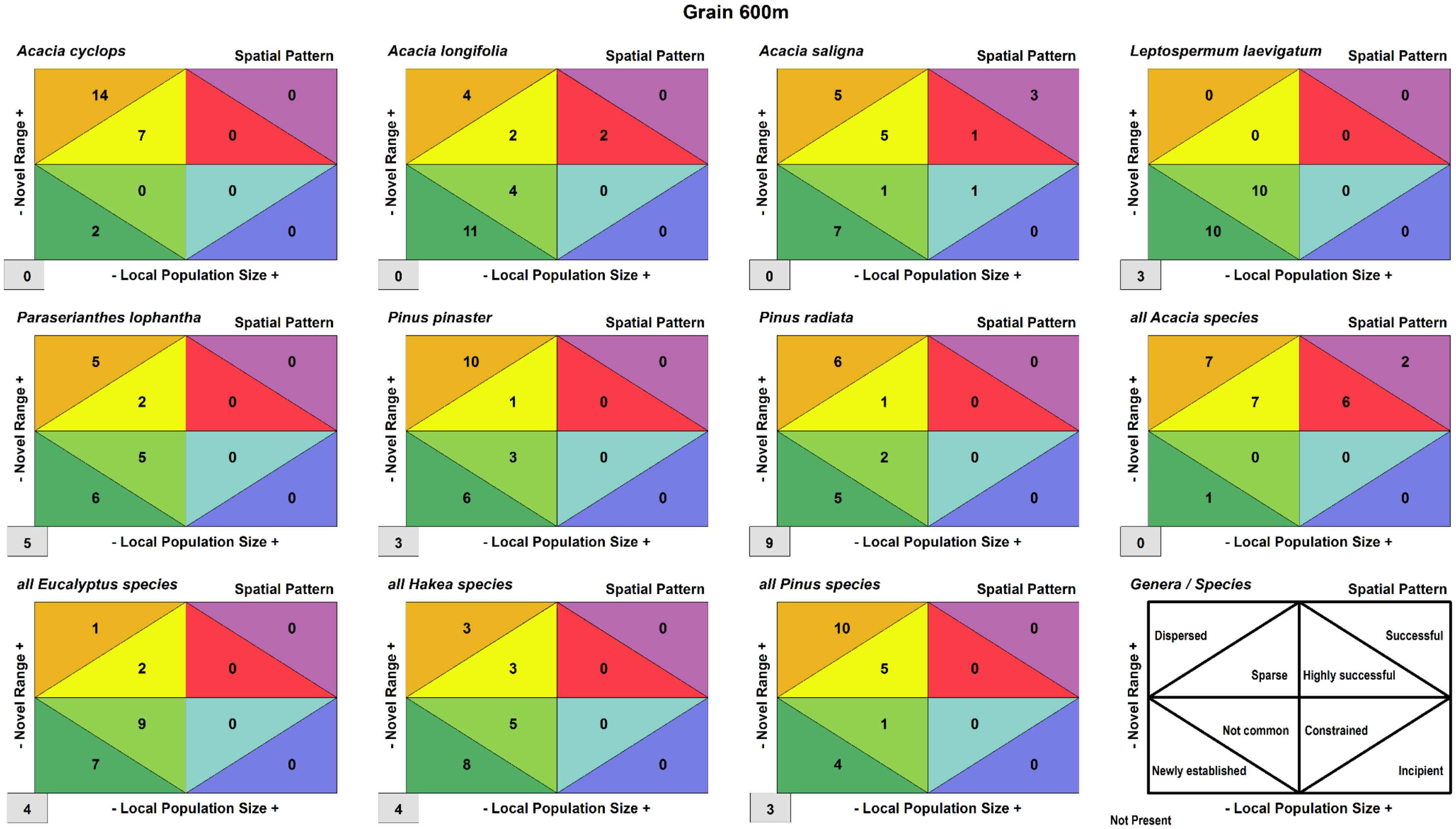
Supplementary Figure 5.1 Area of Occupancy (Log_2 km^2) of species and species groups. Area of Occupancy is used as an intermediate step to calculating D, the box counting fractal dimension.



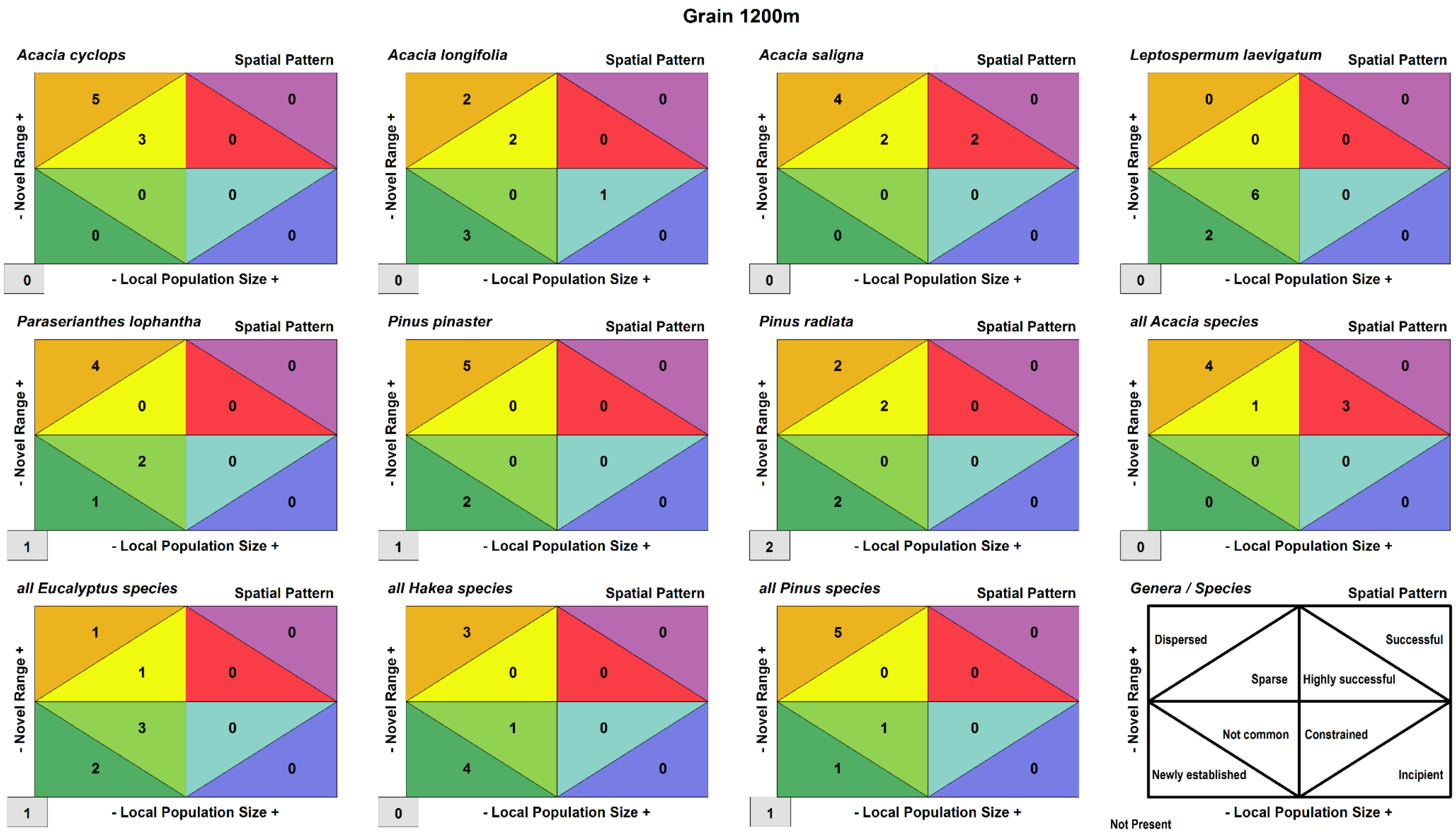
Supplementary Figure 5.2a The number of analysis units for species and species groups falling within each commonness type at a fine analysis grain of 150m



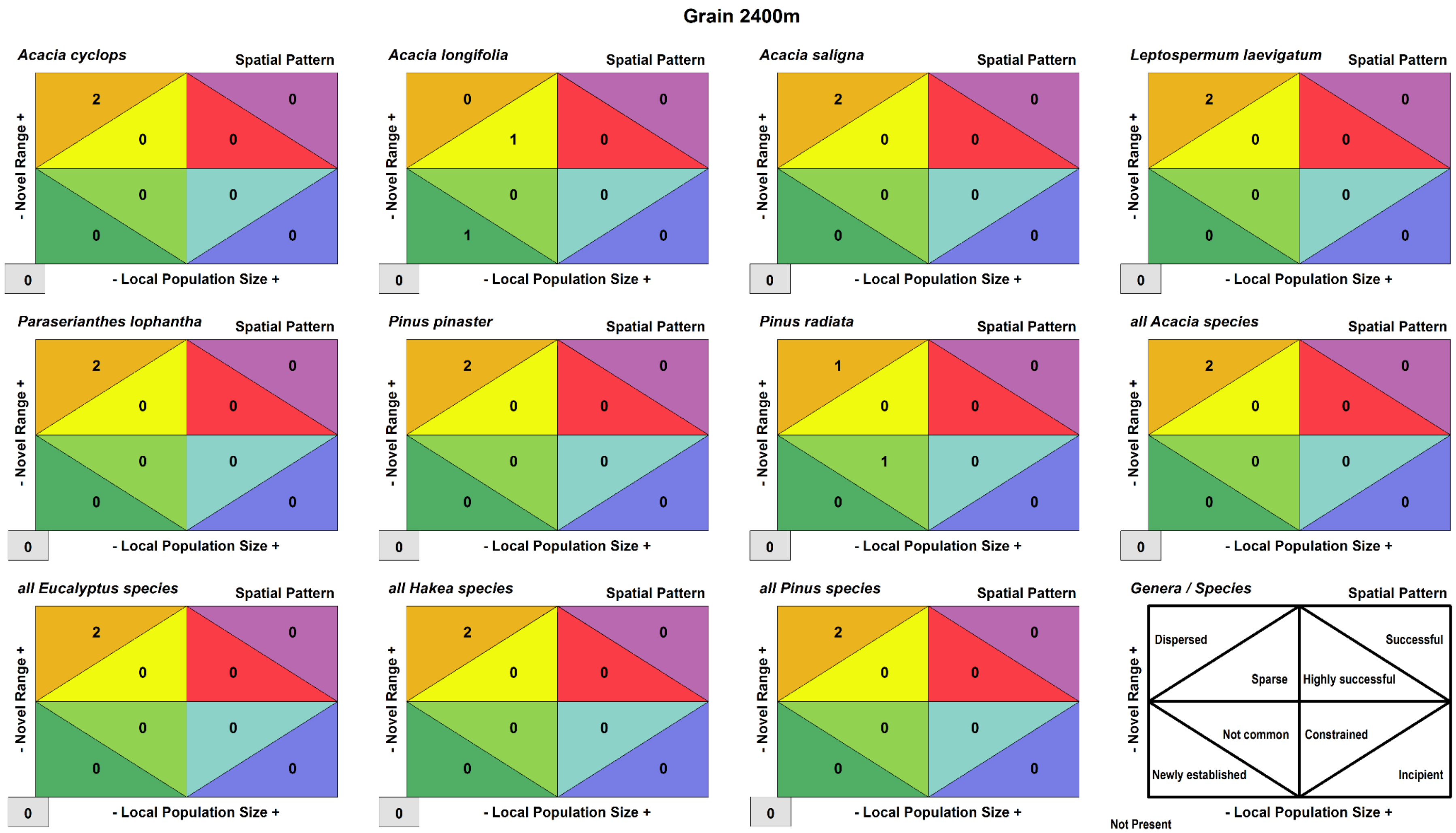
Supplementary Figure 5.2b The number of analysis units for species and species groups falling within each commonness type at a fine analysis grain of 300m



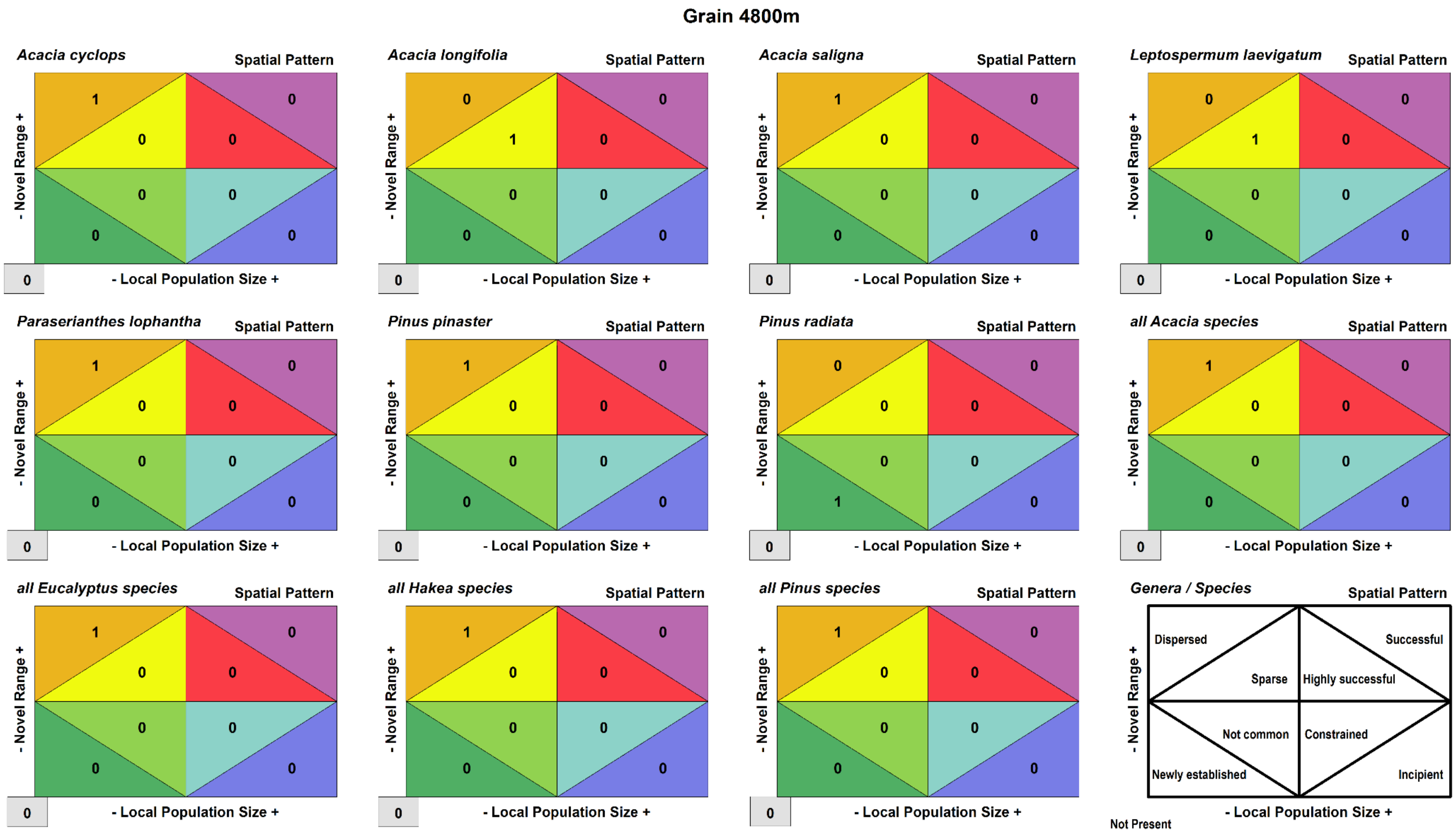
Supplementary Figure 5.2c The number of analysis units for species and species groups falling within each commonness type at a medium analysis grain of 600m



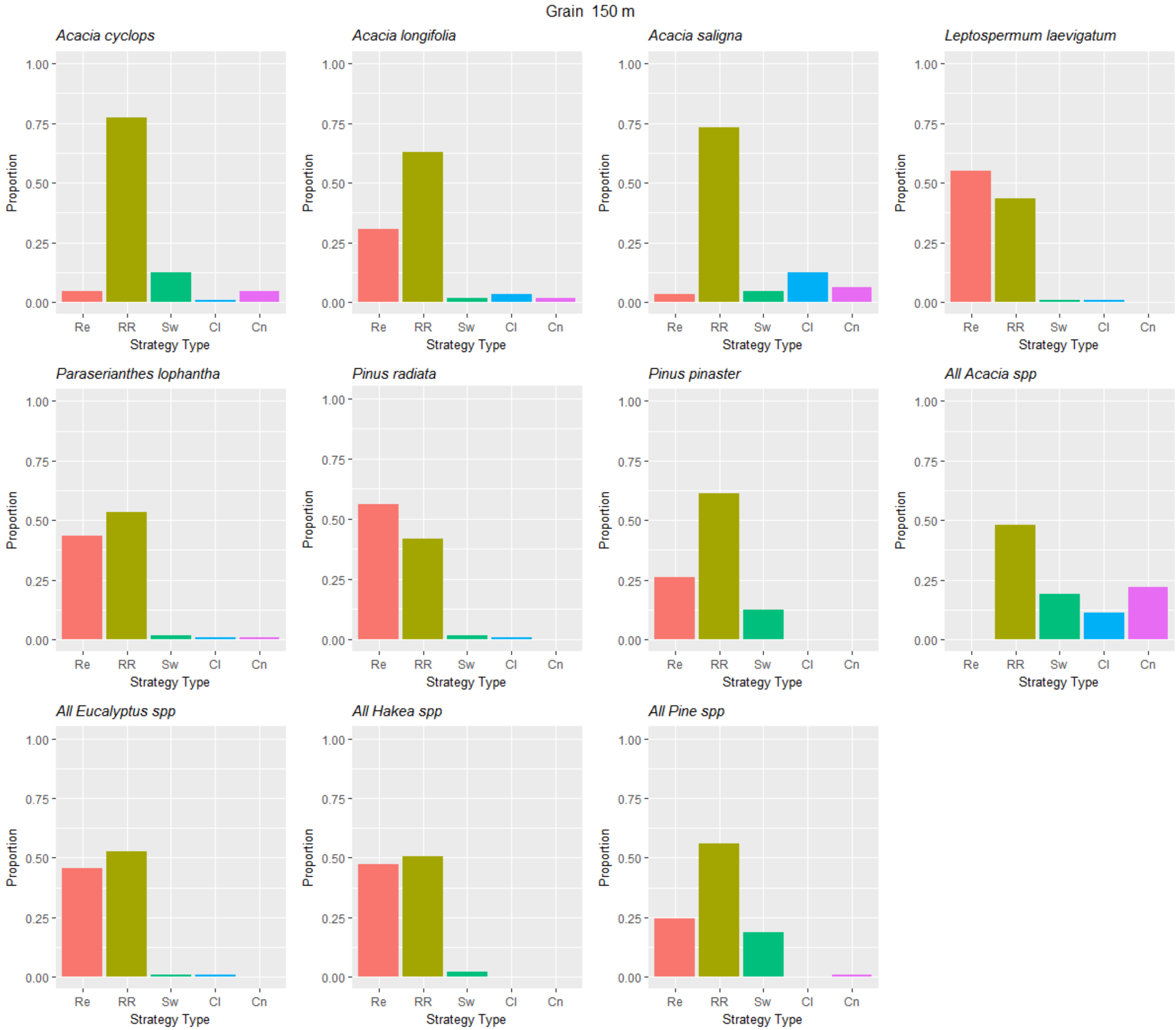
Supplementary Figure 5.2d The number of analysis units for species and species groups falling within each commonness type at a medium analysis grain of 1200m



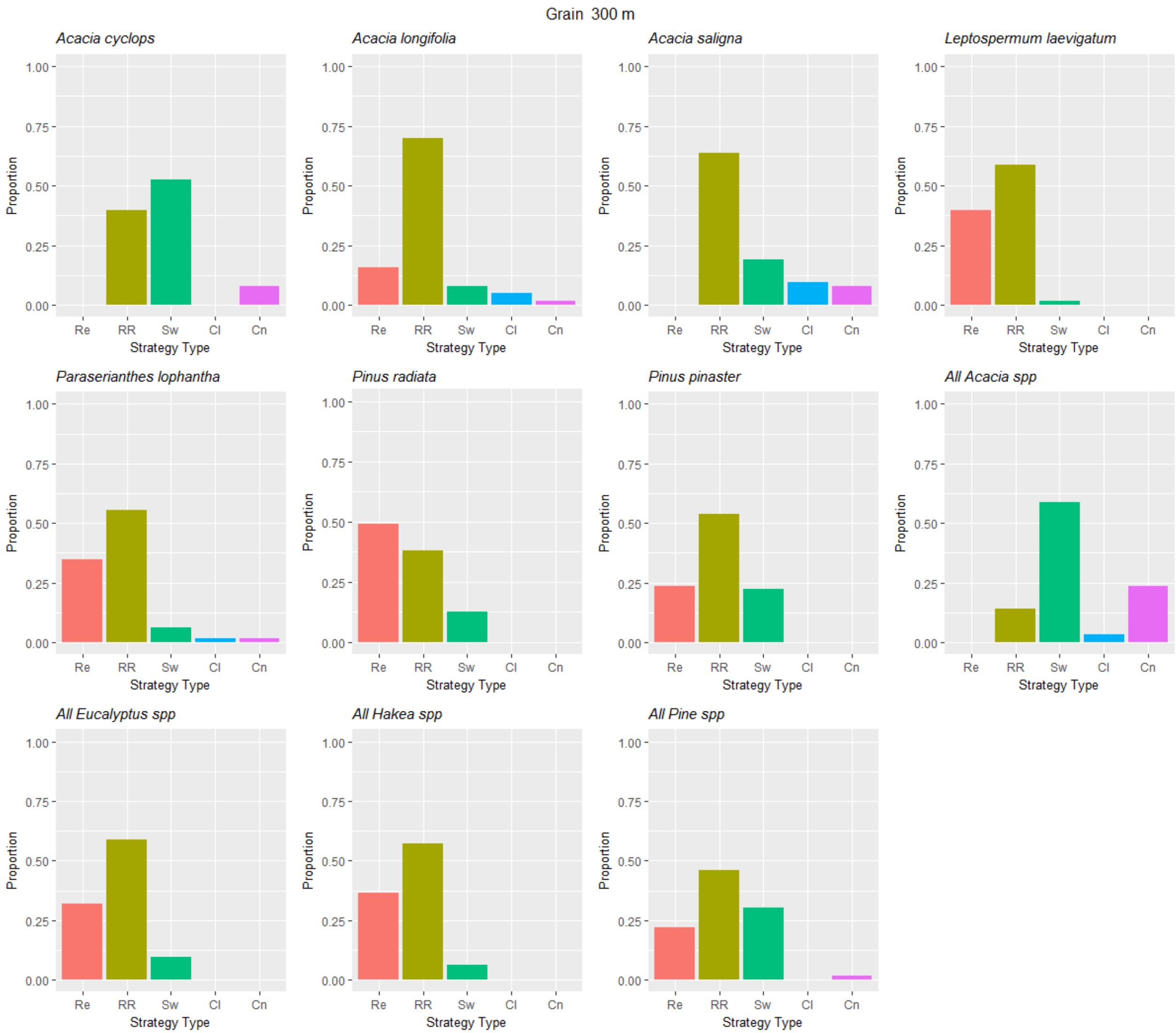
Supplementary Figure 5.2e The number of analysis units for species and species groups falling within each commonness type at a course analysis grain of 2400m



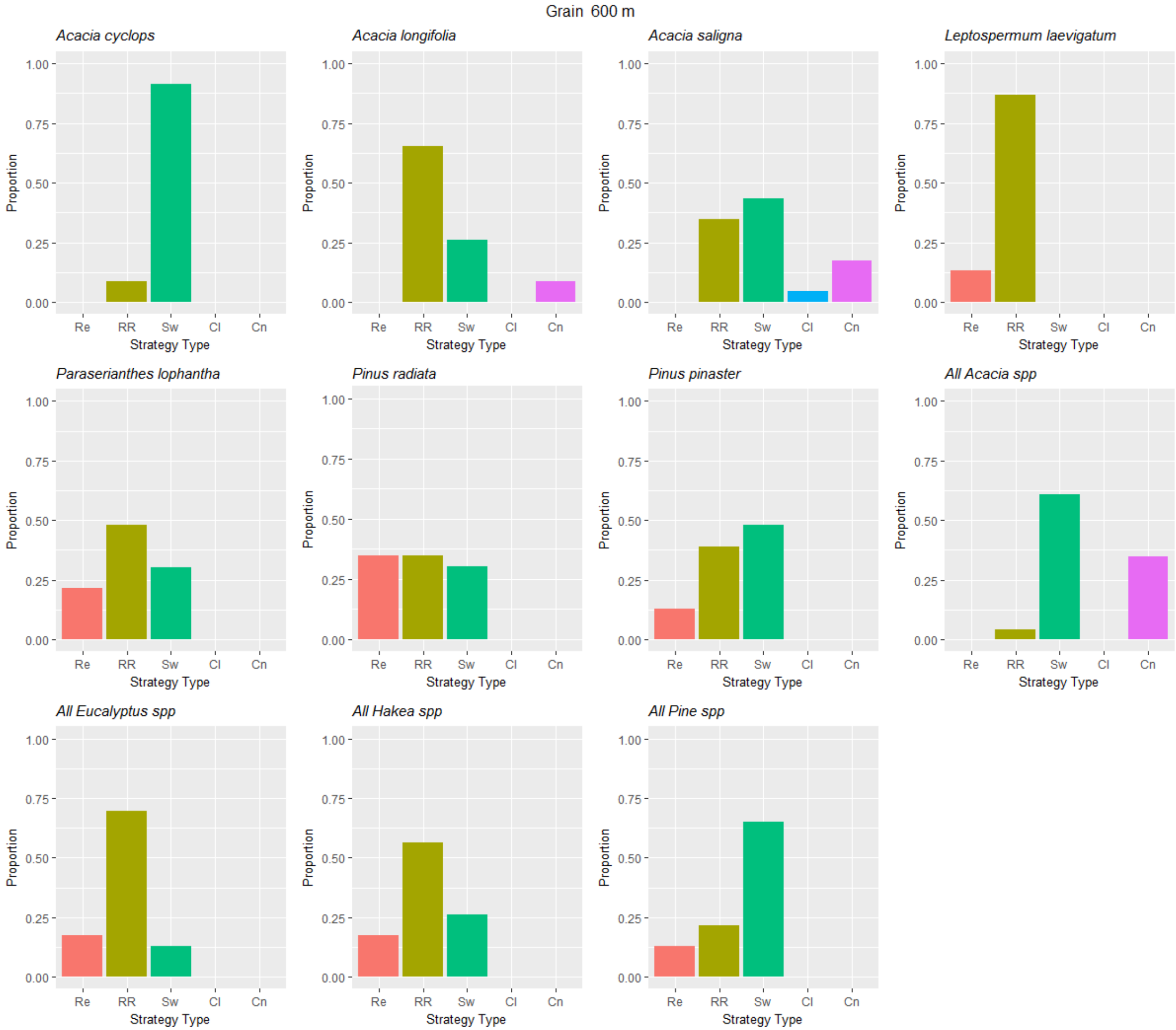
Supplementary Figure 5.2f The number of analysis units for species and species groups falling within each commonness type at a course analysis grain of 4800m



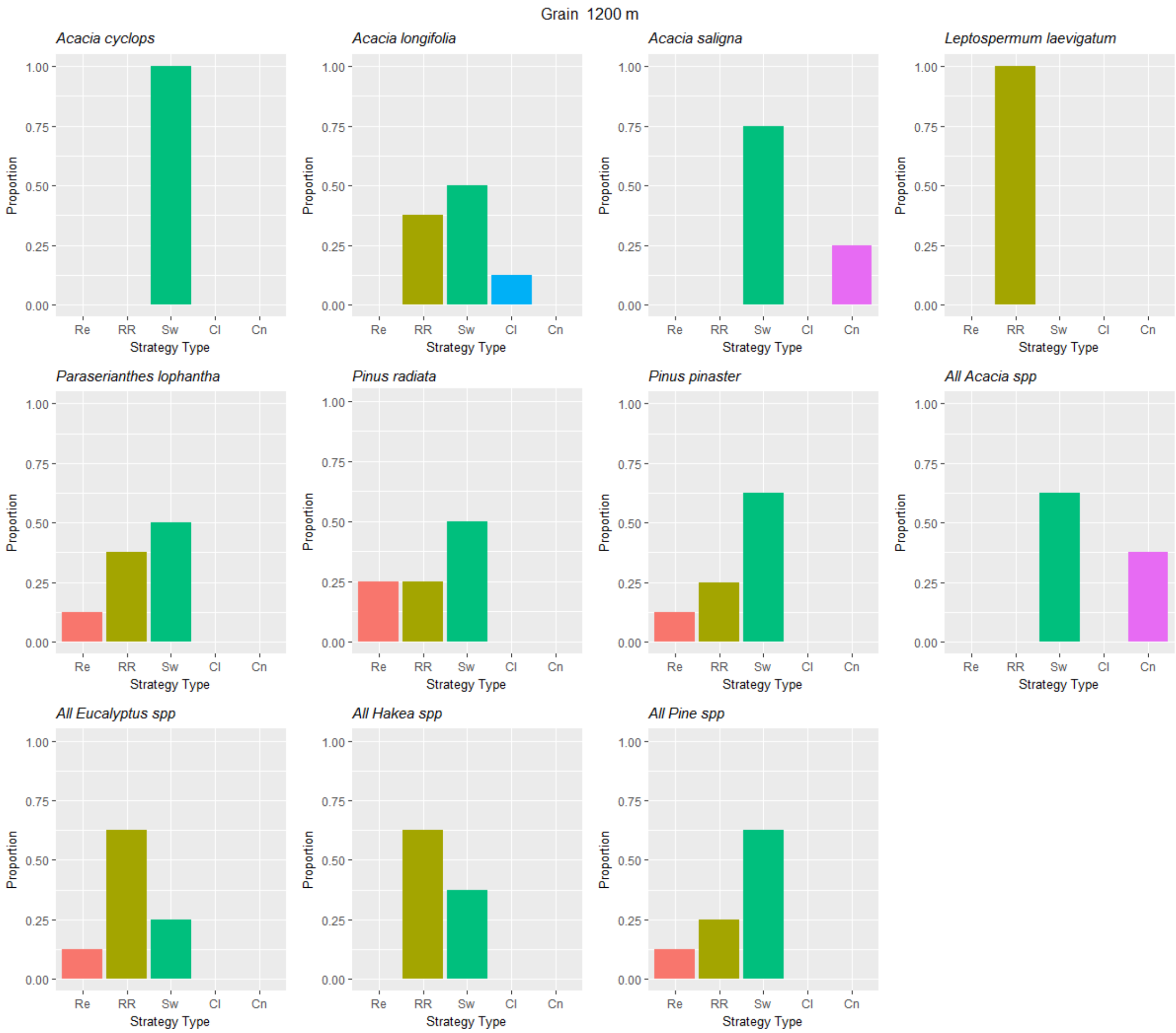
Supplementary Figure 5.3a The proportion of analysis units for species and species groups falling within each management strategy at a fine analysis grain of 150m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



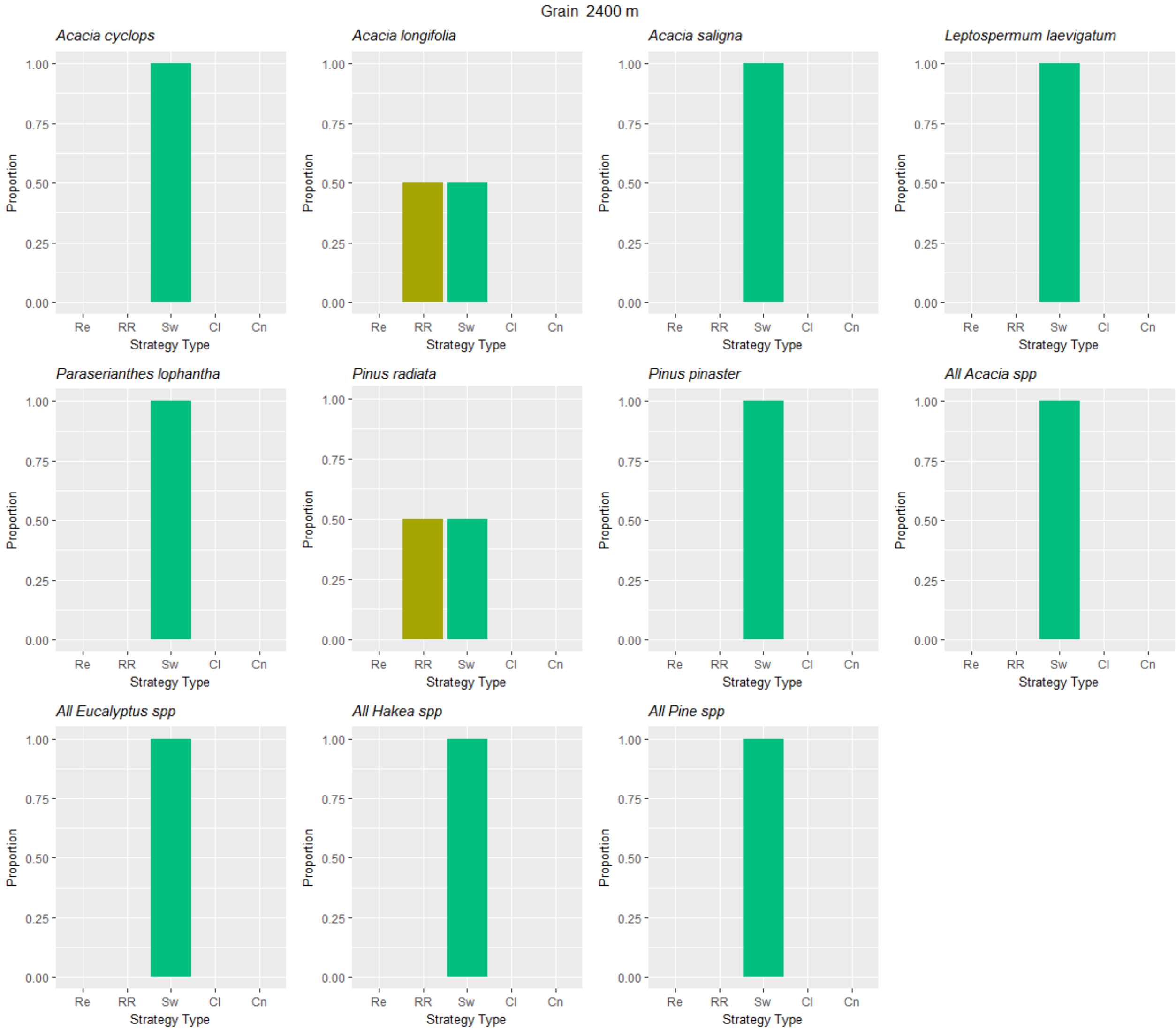
Supplementary Figure 5.3b The proportion of analysis units for species and species groups falling within each management strategy at a fine analysis grain of 300m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



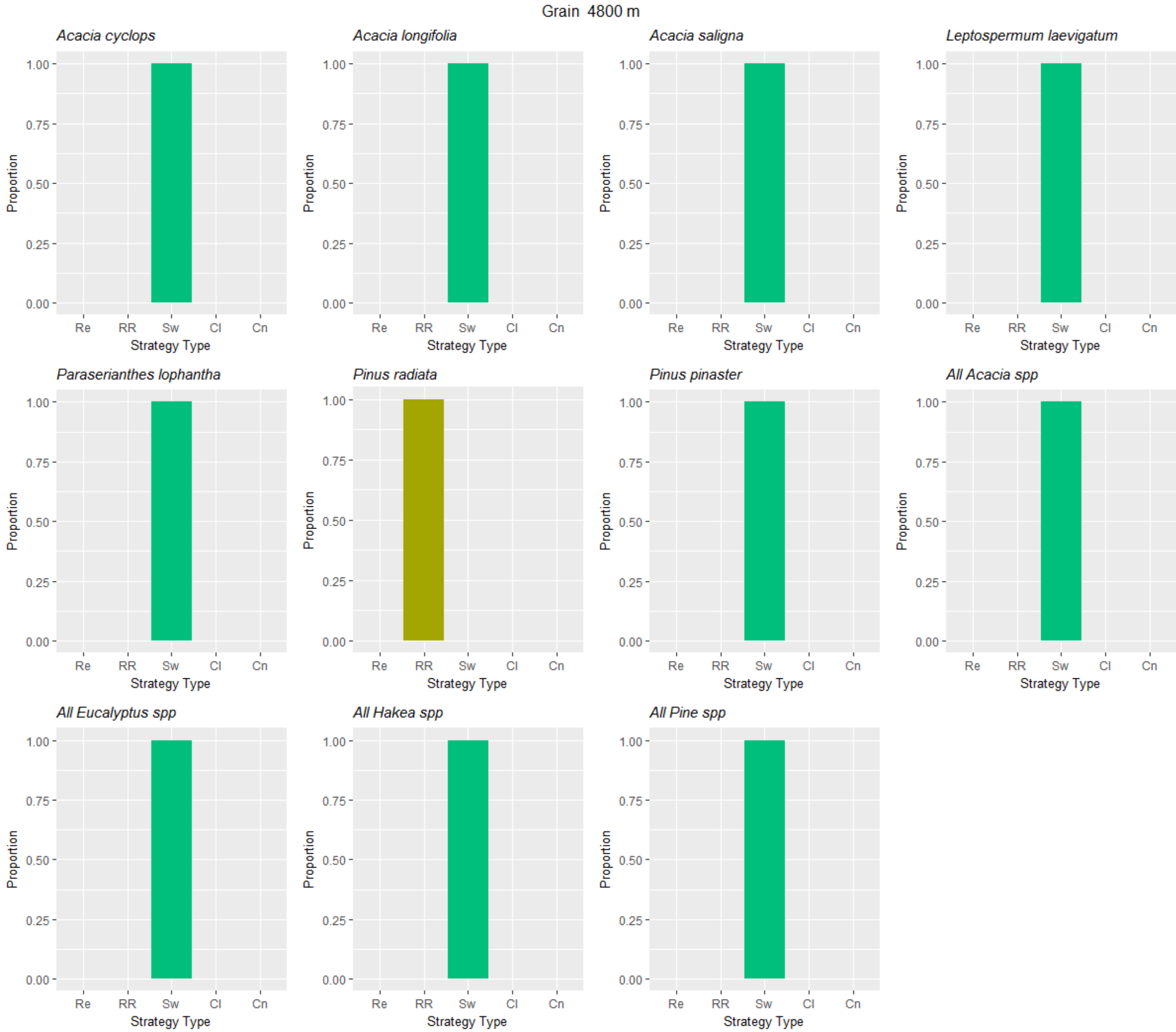
Supplementary Figure 5.3c The proportion of analysis units for species and species groups falling within each management strategy at a medium analysis grain of 600m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



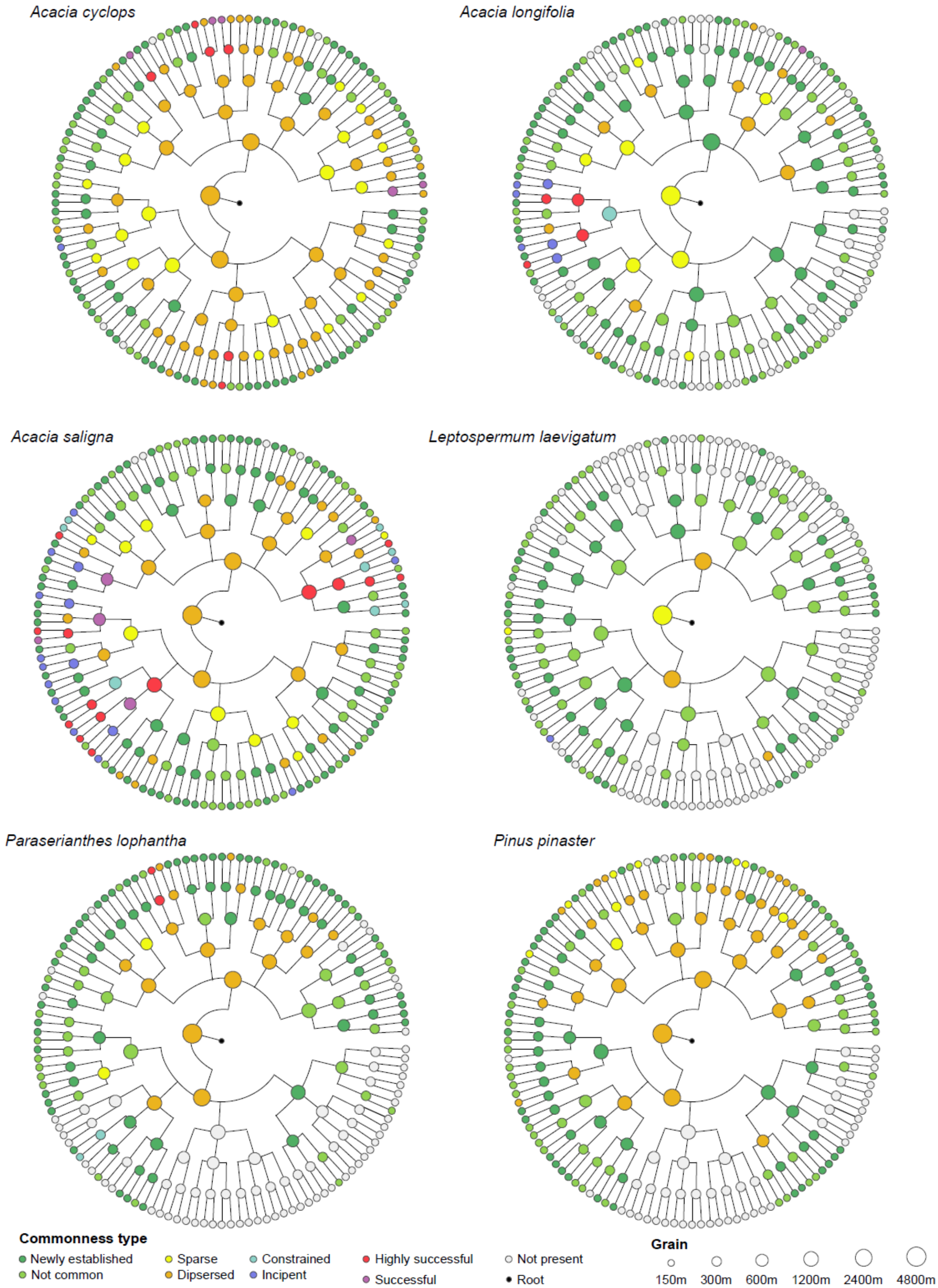
Supplementary Figure 5.3d The proportion of analysis units for species and species groups falling within each management strategy at a medium analysis grain of 1200m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



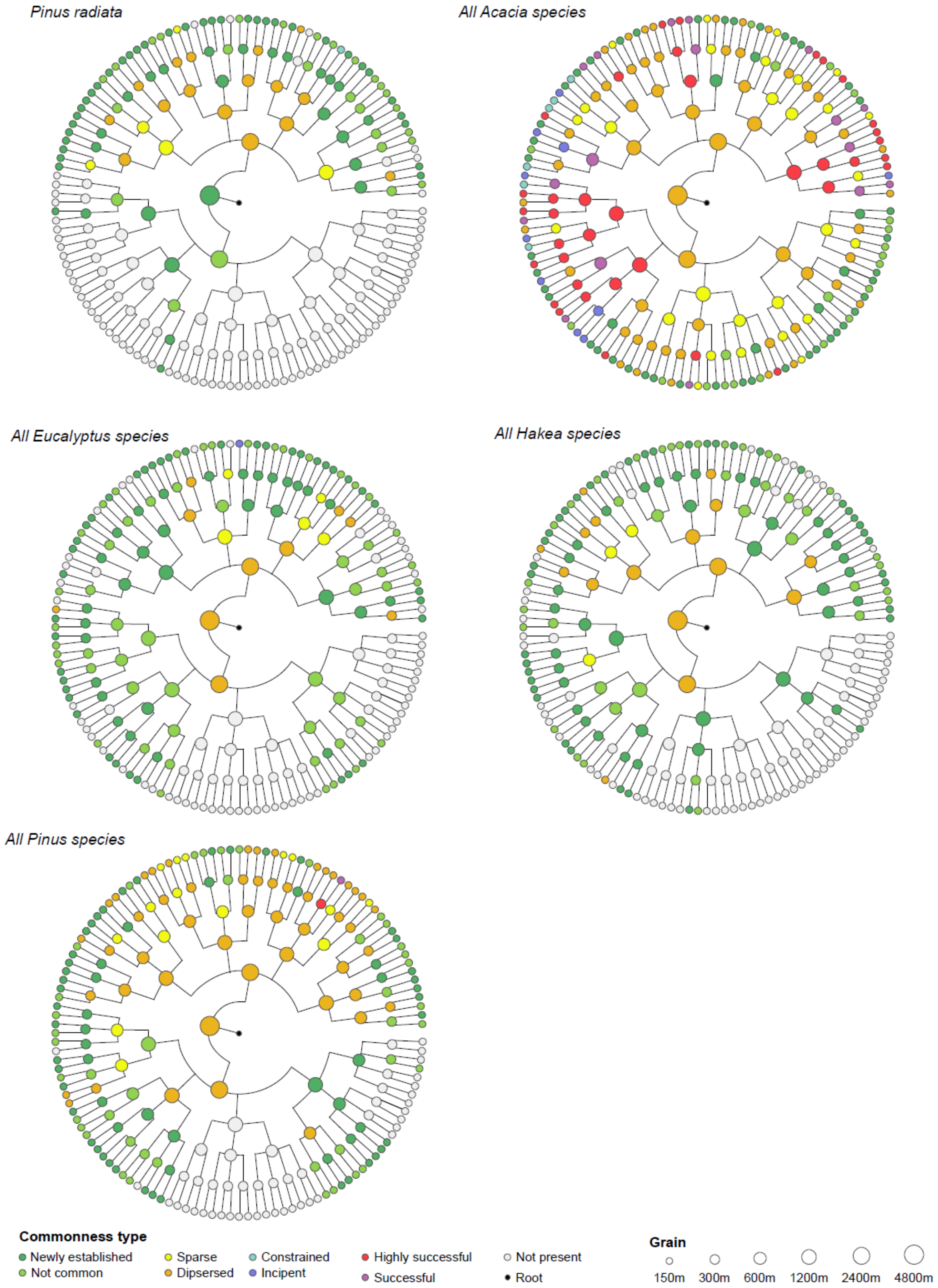
Supplementary Figure 5.3e The proportion of analysis units for species and species groups falling within each management strategy at a coarse analysis grain of 2400m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



Supplementary Figure 5.3f The proportion of analysis units for species and species groups falling within each management strategy at a coarse analysis grain of 4800m. (Re-reconnaissance; RR-rapid response; Sw-sweeping; Cl-control; Cn-containment).



Supplementary Figure 5.4a Hierarchical mapping of analysis units into a 'phylo-tree' at six spatial grains for species and species groups with the commonness type indicates as 1 of 9 colours.



Supplementary Figure 5.4b Hierarchical mapping of analysis units into a ‘phylo-tree’ at six spatial grains for species and species groups with the commonness type indicates as 1 of 9 colours.

Supplementary Table 5.1 Mean and total area of occupancy (AOO) for selected species and species groups at six grains analysed.

Grain	Species	Mean AOO (km^2)	SD	Total AOO (km^2)		Grain	Species	Mean AOO (km^2)	SD	Total AOO (km^2)
150m	*Acacia cyclops*	0.41	0.37	51.91		300m	*Acacia cyclops*	1.83	1.16	115.47
150m	*Acacia longifolia*	0.14	0.20	17.37		300m	*Acacia longifolia*	0.73	0.75	45.72
150m	*Acacia saligna*	0.34	0.32	42.71		300m	*Acacia saligna*	1.61	1.05	101.70
150m	*Acacia spp*	0.76	0.45	96.95		300m	*Acacia spp*	2.90	1.04	182.97
150m	*Eucalyptus spp*	0.08	0.18	10.78		300m	*Eucalyptus spp*	0.50	0.81	31.23
150m	*Hakea spp*	0.08	0.13	10.04		300m	*Hakea spp*	0.46	0.62	29.16
150m	*Leptospermum*	0.03	0.05	3.67		300m	*Leptospermum*	0.19	0.21	11.88
150m	*Paraserianthes*	0.13	0.21	16.09		300m	*Paraserianthes*	0.68	0.85	42.84
150m	*Pinus pinaster*	0.28	0.39	35.19		300m	*Pinus pinaster*	1.22	1.23	76.68
150m	*Pinus radiata*	0.11	0.19	14.45		300m	*Pinus radiata*	0.59	0.82	37.35
150m	*Pinus spp*	0.38	0.49	48.53		300m	*Pinus spp*	1.52	1.47	95.67
600m	*Acacia cyclops*	9.31	2.79	214.20		1200m	*Acacia cyclops*	43.20	7.05	345.60
600m	*Acacia longifolia*	4.52	3.48	104.04		1200m	*Acacia longifolia*	24.84	5.95	198.72
600m	*Acacia saligna*	8.83	3.24	203.04		1200m	*Acacia saligna*	40.86	5.60	326.88
600m	*Acacia spp*	12.05	2.07	277.20		1200m	*Acacia spp*	46.08	4.35	368.64
600m	*Eucalyptus spp*	3.24	3.52	74.52		1200m	*Eucalyptus spp*	20.52	14.42	164.16
600m	*Hakea spp*	3.15	3.25	72.36		1200m	*Hakea spp*	19.26	12.58	154.08
600m	*Leptospermum*	1.64	1.22	37.80		1200m	*Leptospermum*	13.68	8.07	109.44
600m	*Paraserianthes*	4.19	3.77	96.48		1200m	*Paraserianthes*	21.78	14.79	174.24
600m	*Pinus pinaster*	6.20	4.33	142.56		1200m	*Pinus pinaster*	29.34	15.39	234.72
600m	*Pinus radiata*	3.46	3.80	79.56		1200m	*Pinus radiata*	18.54	18.48	148.32
600m	*Pinus spp*	7.06	4.64	162.36		1200m	*Pinus spp*	31.86	16.10	254.88
2400m	*Acacia cyclops*	236.16	8.15	472.32		4800m	*Acacia cyclops*	691.20	Na	691.20
2400m	*Acacia longifolia*	172.80	0.00	345.60		4800m	*Acacia longifolia*	599.04	Na	599.04
2400m	*Acacia saligna*	227.52	20.36	455.04		4800m	*Acacia saligna*	668.16	Na	668.16
2400m	*Acacia spp*	241.92	16.29	483.84		4800m	*Acacia spp*	691.20	Na	691.20
2400m	*Eucalyptus spp*	144.00	65.17	288.00		4800m	*Eucalyptus spp*	529.92	Na	529.92
2400m	*Hakea spp*	155.52	65.17	311.04		4800m	*Hakea spp*	529.92	Na	529.92
2400m	*Leptospermum*	135.36	20.36	270.72		4800m	*Leptospermum*	506.88	Na	506.88
2400m	*Paraserianthes*	152.64	77.39	305.28		4800m	*Paraserianthes*	529.92	Na	529.92
2400m	*Pinus pinaster*	175.68	61.09	351.36		4800m	*Pinus pinaster*	599.04	Na	599.04
2400m	*Pinus radiata*	112.32	118.12	224.64		4800m	*Pinus radiata*	414.72	Na	414.72
2400m	*Pinus spp*	187.20	61.09	374.40		4800m	*Pinus spp*	599.04	Na	599.04

Ends.

Appendix 1

Visual Basic Code for the Alien Clearing Model used in Chapter 3 and Chapter 4.

```
Attribute VB_Name = "Run_Model_Main"
' Step 4
' Main code block that uses the input data formatted in steps 1, 2 & 3
' into the I_Pop_x Sheets as the data that will be used in the model.

' Start  Date : 05-10-2016
' End Development Date : 01-07-2017
' Coded by: Chad Cheney
' To be run from within MS.Excel as part of a workbook set.
'______________________________________________==_____________________________________________

' Common Variables
Dim mTimeStart As Date
Dim mTimeQStart As Date
Dim mTimeQEnd As Date
Dim iModelSimulate As Integer   'Stores the current model simulation (1-50)
Dim iModelYear As Integer       'Stores the current model Year (0-49)
Dim cQuarter As String          'Stores the current model Quarter (Q1, Q2, Q3, Q4)
Dim QAvailDays As Double        'Stores the current number of PD available for a Quarter
Dim mnBal_PdNeed As Single      'Stores the Person Days Needed of the current nBal
Dim nBal_Ha As Single           'Stores the current Hectares of the treated nBal
Dim mPlant_Ha As Single         'Stores the current plants per Ha of the treated nBal
Dim mPlot_Count As Single       'Stores the current plot (row in sheet) that needs to be carried over between
Quarters
Dim mFileLoc As String          'Stores the folder path for the text files
'
_____________________________________________________________________________
'Start Here......
'
_____________________________________________________________________________

Sub Model_Main_1()
  'Model_Setup (moved to "Pre_Run...")
  Application.ScreenUpdating = False
  Application.Calculation = xlCalculationManual
  mTimeStart = Now()
  ActiveWorkbook.Save

  mYears = Worksheets("Model Parameters").Range("Model_Years")
  mSimulate = Worksheets("Model Parameters").Range("Model_Simulate")
  iQuater0 True        ' Setup

  For iModelSimulate = 1 To mSimulate       'Model Iterations are by Quarter over 50 years i.e. 50 x 4
    ' reset the model for the next iteration
    For iModelYear = 0 To mYears - 1
      mTimeQStart = Now
      nBal_ScheduleSort "Systematic"     'Keep It Clean '"Maintain follow-ups"     '"Water production"
'"Random"   '"Consensus" '.... nBals prioritised at beginning of each year
      iQuater1
      iQuater2
      iQuater3
      iQuater4
```

```
      mTimeQEnd = Now
      iQuater5
    Next iModelYear
    'Write the dataout
      Write_SimulationData
      If iModelSimulate <> mSimulate Then Model_ResetNextSimulate 'does not delete the last dataset

  Next iModelSimulate
  Application.ScreenUpdating = True
  Application.Calculation = xlCalculationAutomatic
  MsgBox "Complete"

End Sub

Sub iQuater0(ByVal iCreateFiles As Boolean)
  Application.StatusBar = "Q0 Set-up"
  iQuater0_CleanSheets
  iQuater0_ReloadSheets
  If iCreateFiles = True Then iQuater0_ResetDataFiles

End Sub

Sub iQuater0_CleanSheets()

  'nBals_DynamicData
  d = 2
  Sheets("nBals_DynamicData").Select
  Do Until Sheets("nBals_DynamicData").Cells(d, 1) = ""
    Range(Cells(d, 2), Cells(d, 13)) = ""
    d = d + 1
  Loop
  'Reset: DataOut_Plants
    Sheets("DataOut_Plants").Select
    c = 3
    For r = 2 To 4
      Do Until Cells(r, c) = "" And c > 5
        Cells(r, c) = ""
        c = c + 1
      Loop
      c = 3
    Next r
    r = 6: c = 1
    Do Until Cells(r, c) = ""
      Do Until Cells(r, c) = ""
        Cells(r, c) = ""
        c = c + 1
      Loop
      c = 1
      r = r + 1
    Loop
  'Reset: DataOut_PD
    Sheets("DataOut_PD").Select
    c = 4
    For r = 2 To 5
      Do Until Cells(r, c) = ""
        Cells(r, c) = ""
        c = c + 1
```

```
        Loop
        c = 4
    Next r
    r = 7: c = 1
    Do Until Cells(r, c) = ""
        Do Until Cells(r, c) = "" And c > 4
            Cells(r, c) = ""
            c = c + 1
        Loop
        c = 1
        r = r + 1
    Loop

'Reset: DataOut_Seeds
    Sheets("DataOut_Seeds").Select
    c = 3
    For r = 2 To 4
        Do Until Cells(r, c) = "" And c > 5
            Cells(r, c) = ""
            c = c + 1
        Loop
        c = 3
    Next r
    r = 6: c = 1
    Do Until Cells(r, c) = ""
        Do Until Cells(r, c) = ""
            Cells(r, c) = ""
            c = c + 1
        Loop
        c = 1
        r = r + 1
    Loop

'Reset: nBals_DynamicData
    Sheets("nBals_DynamicData").Select
    r = 2: c = 1
    Do Until Cells(r, c) = ""
        Range(Cells(r, 2), Cells(r, 12)) = ""
        r = r + 1
    Loop

' Reset: DataOut_FireHA
    Sheets("DataOut_FireHA").Select
    Range(Cells(2, 2), Cells(200, 200)) = ""

End Sub

Sub iQuater0_ReloadSheets()

 Sheets("DataOut_Plants").Cells(1, 2) = Format(mTimeStart, "DD-MM-YYYY HH:MM AM/PM")
 Sheets("DataOut_Seeds").Cells(1, 2) = Format(mTimeStart, "DD-MM-YYYY HH:MM AM/PM")

 ' M_nBal_Schedule
 Sheets("I_nBal_Schedule").Select
 Cells.Select
 Selection.Copy
 Sheets("M_nBal_Schedule").Select: Range("A1").Select: ActiveSheet.Paste: Cells(1, 1).Select
```

```
'M_Pop_All
Sheets("M_Pop_All").Select
Cells.Delete
r = 1
Do Until Sheets("M_Pop_All").Cells(r, 1) = "" And Sheets("I_Pop_All").Cells(r, 1) = ""
   'Application.StatusBar = "Q0 Set-up " & r
   For c = 1 To 75
      Sheets("M_Pop_All").Cells(r, c) = Sheets("I_Pop_All").Cells(r, c)
      Sheets("M_Pop_All").Cells(r, c).Interior.Pattern = xlNone
   Next c
   r = r + 1
Loop   'r

'Vary the seed allocation due to the natural variability of seed distribution by SD20
nBal = 2
Do Until Cells(nBal, 1) = ""
   'Application.StatusBar = "Q0 Set-up: Seed Loading " & nBal
   For SeedCo = 64 To 72
      mRndSeed = Application.WorksheetFunction.RandBetween(800, 1200) / 1000
      Cells(nBal, SeedCo) = Cells(nBal, SeedCo) * mRndSeed
   Next SeedCo
   Cells(nBal, 76) = Application.WorksheetFunction.Sum(Range(Cells(nBal, 64), Cells(nBal, 72)))

   'Set a level of Available Invaded Area (AIA) based on  Canopy Cover
   PlantsHaA = Application.WorksheetFunction.Sum(Range(Cells(nBal, 12), Cells(nBal, 61)))
   a = 3.3222:    b = 155.02:   cp = PlantsHaA * -1
   d = b ^ 2 - 4 * a * cp
   mCoverA = ((-b + Sqr(d)) / (2 * a)) / 100

   PlantsHaY = Application.WorksheetFunction.Sum(Range(Cells(nBal, c + 1), Cells(nBal, 11)))
   a = 12.651:    b = 672.36:   cp = PlantsHaY * -1
   d = b ^ 2 - 4 * a * cp
   mCoverY = ((-b + Sqr(d)) / (2 * a)) / 100
   mCover = mCoverA + mCoverY

   If mCover = 0 Then mCover = 0.0001
   If mCover > 1 Then mCover = 1

   Cells(nBal, 74) = mCover
   If Cells(nBal, 2) = "Acacia non-resprouter" Then
      mSeedSatR = Application.WorksheetFunction.RandBetween(950, 1050) / 1000
      mSeedSat = mCover * (2000 * mSeedSatR) * 10000       '2000 seed per m2 *10,000 meters
      Cells(nBal, 75) = mSeedSat
   End If
   If Cells(nBal, 2) = "Acacia resprouter" Then
      mSeedSatR = Application.WorksheetFunction.RandBetween(950, 1050) / 1000
      mSeedSat = mCover * (12000 * mSeedSatR) * 10000      '12000 seed per m2 *10,000 meters
      Cells(nBal, 75) = mSeedSat
   End If
   nBal = nBal + 1
Loop

' Write some Start Output Numbers
'1. Starting nBals and the plants per ha in the nBals
nBal = 2: pTot = 0: pHa = 0: sTot = 0
Do Until Sheets("nBals_StaticData").Cells(nBal, 1) = ""
   nBal_ID = Sheets("nBals_StaticData").Cells(nBal, 1)
```

```
    nBal_Ha = Sheets("nBals_StaticData").Cells(nBal, 3)
    nBal_Age = Sheets("nBals_StaticData").Cells(nBal, 9)
    nWasTreat = Sheets("nBals_StaticData").Cells(nBal, 8)
    nClearYear = Sheets("nBals_StaticData").Cells(nBal, 11)

    'Plants
    Sheets("DataOut_Plants").Cells(nBal + 4, 1) = nBal_ID
    Sheets("DataOut_Plants").Cells(nBal + 4, 2) = nBal_Ha
    mPlantsHA = GetnBal_PlantsHa(nBal_ID)
    Sheets("DataOut_Plants").Cells(nBal + 4, 3) = mPlantsHA

    pHa = pHa + nBal_Ha
    pTot = pTot + (Sheets("DataOut_Plants").Cells(nBal + 4, 3) * nBal_Ha)

    'Person Days
    Sheets("DataOut_PD").Cells(nBal + 5, 1) = nBal_ID
    Sheets("DataOut_PD").Cells(nBal + 5, 2) = nBal_Ha

    'Seeds
    Sheets("DataOut_Seeds").Cells(nBal + 4, 1) = nBal_ID
    Sheets("DataOut_Seeds").Cells(nBal + 4, 2) = nBal_Ha
    Sheets("DataOut_Seeds").Cells(nBal + 4, 3) = GetnBal_SeedsHa(nBal_ID)
    sTot = sTot + (Sheets("DataOut_Seeds").Cells(nBal + 4, 3) * nBal_Ha)

    'Veld Age
    Sheets("nBals_DynamicData").Cells(nBal, 1) = nBal_ID
    Sheets("nBals_DynamicData").Cells(nBal, 8) = nBal_Age
    If nBal_Age = 0 Then
       'Calc Fire Severity for previous fire year.
        iFire_Severity = Fire_Severity(Application.WorksheetFunction.RandBetween(2, 2297))
        Sheets("nBals_DynamicData").Cells(nBal, 10) = iFire_Severity
        Fire_RemoveVegandSeed nBal_ID, iFire_Severity, 0
        'Set Effective Invaded Area to -ve so to allow for reduction in size
        Sheets("nBals_DynamicData").Cells(nBal, 11) = -1
    End If

    'Pre-treatment for post clearing seed germination Q3 routine
    If nWasTreat = 1 Then
       Sheets("nBals_DynamicData").Cells(nBal, 2) = "Y"
       OrigPlantEst = (1 + (Application.WorksheetFunction.RandBetween(1, 100) / 100)) * mPlantsHA
       Sheets("nBals_DynamicData").Cells(nBal, 3) = OrigPlantEst
       Sheets("nBals_DynamicData").Cells(nBal, 4) = OrigPlantEst - mPlantsHA
       Sheets("nBals_DynamicData").Cells(nBal, 5) = 3
    End If

    'Time Since nBal was Cleared: for Prioritisation
       Sheets("nBals_DynamicData").Cells(nBal, 12) = nClearYear

    nBal = nBal + 1
Loop

'Add the Totals
    Sheets("DataOut_Plants").Cells(2, 3) = pTot          'Total Plants
    Sheets("DataOut_Plants").Cells(3, 3) = pTot / pHa      'Plants / Ha
    Sheets("DataOut_Plants").Cells(4, 3) = 1
    Sheets("DataOut_Seeds").Cells(2, 3) = sTot           'Total Seeds
    Sheets("DataOut_Seeds").Cells(3, 3) = sTot / pHa       'Plants / Ha
```

```
    Sheets("DataOut_Seeds").Cells(4, 3) = 1

  'Add timestamp
    mTime = Now() - CDate(Sheets("DataOut_Plants").Cells(1, 2))
    mTime = Right(CStr(Format(mTime, "hh mm ss")), 5)
    Sheets("DataOut_Plants").Cells(1, 3) = mTime
    Sheets("DataOut_Seeds").Cells(1, 3) = mTime

 '2. FireData Sheet
  Sheets("DataOut_FireHA").Cells(5, 1) = "Year "
  For yr = 0 To iModelYear
    Sheets("DataOut_FireHA").Cells(5, yr + 2) = "Year " & yr + 1
  Next yr

End Sub

 Sub iQuater0_ResetDataFiles()

  mFileLoc = "C:\Users\Chad.Cheney\Documents\Model\Chapter III\"

  ' Delete the old output datafiles (these are the ones used for further Stats Analysis)
  Dim fso As New FileSystemObject
  Dim mTextStream As TextStream
  Dim mText As String

  Dim mFileName(1 To 5) As String
  mFileName(1) = mFileLoc & "Plants.txt"
  mFileName(2) = mFileLoc & "Seeds.txt"
  mFileName(3) = mFileLoc & "PersonDays.txt"
  mFileName(4) = mFileLoc & "HaCleared.txt"
  mFileName(5) = mFileLoc & "HaBurnt.txt"
  mFileNameStart = mFileLoc & "ModelStart.txt"
  Set nF = fso.CreateTextFile(mFileNameStart, True)
    nF.Close

  For f = 1 To 5
    Set nF = fso.CreateTextFile(mFileName(f), True)
    nF.Close
    'Add the Headings
    Set mTextStream = fso.OpenTextFile(mFileName(f), ForAppending, True)
    mText = "Sim" & vbTab
    Y = Worksheets("Model Parameters").Range("Model_Years")
    For t = 0 To Y
      mText = mText & "Y" & t & vbTab
    Next t
    mTextStream.WriteLine (mText)          'Write the Data
    mTextStream.Close
  Next f

End Sub

Sub iQuater1()
  'In Q1 (April, May, June)
  cQuarter = "Q1"

  'MANAGEMENT
  'Clear nBals
```

```
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Clear nBals Q1"
    nBals_Clear "Q1"

    'ECOLOGICAL
    'Grow all Alien that are in the seedlings and young
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Grow Alien Q1"
    nBal_GrowAliens_1 "Q1 Grow Alien"

    'MODEL
    'Update Clearing Tags
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Update Clearing Tags Q1"
    nBal_UpdateTags

End Sub

Sub iQuater2()
    'In Q2 (July, Aug, Sept)
    cQuarter = "Q2"

    'ECOLOGICAL
    'Grow all Alien that are in the seedlings and young
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Grow Alien Q2"
    nBal_GrowAliens_1 "Q2 Grow Alien"

    'Germinate Seedlings from Seedbanks
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Germinate Seedlngs Q2"
    nBal_GerminateSeedlings

    'MANAGEMENT
    'Clear nBals
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Clear nBals Q2"
    nBals_Clear "Q2"

    'MODEL
    'Update Clearing Tags
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Update Clearing Tags Q2"
    nBal_UpdateTags

End Sub

Sub iQuater3()
    'In Q3 (Oct, Nov, Dec)
    cQuarter = "Q3"

    'MANAGEMENT
    'Clear nBals
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & "Clear nBals Q3"
    nBals_Clear "Q3"

    'ECOLOGICAL
    'Grow all Alien that are in the seedlings and young and all other cohorts too.
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Grow Alien 2 Q3"
    nBal_GrowAliens_2 "Q3 Grow Alien 2"
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Grow Alien 1 Q3"
    nBal_GrowAliens_1 "Q3 Grow Alien 1"

    'Seedbank movement (vertically) first and then add new seeds
```

```
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Update Seed Cohort Q3"
    Seed_AgeCohort "Q3 Update Seed Cohort"

    'Seed Aliens and Disperse to Seedbanks (Model Notation of this is 'S3')
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Seeding and Dispursal Q3"
    nBal_Plants_Seed

    'MODEL
    'Update Clearing Tags
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Update Clearing Tags Q3"
    nBal_UpdateTags

End Sub

Sub iQuater4()
    'In Q4 (Jan, Feb, March)
    cQuarter = "Q4"

    'Fire Season
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " nBals Burning Q4"
    nBal_Burn

    'MANAGEMENT
    'Clear nBals
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & "Clear nBals Q4"
    nBals_Clear "Q4"

    'ECOLOGICAL
    'Grow all Alien that are in the seedlings and young
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Grow Alien Q4"
    nBal_GrowAliens_1 "Q4 Grow Alien"

    'Increase Veld Age at the end of the Model Year
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Updage Veld Age Q4"
    nBal_VeldAge

    'MODEL
    'Update Clearing Tags
    Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Update Clearing Tags Q4"
    nBal_UpdateTags

End Sub

Sub nBals_Clear(ByVal iQuarter As String)
' The Main Management routine to clear nBals for a Quater

    'Set some Variables
    Dim nBalToClear As Boolean
    'Assign the number of clearing days avaiable. QAvailDays holds the days that are carried over between
Quarters
    If iQuarter = "Q1" Then QAvailDays = Sheets("Model Parameters").Range("Avail_Days_Q1"): mplot = 2
    If iQuarter = "Q2" Then QAvailDays = QAvailDays + Sheets("Model Parameters").Range("Avail_Days_Q2"):
mplot = mPlot_Count
    If iQuarter = "Q3" Then QAvailDays = QAvailDays + Sheets("Model Parameters").Range("Avail_Days_Q3"):
mplot = mPlot_Count
    If iQuarter = "Q4" Then QAvailDays = QAvailDays + Sheets("Model Parameters").Range("Avail_Days_Q4"):
mplot = mPlot_Count
```

```
Dim PDavailable As Boolean
PDavailable = False

If QAvailDays > 0 Then PDavailable = True
nBalToClear = True

iBal = Sheets("M_nBal_Schedule").Cells(mplot, 1)
If iBal = "" Then
  nBalToClear = False
End If

'Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " " & cQuarter & " " & QAvailDays

Do Until PDavailable = False Or nBalToClear = False
  iBal = Sheets("M_nBal_Schedule").Cells(mplot, 1)
  'Catch if all nBals have been done for the Year......
  If iBal = "" Then
  nBalToClear = False
    Exit Do
  End If
  If PDCheck(iBal, QAvailDays) = True Then   ' then there are days avaiable to clear
    'Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " " & cQuarter & " " &
QAvailDays
    nBal_ClearAliens iBal
    '**** Update nBal Clear status re LastCleard, number of TimesCleared & Current Plants per ha
    mRow = GetnBal_Row(iBal, "Dynamic")
    Sheets("nBals_DynamicData").Cells(mRow, 3) = mPlant_Ha
    Sheets("nBals_DynamicData").Cells(mRow, 5) = 4     ' a Tag for: The number of quaters (i.e. within a
year) that seedlings can germinate
    Sheets("nBals_DynamicData").Cells(mRow, 6) = Sheets("nBals_DynamicData").Cells(mRow, 6) + 1 '
Number of Treatments for a nBal
    Sheets("nBals_DynamicData").Cells(mRow, 7) = Sheets("nBals_DynamicData").Cells(mRow, 7) +
mnBal_PdNeed ' The number of pd Used for the year
    Sheets("nBals_DynamicData").Cells(mRow, 12) = -1

    QAvailDays = QAvailDays - mnBal_PdNeed    ' Subtract the pd used to clear the nBal above:
mnBal_PdNeed is a Common Variable
    mplot = mplot + 1
  Else
    PDavailable = False
    'Need to move to the next Q for Q1, Q2, Q3. While Q4 move to the next nBal to see if that one can be
done
    If iQuarter <> "Q4" Then
      Exit Do
    Else
      If QAvailDays >= 50 Then        'the smallest amount needed to make one WIMS Contract
        PDavailable = True
        mRow = GetnBal_Row(iBal, "Dynamic")
        Sheets("nBals_DynamicData").Cells(mRow, 2) = "SNC"        ' Tagged as "Sceduled Not Cleared"
        mplot = mplot + 1           ' move to the next Plot
      End If
    End If
  End If
Loop

'Store the last nBal that was attempted to be treated
```

```
  mPlot_Count = 0
  mPlot_Count = mplot

End Sub

Sub nBal_ClearAliens(ByVal inBalName As String)
  Dim TreatedSucess() As Double           'To hold the return values
  Dim FoundnBal As Boolean               ' Need to catch for nBals with no aliens and no Seeds (i.e.
uninvaded)

  Sheets("M_Pop_All").Select
  ' Clearing has two parts
  ' plants within the nBal need to be found. This is probability density and size
  ' if a plant is found, there is a probability that it will be treated correctly.

  ' Find and loop through the nBals to clear
    nB = 2
    FoundnBal = False
    Do Until Cells(nB, 1) = ""
      If Cells(nB, 1) = inBalName Then
        Cells(nB, 1).Interior.ColorIndex = 4
        FoundnBal = True
        nBalRow = nB
        YoungCoppice = 0: AdultCoppice = 0: mTreatSucc = 0
        PlantForm = Cells(nBalRow, 2)  ' e.g. Resprouter which determines treatment sucess
        For AC = 5 To 61 ' the number of possible age cohorts (columns)
          If Cells(nBalRow, AC) <> "" And Cells(nBalRow, AC) > 0 Then
            'Calculate the total number of plants in that cohort (= plants per ha * nBal Size)
            'for each plant
            PlantHaCohort = Cells(nBalRow, AC).Value ' the number of plants to be treated / ha
            If AC < 9 Then PlantCohort = 1
            If AC >= 9 And AC < 12 Then PlantCohort = 2
            If AC >= 12 Then PlantCohort = AC - 9         'age in the population matrix column

            If PlantHaCohort < 50 Then
            CalcType = 1
              PlantTot = Round(PlantHaCohort * nBal_Ha, 0)   ' number of plants to treat
            Else
              CalcType = 2
              PlantTot = Application.WorksheetFunction.Log10(PlantHaCohort)
              PlantTot = Round(PlantTot * 100, 0)      'keep 2 significant places (by x 100)
            End If

            'Call the subroutine
            TreatedSucess = iTreat(PlantHa, PlantTot, PlantForm, PlantCohort)

            'Process values that are returned
            If CalcType = 1 Then
              ' Population Matrix in plant / ha, so divide by nBal Size
              YoungCoppice = Round((TreatedSucess(2) / nBal_Ha), 2) + YoungCoppice    ' regrowth of young
plants ' Should be added at the end of the cycle
              AdultCoppice = Round((TreatedSucess(3) / nBal_Ha), 2) + AdultCoppice  ' regrowth of old plants
              mTreatSucc = Round(TreatedSucess(1) / nBal_Ha, 2) + mTreatSucc

              iPlantTot = PlantTot - (TreatedSucess(1) + TreatedSucess(2) + TreatedSucess(3))
              iPlantTot = Round((iPlantTot / nBal_Ha), 2)
              Cells(nBalRow, AC) = iPlantTot               'ha new cohort value written back to matrix
```

```
              Else
                YCo = 0: ACo = 0: TS = 0
                If TreatedSucess(2) > 0 Then YCo = Application.WorksheetFunction.Power(10,
(TreatedSucess(2) / 100))
                YoungCoppice = Round(YCo, 2) + YoungCoppice    ' regrowth of young plants ' Should be added
at the end of the cycle
                If TreatedSucess(3) > 0 Then ACo = Application.WorksheetFunction.Power(10,
(TreatedSucess(3) / 100))
                AdultCoppice = Round(ACo, 2) + AdultCoppice  ' regrowth of old plants
                If TreatedSucess(1) > 0 Then TS = Application.WorksheetFunction.Power(10, (TreatedSucess(1)
/ 100))
                mTreatSucc = Round(TS, 2) + mTreatSucc
                PlantTot = Application.WorksheetFunction.Power(10, PlantTot / 100)
                iPlantTot = PlantTot - (TS + YCo + ACo)
                Cells(nBalRow, AC) = Round(iPlantTot, 2)              'ha new cohort value written back to matrix
              End If
            End If
          Next AC 'AgeCohort'
          'Add in the coppice / regrowth plants back in,
          Cells(nBalRow, 5) = Cells(nBalRow, 5) + YoungCoppice
          Cells(nBalRow, 7) = Cells(nBalRow, 7) + AdultCoppice

          'Need to Tag that the nBal was cleared and the percentage cover that was removed.
          'This will be used in the Post Clearing seed germination routine.
          mRow = GetnBal_Row(inBalName, "Dynamic")
          Sheets("nBals_DynamicData").Cells(mRow, 2) = "Y"
          'Tag the number that were treated per the plant type.
          Worksheets("nBals_DynamicData").Cells(mRow, 4) = Worksheets("nBals_DynamicData").Cells(mRow,
4) + mTreatSucc + YoungCoppice + AdultCoppice
          Write_PDused inBalName, nBal_Ha
          'If nBal is post fire and has not seeded the decrease EIA by 4-8%
          If Worksheets("nBals_DynamicData").Cells(mRow, 11) <> "" And
Worksheets("nBals_DynamicData").Cells(mRow, 11) < 0 Then
            mRow = GetnBal_Row(Cells(nB, 1), "Dynamic")
            mEIAincreaseR = Application.WorksheetFunction.RandBetween(4000, 8000) / 100000
            mEIAincrease = Cells(nB, 74) - (mEIAincreaseR * Cells(nB, 74))
            If mEIAincrease < 0 Then mEIAincrease = 0
            Cells(nB, 74) = mEIAincrease
          End If
        End If
        nB = nB + 1
      Loop

      If FoundnBal = False Then      'nBal has no Plants nor no Seed, but was swept
        mRow = GetnBal_Row(inBalName, "Dynamic")
        Sheets("nBals_DynamicData").Cells(mRow, 2) = "Y"
        Worksheets("nBals_DynamicData").Cells(mRow, 4) = 0
        'need to calc the min pd needed and log those
        Write_PDused inBalName, nBal_Ha
      End If

End Sub

Private Function PDCheck(ByVal inBalName As String, ByVal iAvailDays As Single) As Boolean
  mBal = inBalName
  mPlant_Ha = GetnBal_PlantsHa(mBal)
```

```
  PDCheck = False
  mnBal_PdNeedAdult = 0
  mnBal_PdNeedYoung = 0

    mnBal_PdNeedAdult = GetnBal_pdAdult(mBal)      ' Returned as pd / ha
    mnBal_PdNeedYoung = GetnBal_pdYoung(mBal)      ' Returned as pd / ha
    mnBal_PdNeed = 0          'NOTE: This is a Global Variable
    'find the Hectares of the nBal
    mRow = GetnBal_Row(mBal, "Static")
    nBal_Ha = Sheets("nBals_StaticData").Cells(mRow, 3)          ' Global Variable Set
    mnBal_PdNeed = (mnBal_PdNeedAdult + mnBal_PdNeedYoung)
    If mnBal_PdNeed > 110 Then mnBal_PdNeed = 110               ' upper limit of pd/ha in the TMNP
    mnBal_PdNeed = (mnBal_PdNeedAdult + mnBal_PdNeedYoung) * nBal_Ha
    pdModelled = Application.WorksheetFunction.RoundUp(nBal_Ha * 0.4, 2)        '0.4 is the pd per ha set for
'sweeping' a nBal by the Park
    If pdModelled > mnBal_PdNeed Then mnBal_PdNeed = pdModelled

    nBal_Drive = 0     'Additional PD to allow for Drive Time to far sites
    nBal_Site = 0      'Additional PD to allow for Walk In time to far sites
    nBal_Slope = 0     'Additional Ha added to base Ha due to slope of the nBal

    'Adjust Pd for drive and slope
    nBal_Drive = Sheets("nBals_StaticData").Cells(mRow, 4)  ' in minutes
    nBal_Site = Sheets("nBals_StaticData").Cells(mRow, 5)   ' in minutes
    nBal_Slope = Sheets("nBals_StaticData").Cells(mRow, 7)

    pd_Adjust = (((nBal_Drive + nBal_Site) / 60) / 8) * mnBal_PdNeed       ' Drive Time + Site Time / 60 minutes
/ 8 hours in the work day 8 the pd needed
    pd_Adjust = pd_Adjust * nBal_Slope                         ' Slope factor is in format 1.xxxx so just multiply

    mnBal_PdNeed = Round(mnBal_PdNeed + pd_Adjust, 0)

    If iAvailDays - mnBal_PdNeed > 0 Then
      PDCheck = True ' Days are avaiable to clear the nBal
    End If

    If PDCheck = False Then
      a = a
    End If

End Function

Private Function GetnBal_PlantsHa(ByVal inBal As String) As Double
GetnBal_PlantsHa = 0
GetnBal_PlantsHa = Application.WorksheetFunction.SumIf(Sheets("M_Pop_All").Range("A2:A2000"), _
      inBal, Sheets("M_Pop_All").Range("C2:C2000"))
End Function

Private Function GetnBal_pdAdult(ByVal inBal As String) As Double ' Value is returned as pd / ha
GetnBal_pdAdult = 0
  ' Calculate the number PD required to treat the nBal
  'Step 1. Convert density to Cover (Le Mat 1994)
  ' 100% plants per ha : y = 3.3222x2 + 155.02x solved via quadratic equation of
  ' y = ax2 + bx + c
  'Step 2. Convert Cover to Pd (WIMS NORMs Table 2014)
  ' by calculating Condensed Ha and multiply by 100% norm
```

```
  ' Find Total Stems for nBal her Ha
  nBalC = 2
  PlantsHaA = 0
  Do Until Sheets("M_Pop_All").Cells(nBalC, 1) = ""
    If Sheets("M_Pop_All").Cells(nBalC, 1) = inBal Then
      For CohortA = 12 To 61
        PlantsHaA = PlantsHaA + Sheets("M_Pop_All").Cells(nBalC, CohortA)
      Next
    End If
   nBalC = nBalC + 1
  Loop

    a = 3.3222:   b = 155.02:   c = PlantsHaA * -1
    d = b ^ 2 - 4 * a * c
    mCover = (-b + Sqr(d)) / (2 * a)

    PdNeedHa = (mCover / 100) * Worksheets("Model Parameters").Range("PD_Norm")

    GetnBal_pdAdult = PdNeedHa

End Function

Private Function GetnBal_CoverAdult(ByVal inBal As String) As Double ' Value is returned as Percentage Cover
GetnBal_CoverAdult = 0
  ' Calculate the number PD required to treat the nBal
  'Step 1. Convert density to Cover (Le Mat 1994)
  ' 100% plants per ha : y = 3.3222x2 + 155.02x solved via quadratic equation of
  ' y = ax2 + bx + c
  ' Find Total Stems for nBal her Ha
  nBalC = 2
  PlantsHaA = 0
  Do Until Sheets("M_Pop_All").Cells(nBalC, 1) = ""
    If Sheets("M_Pop_All").Cells(nBalC, 1) = inBal Then
      For CohortA = 12 To 61
        PlantsHaA = PlantsHaA + Sheets("M_Pop_All").Cells(nBalC, CohortA)
      Next
    End If
   nBalC = nBalC + 1
  Loop

  a = 3.3222:   b = 155.02:   c = PlantsHaA * -1
  d = b ^ 2 - 4 * a * c
  mCover = (-b + Sqr(d)) / (2 * a)
  GetnBal_CoverAdult = mCover

End Function

Private Function GetnBal_pdYoung(ByVal inBal As String) As Double ' Value is returned as pd / ha
GetnBal_pdYoung = 0
  ' Calculate the number PD required to treat the nBal
  'Step 1. Convert density to Cover (Le Mat 1994)
  ' 100% plants per ha : y = 12.651x2 + 672.36x solved via quadratic equation of
  ' y = ax2 + bx + c
  'Step 2. Convert Cover to Pd (WIMS NORMs Table 2014)
  ' by calculating Condensed Ha and multiply by 100% norm

  ' Find Total Stems for nBal her Ha
```

```
    nBalC = 2
    PlantsHaY = 0
    Do Until Sheets("M_Pop_All").Cells(nBalC, 1) = ""
       If Sheets("M_Pop_All").Cells(nBalC, 1) = inBal Then
          For CohortY = 5 To 11
            PlantsHaY = PlantsHaY + Sheets("M_Pop_All").Cells(nBalC, CohortY)
          Next
       End If
     nBalC = nBalC + 1
    Loop

       a = 12.651:    b = 672.36:   c = PlantsHaY * -1
       d = b ^ 2 - 4 * a * c
       mCover = (-b + Sqr(d)) / (2 * a)

       PdNeedHa = (mCover / 100) * Worksheets("Model Parameters").Range("PD_Norm")

       GetnBal_pdYoung = PdNeedHa

End Function

Private Function GetnBal_CoverYoung(ByVal inBal As String) As Double  ' Value is returned as Percentage
Cover
GetnBal_CoverYoung = 0
    ' Calculate the number PD required to treat the nBal
    'Step 1. Convert density to Cover (Le Mat 1994)
    ' 100% plants per ha : y = 12.651x2 + 672.36x solved via quadratic equation of
    ' y = ax2 + bx + c
    'Step 2. Convert Cover to Pd (WIMS NORMs Table 2014)
    ' by calculating Condensed Ha and multiply by 100% norm

    ' Find Total Stems for nBal her Ha

    nBalC = 2
    PlantsHaY = 0
    Do Until Sheets("M_Pop_All").Cells(nBalC, 1) = ""
       If Sheets("M_Pop_All").Cells(nBalC, 1) = inBal Then
          For CohortY = 8 To 11
            PlantsHaY = PlantsHaY + Sheets("M_Pop_All").Cells(nBalC, CohortY)
          Next
       End If
     nBalC = nBalC + 1
    Loop

       a = 12.651:    b = 672.36:   c = PlantsHaY * -1
       d = b ^ 2 - 4 * a * c
       mCover = (-b + Sqr(d)) / (2 * a)
       GetnBal_CoverYoung = mCover

End Function

Private Function GetnBal_CoverSeedlings(ByVal inBal As String) As Double  ' Value is returned as Percentage
Cover
GetnBal_CoverSeedlings = 0
    ' Calculate the number PD required to treat the nBal
    'Step 1. Convert density to Cover (Le Mat 1994)
```

```
    ' 100% plants per ha : y = 12.651x2 + 672.36x solved via quadratic equation of
    ' y = ax2 + bx + c
    ' Find Total Stems for nBal her Ha

    nBalC = 2
    PlantsHaS = 0
    Do Until Sheets("M_Pop_All").Cells(nBalC, 1) = ""
      If Sheets("M_Pop_All").Cells(nBalC, 1) = inBal Then
        For CohortS = 5 To 7
          PlantsHaS = PlantsHaS + Sheets("M_Pop_All").Cells(nBalC, CohortS)
        Next
      End If
     nBalC = nBalC + 1
    Loop

      a = 12.651:    b = 672.36:   c = PlantsHaS * -1
      d = b ^ 2 - 4 * a * c
      mCover = (-b + Sqr(d)) / (2 * a)
      GetnBal_CoverSeedlings = mCover

End Function

Private Function GetnBal_SeedsHa(ByVal inBal As String) As Double
GetnBal_SeedsHa = 0
GetnBal_SeedsHa = Application.WorksheetFunction.SumIf(Sheets("M_Pop_All").Range("A2:A2000"), _
        inBal, Sheets("M_Pop_All").Range("BX2:BX2000"))
End Function

Private Function GetnBal_VeldAge(ByVal inBal As String) As Single
GetnBal_VeldAge = 0
GetnBal_VeldAge = Application.WorksheetFunction.SumIf(Sheets("nBals_DynamicData").Range("A2:A900"), _
        inBal, Sheets("nBals_DynamicData").Range("H2:H900"))
End Function

Private Function GetnBal_Row(ByVal inBal As String, ByVal mDataSheet As String) As Double
GetnBal_Row = 0
      Dim mRange1 As Range
      Dim mRange2 As Range

      If mDataSheet = "Static" Then mDataSheet = "nBals_StaticData"
      If mDataSheet = "Dynamic" Then mDataSheet = "nBals_DynamicData"

      Set mRange2 = Sheets(mDataSheet).Range("A1:A1000")
      Set mRange1 = mRange2.Cells.Find(inBal, LookAt:=xlWhole)
      If mRange1 Is Nothing = False Then
        GetnBal_Row = mRange1.Row
      End If
End Function

Private Function GetnBal_Ha(ByVal inBal As String) As Single
GetnBal_Ha = 0
      Dim mRange1 As Range
      Dim mRange2 As Range
      Set mRange2 = Sheets("nBals_StaticData").Range("A1:A1000")
      Set mRange1 = mRange2.Cells.Find(inBal, LookAt:=xlWhole)
      If mRange1 Is Nothing = False Then
        GetnBal_Ha = Sheets("nBals_StaticData").Cells(mRange1.Row, 3)
```

```
    End If
End Function

Private Function GetnBal_Topo1(ByVal inBal As String) As Double
GetnBal_Topo1 = 0
GetnBal_Topo1 = Application.WorksheetFunction.SumIf(Sheets("nBals_StaticData").Range("A2:A2000"), _
        inBal, Sheets("nBals_StaticData").Range("O2:O2000"))
End Function

Private Function GetnBal_Topo2(ByVal inBal As String) As Double
GetnBal_Topo2 = 0
GetnBal_Topo2 = Application.WorksheetFunction.SumIf(Sheets("nBals_StaticData").Range("A2:A2000"), _
        inBal, Sheets("nBals_StaticData").Range("P2:P2000"))
End Function

Private Function GetnBal_ClearTime(ByVal inBal As String) As Double
  GetnBal_ClearTime = 0
  GetnBal_ClearTime =
Application.WorksheetFunction.SumIf(Sheets("nBals_DynamicData").Range("A2:A2000"), _
        inBal, Sheets("nBals_DynamicData").Range("L2:L2000"))
End Function

Private Function iTreat(ByVal iPlantHa As Single, ByVal iPlantTot As Single, ByVal iPlantForm As String, ByVal
iPlantCohort As Single) As Double()
'  1. Attempt to find it
'  if Found, 2. Attempt to correctly treat it
'  if treated, then subtract from cohort total
'Returns the number of successfully treated plants
  'iTreat is an Array(1-3) to hold the values
  Dim iTreatArr(1 To 3) As Double
    iTreatArr(1) = 0: iTreatArr(2) = 0: iTreatArr(3) = 0:

  'LIKELYHOOD of finding a plant to treat
  'Calc plant cover value for all individuals of all spp in the nBal.
  'The higher the total cover value the greater the chance that alien plants will be seen
  'Quadratic Equation derived from Le Matrae Table of Density to Cover
    a = 3.3222:   b = 155.02:   c = iPlantHa * -1: d = b ^ 2 - 4 * a * c
    mCover = (-b + Sqr(d)) / (2 * a)    'Solve the Quadratic Equation

  ' RELATE cover to logistic curve of probability of seeing plants at a given cover
    L = 0.5
    k = 0.1
    X0 = 20

    probCover = L / (1 + Exp(-k * (mCover - X0))) 'Solve the Logistic Equation' value 0-1 where 1 is 100%

   ' ACCOUNT for plant age (i.e. height), taller plants are easier to spot even at low density, via
   ' logistic curve of probability of seeing plants at a given age

    X0 = 1.5                ' age in plant years
    k = 1
    probAge = L / (1 + Exp(-k * (iPlantCohort - X0)))

    'The probability if cover and the probability of age are added
    probSearch = Round(probCover + probAge, 5)
```

```
    For pl_Cor = 1 To iPlantTot
      'For each Plant in a cohort, test the probability of being found and treated correctly
      ' i.e. pFound and pTreatment
      pFound = 0  'Used to turn off variable contractor search ability
      'pFound = Round((Application.WorksheetFunction.RandBetween(1, 10000) / 10000), 5)

      If pFound <= probSearch Then     ' the random value falls within the curve thus the plant is seen
        pTreatment = Round((Application.WorksheetFunction.RandBetween(1, 10000) / 10000), 5)   ' the
chance that the plant will be treated (killed)
        pTreatmentR = 0
        Select Case iPlantForm
          Case Is = "Acacia non-resprouter"
            'pTreatmentR = Application.WorksheetFunction.RandBetween(1, 999) / 1000
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 80, 5) / 100    'mean
80%
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 95, 1.25) / 100    'mean
95%
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 77, 7.53) / 100
'mean project
            pTreatmentR = 2                                  'Used to turn off variable contractor
effectiveness
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 65, 8.75) / 100
'Incremtal Analysys

            If pTreatment <= pTreatmentR Then
              'The plant is killed
              iTreatArr(1) = iTreatArr(1) + 1
            Else
              'Plant is cut but will grow again
              If iPlantCohort < 8 Then      ' plant is 'young'
                iTreatArr(2) = iTreatArr(2) + 1
              Else
                iTreatArr(3) = iTreatArr(3) + 1
              End If
            End If

          Case Is = "Acacia resprouter"
            'pTreatmentR = Application.WorksheetFunction.RandBetween(1, 999) / 1000
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 80, 5) / 100    'mean
80%
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 95, 1.25) / 100    'mean
95%
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 53.93, 14.98) / 100
'mean project
            pTreatmentR = 2                                  'Used to turn off variable contractor
effectiveness
            'pTreatmentR = Application.WorksheetFunction.Norm_Inv(pTreatmentR, 65, 8.75) / 100
''Incremtal Analysys

            If pTreatment <= pTreatmentR Then      ' consider this a model parameter, Done
              'The plant is killed
              iTreatArr(1) = iTreatArr(1) + 1
            Else
              'Plant is cut but will grow again
              If iPlantCohort < 8 Then      ' plant is 'young'
                iTreatArr(2) = iTreatArr(2) + 1
              Else
```

```
                iTreatArr(3) = iTreatArr(3) + 1
              End If
            End If

          Case Else
        End Select

      End If
    Next pl_Cor
  iTreat = iTreatArr()
End Function

Sub nBal_GrowAliens_1(ByVal iQuarter As String)
  ' Grow those co-horts within a quater i.e. between seedlings and young
  Sheets("M_Pop_All").Select
  nBal = 2

  Do Until Cells(nBal, 1) = ""
    ' Application.StatusBar = iQuarter & " - " & Cells(nBal, 1)
    For c = 11 To 5 Step -1
      cCohort = Cells(nBal, c)
      If cCohort > 0 Then
        mCoverA = 0
        x = ((c - 1) / 4) + 0.25
        CohortLimit = x ^ -3.761
        CohortLimit = CohortLimit * 5000000  'Power Curve of cohort max
        'Adjust buy the Avaiable Invaded Area (AIA)
        PlantsHaA = Application.WorksheetFunction.Sum(Range(Cells(nBal, 12), Cells(nBal, 61)))
        a = 3.3222:    b = 155.02:   cp = PlantsHaA * -1
        d = b ^ 2 - 4 * a * cp
        mCoverA = ((-b + Sqr(d)) / (2 * a)) / 100

        mCountPlanstY = 11 - c
        mCoverY = 0
        If mCountPlanstY > 0 Then
          PlantsHaY = Application.WorksheetFunction.Sum(Range(Cells(nBal, c + 1), Cells(nBal, 11)))
          a = 12.651:    b = 672.36:   cp = PlantsHaY * -1
          d = b ^ 2 - 4 * a * cp
          mCoverY = ((-b + Sqr(d)) / (2 * a)) / 100
        End If

        mAIA = Cells(nBal, 74) - mCoverA - mCoverY
        If mAIA < 0 Then mAIA = 0
        If mAIA > 1 Then mAIA = 1
        CohortLimit = CohortLimit * mAIA

        If cCohort > CohortLimit Then
          cCohort = CohortLimit
          cCohortR = Application.WorksheetFunction.RandBetween(9500, 10500) / 10000
          cCohort = cCohort * cCohortR
        End If
      End If
      Cells(nBal, c + 1) = Cells(nBal, c + 1) + cCohort
      Cells(nBal, c) = 0
    Next c
    nBal = nBal + 1
  Loop
```

```
End Sub

Sub nBal_GrowAliens_2(ByVal iQuarter As String)
  ' Grow those co-horts at the end of a grow season (Q3)

  Sheets("M_Pop_All").Select
  nBal = 2
  Do Until Cells(nBal, 1) = ""
    ' Application.StatusBar = iQuarter & " - " & Cells(nBal, 1)
    Cells(nBal, 61) = 0
    If Application.WorksheetFunction.Sum(Range(Cells(nBal, 12), Cells(nBal, 61))) > 0 Then
      For c = 60 To 12 Step -1
        cCohort = Cells(nBal, c)
        If cCohort > 0 Then
          mCoverA = 0
          x = c - 10 + 1
          CohortLimit = x ^ -3.761
          CohortLimit = CohortLimit * 5000000  'Power Curve of cohort max
          'Adjust buy the Available Invaded Area (AIA)
          PlantsHaA = Application.WorksheetFunction.Sum(Range(Cells(nBal, c), Cells(nBal, 61)))
          a = 3.3222:    b = 155.02:   cp = PlantsHaA * -1
          d = b ^ 2 - 4 * a * cp
          mCoverA = ((-b + Sqr(d)) / (2 * a)) / 100

          mAIA = Cells(nBal, 74) - mCoverA
          If mAIA < 0 Then mAIA = 0
          If mAIA > 1 Then mAIA = 1
          CohortLimit = CohortLimit * mAIA

          If cCohort > CohortLimit Then
            cCohort = CohortLimit
            cCohortR = Application.WorksheetFunction.RandBetween(9500, 10500) / 10000
            cCohort = cCohort * cCohortR
          End If
        End If
        Cells(nBal, c + 1) = Cells(nBal, c + 1) + cCohort
        Cells(nBal, c) = 0
      Next c
    End If
    nBal = nBal + 1
  Loop

End Sub

Private Sub nBal_VeldAge()
  Sheets("nBals_DynamicData").Select
  nBal = 2
  Do Until Cells(nBal, 1) = ""
    Cells(nBal, 8) = Cells(nBal, 8) + 1
    nBal = nBal + 1
  Loop
End Sub

Sub nBal_Plants_Seed()
  'Determine the amount of seed will contribute to the seed bank
```

```
    'Acacia resprouters about 4250 per m2 at about 8 years seeds after Year 8, as determined by logistic
equation
    'Trees slow down production after about 40 years, also a logistic equation used

    Sheets("M_Pop_All").Select
    nBal = 2
    SeedTotal = 0
    SeedProduce = 0

    Do Until Cells(nBal, 1) = ""
      mRow = GetnBal_Row(Cells(nBal, 1), "Static")
      nBal_Ha = Sheets("nBals_StaticData").Cells(mRow, 3)
      nBal_ID = Sheets("nBals_StaticData").Cells(mRow, 1)
      ' Application.StatusBar = "nBal Flower and Seed " & nBal_ID
      nBal_PlantType = Cells(nBal, 2)        ' Used to differentate seed production
      SeedTotal = 0
      cAdult = Application.WorksheetFunction.Sum(Range(Cells(nBal, 12), Cells(nBal, 61)))
      If cAdult > 0 Then
        SeedProduce = 0        'The rate of accumilation into seed bank (Miltion et al) per ha
        For c = 12 To 61  'Seed co-horts
            cPlantTot = Cells(nBal, c)
            If cPlantTot > 0 And Cells(nBal, c) <> "" Then
            'Calc % Cover of the Cohort
            a = 3.3222:    b = 155.02:   cp = cPlantTot * -1
            d = b ^ 2 - 4 * a * cp
            mCover = ((-b + Sqr(d)) / (2 * a)) / 100
            If mCover > 1 Then mCover = 1
            plantAge = c - 11
            If plantAge <= 8 Then
              If nBal_PlantType = "Acacia non-resprouter" Then
                SeedProducem2 = (50.814 * plantAge) - 46.514
                SeedProducem2R = Application.WorksheetFunction.RandBetween(95, 105) / 100
                SeedProducem2 = (SeedProducem2 * SeedProducem2R) * mCover
                SeedProduce = SeedProduce + (SeedProducem2 * 10000)
              End If
              If nBal_PlantType = "Acacia resprouter" Then
                SeedProducem2 = (531.43 * plantAge) - 1.4286
                SeedProducem2R = Application.WorksheetFunction.RandBetween(95, 105) / 100
                SeedProducem2 = (SeedProducem2 * SeedProducem2R) * mCover
                SeedProduce = SeedProduce + (SeedProducem2 * 10000)
              End If
            End If      'plantAge <= 8
            If plantAge > 8 And plantAge <= 30 Then
              If nBal_PlantType = "Acacia non-resprouter" Then
                SeedProducem2 = 360
                SeedProducem2R = Application.WorksheetFunction.RandBetween(95, 105) / 100
                SeedProducem2 = (SeedProducem2 * SeedProducem2R) * mCover
                SeedProduce = SeedProduce + (SeedProducem2 * 10000)
              End If
              If nBal_PlantType = "Acacia resprouter" Then
                SeedProducem2 = 4250
                SeedProducem2R = Application.WorksheetFunction.RandBetween(95, 105) / 100
                SeedProducem2 = (SeedProducem2 * SeedProducem2R) * mCover
                SeedProduce = SeedProduce + (SeedProducem2 * 10000)
              End If
            End If      'plantAge >8 <=30
            If plantAge > 30 Then
```

```
            If nBal_PlantType = "Acacia non-resprouter" Then L = 360        ' Peak Seed production, This will a
variable based on Growth form
            If nBal_PlantType = "Acacia resprouter" Then L = 4250        ' Peak Seed production, This will a
variable based on Growth form
            k = -0.4          ' Slope of the Curve (also call r sometimes)
            X0 = 55           ' point on the x-axis that will have the steepest curve
            SeedProducem2 = L / (1 + Exp(-k * (plantAge - X0))) 'Solve the Logistic Equation for the cohourt
            SeedProducem2R = Application.WorksheetFunction.RandBetween(95, 105) / 100
            SeedProducem2 = (SeedProducem2 * SeedProducem2R) * mCover
            SeedProduce = SeedProduce + (SeedProducem2 * 10000)
          End If
        End If
      Next c  'cohort

      SeedTotal = SeedProduce
      ' Tag Effective Invaded Area to increase and increase by 4-8%
      mRow = GetnBal_Row(Cells(nBal, 1), "Dynamic")
      Sheets("nBals_DynamicData").Cells(mRow, 11) = 1
      mEIAincreaseR = Application.WorksheetFunction.RandBetween(4000, 8000) / 100000
      mEIAincrease = (mEIAincreaseR * Cells(nBal, 74)) + Cells(nBal, 74)
      If mEIAincrease < 0 Then mEIAincrease = 0
      Cells(nBal, 74) = mEIAincrease
      'For a nBal disperse upto 5% to neighbouring nBals
      ' Determine the number of seeds available to be dispersed, up to 5%
      mRseed = (Application.WorksheetFunction.RandBetween(1, 500) / 100) / 100
      rSeedDispersal = Round(SeedTotal * mRseed, 0)
      SeedRemainPostDispersal = SeedDispersal(nBal_ID, rSeedDispersal, nBal_PlantType)
      SeedTotal = (SeedTotal - rSeedDispersal) + SeedRemainPostDispersal
      'Add the Remainder of Seed to the Litter Fall
        Cells(nBal, 63) = Round(Cells(nBal, 63) + (SeedTotal), 2)  ' Data Stored as seeds per Ha and to 2
Decimal Places
      'Move to next nBal
    End If
    nBal = nBal + 1
  Loop

End Sub

Private Function SeedDispersal(ByVal inBalName As String, ByVal iSeeds As Double, ByVal inBal_PlantType As
String) As Double
  SeedDispersal = iSeeds
  ' Find and loop through the nBals list to Spread seed
    nB = 2
    Do Until Sheets("nBal_Neighbours").Cells(nB, 1) = ""
      If Sheets("nBal_Neighbours").Cells(nB, 1) = inBalName Then
        nBalRow = nB
        'Allocate seeds based in the percentage of common boundary
        cBoundary = Sheets("nBal_Neighbours").Cells(nBalRow, 3) /
Sheets("nBal_Neighbours").Cells(nBalRow, 4)
        SeedsAllocated = Round(iSeeds * cBoundary, 0)
        DestnBal = Sheets("nBal_Neighbours").Cells(nBalRow, 2)
        SeedsSend DestnBal, SeedsAllocated, inBal_PlantType
        SeedDispersal = SeedDispersal - SeedsAllocated
      End If
      nB = nB + 1
    Loop
End Function
```

```
Sub SeedsSend(ByVal iDestnBal As String, ByVal iSeedsAllocated As Double, ByVal inBal_PlantType As String)
' Write the values of the seeds to the adjaicent nBal

    nB = 2
    FoundnBal = False
    Do Until Sheets("M_Pop_All").Cells(nB, 1) = ""
      If Sheets("M_Pop_All").Cells(nB, 1) = iDestnBal And Sheets("M_Pop_All").Cells(nB, 2) = inBal_PlantType
Then
        nBalRow = nB
        Sheets("M_Pop_All").Cells(nBalRow, 63) = Sheets("M_Pop_All").Cells(nBalRow, 63) +
Round(iSeedsAllocated, 2)
        mEIAincrease = Cells(nB, 74) + 0.01  '1%increase to the receving EAI
        If mEIAincrease > 1 Then mEIAincrease = 1
        If mEIAincrease < 0 Then mEIAincrease = 0
        Cells(nB, 74) = mEIAincrease
        FoundnBal = True
        Exit Sub
      End If
      nB = nB + 1
    Loop

  'Need to catch if nBal does not have plant type already... if so add to the end.

  If FoundnBal = False Then
    DestHa = GetnBal_Ha(iDestnBal)
    Sheets("M_Pop_All").Cells(nB, 1) = iDestnBal
    Sheets("M_Pop_All").Cells(nB, 2) = inBal_PlantType
    Sheets("M_Pop_All").Cells(nB, 63) = Round(iSeedsAllocated, 2)  ' Values stored as seeds per ha and to 2
Decimal places
    mEIAincrease = Cells(nB, 74) + 0.01  '1%increase to the receiving EAI
    If mEIAincrease > 1 Then mEIAincrease = 1
    If mEIAincrease < 0 Then mEIAincrease = 0
    Cells(nB, 74) = mEIAincrease
  End If

  If Sheets("M_Pop_All").Cells(nB, 63) < 0 Then
    a = a
  End If

End Sub

Sub nBal_GerminateSeedlings()
  ' There are 3 types of germination
  '1. A small %, up to 3% of small scale germination of non- resprouters after 2 years in the soil
  '2. A significant portion of non-resprouters after clearing (Holmes 1987)
  '3. Major recruitment of up to 95% in top seed back and 10% from deep bank based on the intensity of the
fire
  'Note Seed germination is spread over 2 quarters i.e. Q2 and Q3

  nBal = 2
  Do Until Sheets("M_Pop_All").Cells(nBal, 1) = ""
  ' Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " " & cQuarter & " Seedling
Germinate " & Sheets("M_Pop_All").Cells(nBal, 1)
  'Determine the pre germination cover
    mPlantsHA = Application.WorksheetFunction.Sum(Range(Cells(nBal, 5), Cells(nBal, 61)))
    a = 3.3222:   b = 155.02:   c = mPlantsHA * -1
```

```
    d = b ^ 2 - 4 * a * c
    mCover = (-b + Sqr(d)) / (2 * a)
    mCover = mCover / 100

    If nBal_WasBurnt(Sheets("M_Pop_All").Cells(nBal, 1)) = False Then
      Germinate_NonDormant nBal          ' This is the small amount of non- resprouters after 2 years
      If (nBal_WasCleared(Cells(nBal, 1)) = True) Then
        Germinate_ClearedDormant nBal      ' This is the amount of seedling that germinate post clearing
      End If
    Else
      Germinate_PostFire nBal
    End If
    'Density limit of seedlings per Ha (esp for post fire Germination)
    SeedlingTotal = Cells(nBal, 5) + Cells(nBal, 6)
    mAIA = Cells(nBal, 74) - mCover
    If mAIA < 0 Then mAIA = 0: If mAIA > 1 Then mAIA = 1
    SeedlingSat = Cells(nBal, 74) * 1200000

    If SeedlingTotal > SeedlingSat Then
     SeedlingTotal_1 = Cells(nBal, 5) / SeedlingTotal
     SeedlingTotal_2 = Cells(nBal, 6) / SeedlingTotal
      mDenRnd = (Application.WorksheetFunction.RandBetween(95000, 105000) / 100000)
      SeedlingTotal = SeedlingSat * mDenRnd
      Cells(nBal, 5) = SeedlingTotal * SeedlingTotal_1
      Cells(nBal, 6) = SeedlingTotal * SeedlingTotal_2
    End If
    Cells(nBal, 76) = Application.WorksheetFunction.Sum(Range(Cells(nBal, 64), Cells(nBal, 72)))
    nBal = nBal + 1
  Loop

End Sub

Sub Germinate_NonDormant(ByVal iBal As Integer)
' This is the small amount of non- resprouters seed germination after 2 years in the soil
' Only the top/upper seed back is affected

  Sheets("M_Pop_All").Select
  mSeedTotoTest = Cells(8, 80)
  nBal = iBal
  SeedGerminate = 0

  mRow = GetnBal_Row(Cells(nBal, 1), "Static")
  nBal_Ha = Sheets("nBals_StaticData").Cells(mRow, 3)
  nBal_ID = Sheets("nBals_StaticData").Cells(mRow, 1)
  mVeldAge = GetnBal_VeldAge(nBal_ID)
  nBal_PlantType = Cells(nBal, 2)        ' Used to differentiate seed type

  If mVeldAge > 2 Then
    If Cells(nBal, 2) = "Acacia non-resprouter" Then
      'Determine if the germinated seed will survive into a seedling based on current veg age
      ' RELATE cover to logistic curve of probability of seeing plants at a given cover
        L = 1
        k = -0.4
        X0 = 2     ' 2 years old , so buy year 4 very low rate of survival
        probSurvive = L / (1 + Exp(-k * (mVeldAge - X0))) 'Solve the Logistic Equation

      For sc = 66 To 69      ' Top layers of seed bank
```

```
        SeedlingTotal = 0
        'Determine the amount of seed to germinate
        If Cells(nBal, sc) <> "" And Cells(nBal, sc) < 0 Then Cells(nBal, sc) = 0
        If Cells(nBal, sc) <> "" And Cells(nBal, sc) > 0 Then
          mRseed = ((Application.WorksheetFunction.RandBetween(1, 300) / 100) / 100)   'up to 3%
          nBal_Seeds = Round(Cells(nBal, sc) * mRseed, 0)
          Cells(nBal, sc) = Cells(nBal, sc) - nBal_Seeds      'Remove from Seed Bank

          CalcType = 0
          If nBal_Seeds > 250 Then
            'adjust to log of base 10
            sdLog = Application.WorksheetFunction.Log10(nBal_Seeds)
            ToTsd = Round(sdLog * 100, 0)      'keep 2 signifcant places (by x 100)
            nBal_Seeds = ToTsd
            CalcType = 1
          End If

          For g = 1 To nBal_Seeds
              'Apply a Random survival test
              mRsurvive = Application.WorksheetFunction.RandBetween(0, 1000) / 1000
              If mRsurvive < probSurvive Then ' the Seedling survives, i.e underneath the logistic curve
                SeedlingTotal = SeedlingTotal + 1
              End If
          Next g      'Germinate

          'adjust for the Log Calc
          If CalcType = 1 Then
            SeedlingTotal = SeedlingTotal / 100
            nBal_Seeds = nBal_Seeds / 100
            If SeedlingTotal > 0 Then SeedlingTotal = Application.WorksheetFunction.Power(10,
SeedlingTotal)
            nBal_Seeds = Application.WorksheetFunction.Power(10, nBal_Seeds)
          End If
          'Add the seedlings to the Seedling cohort & Y_1 as the routine is now only called once in Q3
          If SeedlingTotal > 0 Then
            SeedlingAllocateR = (Application.WorksheetFunction.RandBetween(1, 3000) / 100) / 100
            SeedlingAllocateA = SeedlingAllocateR * SeedlingTotal
            SeedlingTotal_1 = SeedlingTotal + SeedlingAllocateA
            SeedlingTotal_2 = SeedlingTotal - SeedlingAllocateA

            SeedlingAllocateR = Application.WorksheetFunction.RandBetween(0, 100)
            If SeedlingAllocateR > 49 Then
              Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_1, 2)
              Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_2, 2)
            Else
              Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_2, 2)
              Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_1, 2)
            End If
          End If
        End If
      Next sc       ' seed cohort

    End If
  End If  ' nBal_VeldAge > 2

End Sub
```

```
Sub Germinate_ClearedDormant(ByVal iBal As Integer)
' Holmes et al Non- resprouters between 70% to 90% seeds can germinate post clearing while resprouters only
5%
' This is clearing without fire treatment.
' The model only considers the first year post felling which has the significant direct effect.

  Sheets("M_Pop_All").Select
  mSeedTotoTest = Cells(8, 80)
  nBal = iBal
  SeedGerminate = 0

  ' Test to see if the nBal was cleared
  If nBal_WasCleared(Cells(nBal, 1)) = True Then
    mRow = GetnBal_Row(Cells(nBal, 1), "Static")
    nBal_Ha = Sheets("nBals_StaticData").Cells(mRow, 3)
    nBal_ID = Sheets("nBals_StaticData").Cells(mRow, 1)

    nBal_PlantType = Cells(nBal, 2)       ' Used to differentiate seed production
    mRow = GetnBal_Row(Cells(nBal, 1), "Dynamic")

    ' Quadratic Equation to convert Density to Cover
    a = 3.3222:    b = 155.02:    c = Sheets("nBals_DynamicData").Cells(mRow, 4) * -1
    d = b ^ 2 - 4 * a * c
    mCover = (-b + Sqr(d)) / (2 * a)

    nBal_ClearedPrecent = mCover / 100
    If nBal_ClearedPrecent > 1 Then nBal_ClearedPrecent = 1

      For sc = 66 To 72      ' Top layers of seed bank older than 2 years
      SeedlingTotal = 0
        'Determine the amount of seed to germinate
        If Cells(nBal, sc) <> "" And Cells(nBal, sc) < 0 Then Cells(nBal, sc) = 0
        If Cells(nBal, sc) <> "" And Cells(nBal, sc) > 0 Then
          'Different Plants have different germination % (See Holmes 1987)
          mRseed = 0
          If nBal_PlantType = "Acacia non-resprouter" Then mRseed =
(Application.WorksheetFunction.RandBetween(7000, 9500) / 10000)  'between 70 and 95% germinate
          If nBal_PlantType = "Acacia resprouter" Then mRseed =
(Application.WorksheetFunction.RandBetween(1, 500) / 10000)  'between 1 and 5% germinate
          nBal_Seeds = Cells(nBal, sc) * mRseed
          'Adjust for % of cover that was actually aliens. These germination rates are for 100% Alien Cover pre
clearing
          nBal_Seeds = Round(nBal_Seeds * nBal_ClearedPrecent, 0)
          Cells(nBal, sc) = Cells(nBal, sc) - nBal_Seeds

          CalcType = 0
          If nBal_Seeds > 250 Then
            'adjust to log of base 10 calculation
            sdLog = Application.WorksheetFunction.Log10(nBal_Seeds)
            ToTsd = Round(sdLog * 100, 0)      'keep 2 significant places (by x 100)
            nBal_Seeds = ToTsd
            CalcType = 1
          End If

          For g = 1 To nBal_Seeds
            ' Seeds have a high probability of making it to a seedling (90%)
            probSurvive = 0.9
```

```
            'Apply a Random survival test
            mRsurvive = Application.WorksheetFunction.RandBetween(0, 1000) / 1000
            If mRsurvive < probSurvive Then ' the Seedling survives, i.e underneath the logistic curve
              SeedlingTotal = SeedlingTotal + 1
            End If
          Next g     'Germinate

          'adjust for the Log Calc
          If CalcType = 1 Then
            SeedlingTotal = SeedlingTotal / 100
            nBal_Seeds = nBal_Seeds / 100
            If SeedlingTotal > 0 Then SeedlingTotal = Application.WorksheetFunction.Power(10,
SeedlingTotal)
            nBal_Seeds = Application.WorksheetFunction.Power(10, nBal_Seeds)
          End If

          'Add the seedlings to the Seedling cohort & Y_1 as the routine is now only called once in Q3
          If SeedlingTotal > 0 Then
            SeedlingAllocateR = (Application.WorksheetFunction.RandBetween(1, 3000) / 100) / 100
            SeedlingAllocateA = SeedlingAllocateR * SeedlingTotal
            SeedlingTotal_1 = SeedlingTotal + SeedlingAllocateA
            SeedlingTotal_2 = SeedlingTotal - SeedlingAllocateA

            SeedlingAllocateR = Application.WorksheetFunction.RandBetween(0, 100)
            If SeedlingAllocateR > 49 Then
              Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_1, 2)
              Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_2, 2)
            Else
              Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_2, 2)
              Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_1, 2)
            End If
          End If
        End If
      Next sc       ' seed cohort
  End If

  'Debug check on total seed count
  If mSeedTotoTest < Cells(80, 8) Then
    a = a
  End If
End Sub

Private Sub Germinate_PostFire(ByVal iBal As Integer)
  Sheets("M_Pop_All").Select
  mSeedTotoTest = Cells(8, 80)

  nBal = iBal
  SeedGerminate = 0

  mRow = GetnBal_Row(Cells(nBal, 1), "Static")
  mRowD = GetnBal_Row(Cells(nBal, 1), "Dynamic")
  mFireSeverity = Sheets("nBals_DynamicData").Cells(mRowD, 10)

  If mFireSeverity <= 20 Then
    Seed0 = 1
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 63) * Seed0), 2)
```

```
        Cells(nBal, 63) = Cells(nBal, 63) - Round((Cells(nBal, 63) * Seed0), 2)
    Seed1 = (Application.WorksheetFunction.NormInv(Rnd(), 90, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 64) * Seed1), 2)
        Cells(nBal, 64) = Cells(nBal, 64) - Round((Cells(nBal, 64) * Seed1), 2)
    Seed2 = (Application.WorksheetFunction.NormInv(Rnd(), 70, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 65) * Seed2), 2)
        Cells(nBal, 65) = Cells(nBal, 65) - Round((Cells(nBal, 65) * Seed2), 2)
End If
If mFireSeverity > 20 And mFireSeverity <= 45 Then
    Seed0 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 63) * Seed0), 2)
        Cells(nBal, 63) = Cells(nBal, 63) - Round((Cells(nBal, 63) * Seed0), 2)
    Seed1 = (Application.WorksheetFunction.NormInv(Rnd(), 90, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 64) * Seed1), 2)
        Cells(nBal, 64) = Cells(nBal, 64) - Round((Cells(nBal, 64) * Seed1), 2)
    Seed2 = (Application.WorksheetFunction.NormInv(Rnd(), 70, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 65) * Seed2), 2)
        Cells(nBal, 65) = Cells(nBal, 65) - Round((Cells(nBal, 65) * Seed2), 2)
    Seed3 = (Application.WorksheetFunction.NormInv(Rnd(), 60, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 66) * Seed3), 2)
        Cells(nBal, 66) = Cells(nBal, 66) - Round((Cells(nBal, 66) * Seed3), 2)
End If
If mFireSeverity > 45 And mFireSeverity <= 60 Then
    Seed0 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 63) * Seed0), 2)
        Cells(nBal, 63) = Cells(nBal, 63) - Round((Cells(nBal, 63) * Seed0), 2)
    Seed1 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 64) * Seed1), 2)
        Cells(nBal, 64) = SeedGerminate - Round((Cells(nBal, 64) * Seed1), 2)
    Seed2 = (Application.WorksheetFunction.NormInv(Rnd(), 90, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 65) * Seed2), 2)
        Cells(nBal, 65) = Cells(nBal, 65) - Round((Cells(nBal, 65) * Seed2), 2)
    Seed3 = (Application.WorksheetFunction.NormInv(Rnd(), 80, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 66) * Seed3), 2)
        Cells(nBal, 66) = Cells(nBal, 66) - Round((Cells(nBal, 66) * Seed3), 2)
    Seed4 = (Application.WorksheetFunction.NormInv(Rnd(), 70, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 67) * Seed4), 2)
        Cells(nBal, 67) = Cells(nBal, 67) - Round((Cells(nBal, 67) * Seed4), 2)
    Seed5 = (Application.WorksheetFunction.NormInv(Rnd(), 60, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 68) * Seed5), 2)
        Cells(nBal, 68) = Cells(nBal, 68) - Round((Cells(nBal, 68) * Seed5 / 2), 2)
End If
If mFireSeverity > 60 And mFireSeverity <= 75 Then
    Seed0 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 63) * Seed0), 2)
        Cells(nBal, 63) = Cells(nBal, 63) - Round((Cells(nBal, 63) * Seed0), 2)
    Seed1 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 64) * Seed1), 2)
        Cells(nBal, 64) = SeedGerminate - Round((Cells(nBal, 64) * Seed1), 2)
    Seed2 = 1
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 65) * Seed2), 2)
        Cells(nBal, 65) = SeedGerminate - Round((Cells(nBal, 65) * Seed2), 2)
    Seed3 = (Application.WorksheetFunction.NormInv(Rnd(), 90, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 66) * Seed3), 2)
        Cells(nBal, 66) = Cells(nBal, 66) - Round((Cells(nBal, 66) * Seed3), 2)
    Seed4 = (Application.WorksheetFunction.NormInv(Rnd(), 80, 10) / 100)
        SeedGerminate = SeedGerminate + Round((Cells(nBal, 67) * Seed4), 2)
```

```
      Cells(nBal, 67) = Cells(nBal, 67) - Round((Cells(nBal, 67) * Seed4), 2)
    Seed5 = (Application.WorksheetFunction.NormInv(Rnd(), 70, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 68) * Seed5), 2)
      Cells(nBal, 68) = Cells(nBal, 68) - Round((Cells(nBal, 68) * Seed5), 2)
    Seed6 = (Application.WorksheetFunction.NormInv(Rnd(), 60, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 69) * Seed6), 2)
      Cells(nBal, 69) = Cells(nBal, 69) - Round((Cells(nBal, 69) * Seed6), 2)
    Seed7 = (Application.WorksheetFunction.NormInv(Rnd(), 50, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 70) * Seed7), 2)
      Cells(nBal, 70) = Cells(nBal, 70) - Round((Cells(nBal, 70) * Seed7), 2)
  End If
  If mFireSeverity > 75 Then
    Seed0 = 1
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 63) * Seed0), 2)
      Cells(nBal, 63) = Cells(nBal, 63) - Round((Cells(nBal, 63) * Seed0), 2)
    Seed1 = 1
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 64) * Seed1), 2)
      Cells(nBal, 64) = SeedGerminate - Round((Cells(nBal, 64) * Seed1), 2)
    Seed2 = 1
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 65) * Seed2), 2)
      Cells(nBal, 65) = SeedGerminate - Round((Cells(nBal, 65) * Seed2), 2)
    Seed3 = 1
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 66) * Seed3), 2)
      Cells(nBal, 66) = Cells(nBal, 66) - Round((Cells(nBal, 66) * Seed3), 2)
    Seed4 = (Application.WorksheetFunction.NormInv(Rnd(), 90, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 67) * Seed4), 2)
      Cells(nBal, 67) = Cells(nBal, 67) - Round((Cells(nBal, 67) * Seed4), 2)
    Seed5 = (Application.WorksheetFunction.NormInv(Rnd(), 80, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 68) * Seed5), 2)
      Cells(nBal, 68) = Cells(nBal, 68) - Round((Cells(nBal, 68) * Seed5), 2)
    Seed6 = (Application.WorksheetFunction.NormInv(Rnd(), 70, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 69) * Seed6), 2)
      Cells(nBal, 69) = Cells(nBal, 69) - Round((Cells(nBal, 69) * Seed6), 2)
    Seed7 = (Application.WorksheetFunction.NormInv(Rnd(), 60, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 70) * Seed7), 2)
      Cells(nBal, 70) = Cells(nBal, 70) - Round((Cells(nBal, 70) * Seed7), 2)
    Seed8 = (Application.WorksheetFunction.NormInv(Rnd(), 50, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 71) * Seed8), 2)
      Cells(nBal, 71) = Cells(nBal, 71) - Round((Cells(nBal, 71) * Seed8), 2)
    Seed9 = (Application.WorksheetFunction.NormInv(Rnd(), 40, 10) / 100)
      SeedGerminate = SeedGerminate + Round((Cells(nBal, 72) * Seed9), 2)
      Cells(nBal, 72) = Cells(nBal, 72) - Round((Cells(nBal, 72) * Seed9), 2)
  End If

  'Write out the total for SeedGerminate
  'As seed is aggregated so will be the seedlings.
  'Max Seedling density is taken as 1,200,000 seedlings per ha.
  SeedlingAggri = Cells(nBal, 74) * 1200000
  SeedlingTotal = SeedGerminate
  If SeedlingTotal > SeedlingAggri Then
    SeedlingTotal = SeedlingAggri * (Application.WorksheetFunction.RandBetween(95, 105) / 100)
  End If

  If SeedlingTotal > 0 Then
    SeedlingAllocateR = (Application.WorksheetFunction.RandBetween(1, 3000) / 100) / 100
    SeedlingAllocateA = SeedlingAllocateR * SeedlingTotal
    SeedlingTotal_1 = SeedlingTotal + SeedlingAllocateA 'allocation between the 2 seedling quarters
```

```
        SeedlingTotal_2 = SeedlingTotal - SeedlingAllocateA

        SeedlingAllocateR = Application.WorksheetFunction.RandBetween(0, 100)
        If SeedlingAllocateR > 49 Then
            Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_1, 2)
            Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_2, 2)
        Else
            Cells(nBal, 5) = Cells(nBal, 5) + Round(SeedlingTotal_2, 2)
            Cells(nBal, 6) = Cells(nBal, 6) + Round(SeedlingTotal_1, 2)
        End If
    End If

End Sub

Private Sub Seed_AgeCohort(ByVal iQuater As String)
    nBal = 2
    Sheets("M_Pop_All").Select
    nBal = 2
    Do Until Cells(nBal, 1) = ""
        nBalIDseed = Cells(nBal, 1)
        ' Application.StatusBar = iQuater & " - " & nBalIDseed
        mBalRowS = GetnBal_Row(nBalIDseed, "nBals_DynamicData")
        For SeedCo = 72 To 63 Step -1
            'decay seed in Bank between 0.1-0.17
            mSeedRandom = 1 - (Application.WorksheetFunction.RandBetween(1000, 1700) / 10000)
            Cells(nBal, SeedCo) = Cells(nBal, SeedCo) * mSeedRandom
            If Cells(nBal, SeedCo) < 0 Then Cells(nBal, SeedCo) = 0
            'Move the Seed deeper
            mSeedRandom = Application.WorksheetFunction.RandBetween(5000, 15000) / 10000
            cSeeds = Cells(nBal, SeedCo)
            cSeeds = cSeeds * 0.1
            cSeeds = cSeeds * mSeedRandom
            Cells(nBal, SeedCo) = Cells(nBal, SeedCo) - cSeeds
            If Cells(nBal, SeedCo) < 0 Then Cells(nBal, SeedCo) = 0
            Cells(nBal, SeedCo + 1) = Cells(nBal, SeedCo + 1) + cSeeds
            If Cells(nBal, SeedCo + 1) < 0 Then Cells(nBal, SeedCo + 1) = 0
        Next SeedCo
        'adjust for seed bank saturation
        SeedTot = Application.WorksheetFunction.Sum(Range(Cells(nBal, 63), Cells(nBal, 72)))
        SeedSaturate = Cells(nBal, 75)
        If SeedTot > SeedSaturate Then
            'determine the amount of seed over the saturation
            SeedOver = (SeedTot - SeedSaturate) / SeedSaturate
            SeedAdjust = 1 - SeedOver
            For SeedCo = 63 To 75
                Cells(nBal, SeedCo) = Cells(nBal, SeedCo) * SeedAdjust
                If Cells(nBal, SeedCo) < 0 Then Cells(nBal, SeedCo) = 0
            Next
        End If
        Cells(nBal, 76) = Application.WorksheetFunction.Sum(Range(Cells(nBal, 64), Cells(nBal, 72)))
        nBal = nBal + 1
    Loop
End Sub

Private Sub nBal_UpdateTags()
    ' 1. The Status of nBal wrt Seed Germination
    Sheets("nBals_DynamicData").Select
```

```
    nBal = 2
    Do Until Cells(nBal, 1) = ""
      If Cells(nBal, 5) > 0 Then
        Cells(nBal, 5) = Cells(nBal, 5) - 1
      End If
      If Cells(nBal, 5) = 0 Then
        Cells(nBal, 2) = ""
        Cells(nBal, 3) = 0
        Cells(nBal, 4) = 0
      End If
      nBal = nBal + 1
    Loop

End Sub

Private Function nBal_WasCleared(inBalID As String) As Boolean
    nBal_WasCleared = False
    iBal = 2
    Do Until Worksheets("nBals_DynamicData").Cells(iBal, 1) = ""
      If Worksheets("nBals_DynamicData").Cells(iBal, 1) = inBalID Then
        If Worksheets("nBals_DynamicData").Cells(iBal, 5) > 0 And
Worksheets("nBals_DynamicData").Cells(iBal, 4) > 0 Then
          nBal_WasCleared = True
        End If
        Exit Do
      End If
     iBal = iBal + 1
    Loop
End Function

Sub nBal_Burn()
' 1a. Determine the number of fires in a year. Mean =73.54545455 Stdev = 19.2229202
' 1b. Determine the number of Ha that will be burnt in a year. Mean =  1,185 Ha StDev =  1,646 ha
' 2. For each Fire Ignition assign a random number to a nbal Fire Probability Class (1 of 5 Classes based on Fire
ignition database)
' 2b. Once the nBal is selected determine if the ignition will turn into a fire
' 3. If ignite then how much will burn depends on the mean of each fire year as un upper target, and the mean
of each fire as a single fire target.
' 4. The intensity of the fire depends on a weather selected randomly for the day..

    '(1a & 1b) The number of fire for the FireSeason
    mFireIgnition = Round(Application.WorksheetFunction.NormInv(Rnd(), 73.55, 19.22), 0) ' 73.55 the mean
number of fire ignitions between 2006 and 2016
    mFireYearHa = Round(Application.WorksheetFunction.NormInv(Rnd(), 1185, 1646), 0) ' 1,185 the mean area
of fire ignitions between 1960 and 2016
    If mFireYearHa < 1 Then mFireYearHa = 1     ' At least one Ha burns each year
    mFireYearHaBurnt = 0          ' The counter for the total size of all fires for the year
    mIgnition = 1
    mFireCount = 0
    Do Until (mIgnition = mFireIgnition) Or (mFireYearHaBurnt >= mFireYearHa)
    'Two Counters Either the number of igntions has been reached or the total number of Ha has been reached

      'Determine which fire frequency class the nBal will be drawn from that will have the ignition point
      mFireRnd = Application.WorksheetFunction.RandBetween(1, 1000)
      mFireClass = Fire_GetFireClass(mFireRnd)       'The class from where the nBal will be drawn
      mFirenBal = Fire_GetFirenBal(mFireClass)       'Selects a nBal from the selected fire class
      mFireIsBig = Fire_GetFireStatus(mFirenBal)      'tests to see if the nBal will burn or the ignition will die out
```

```
    If mFireIsBig = True Then
      ' Set the size of the fire (min area to be burnt) : Mean = 92.22954654 Ha StDev = 359.1148 from fire database of indivual fires
      mFireArea = Round(Application.WorksheetFunction.NormInv(Rnd(), 92.2295, 359.1148), 0)
      mFireSeverity = Fire_Severity(Application.WorksheetFunction.RandBetween(2, 2297))   'the number of FDI days that are in the Fire_FDI List
      mFireAreal = Fire_BurnIndFire(mFireArea, mFirenBal, mFireSeverity) ' Exact area burnt based on the nBals in the area
      mFireYearHaBurnt = mFireYearHaBurnt + mFireAreal
      mFireCount = mFireCount + 1
      Sheets("DataOut_FireHA").Cells(mFireCount + 5, 1) = mFireCount
      Sheets("DataOut_FireHA").Cells(mFireCount + 5, iModelYear + 2) = mFireAreal
    End If
    mIgnition = mIgnition + 1
  Loop 'mIgnition

  Sheets("DataOut_FireHA").Cells(2, iModelYear + 2) = mFireYearHaBurnt
  Sheets("DataOut_FireHA").Cells(3, iModelYear + 2) = mFireCount

End Sub

Private Function Fire_GetFireClass(ByVal mFireRnd As Single) As Single
  'nBals_StaticData column 10 holds the fire classes where class 1 has the lowest proablity of being a fire source
  ' mFireRnd will be a vaslue between 1-1000 thus 5% will = 50
  Fire_GetFireClass = 0
  If mFireRnd > 0 And mFireRnd <= 50 Then Fire_GetFireClass = 1     ' 5% Chance
  If mFireRnd > 50 And mFireRnd <= 175 Then Fire_GetFireClass = 2    ' 12.5%
  If mFireRnd > 175 And mFireRnd <= 375 Then Fire_GetFireClass = 3   ' 20 %
  If mFireRnd > 375 And mFireRnd <= 650 Then Fire_GetFireClass = 4   ' 27.5%
  If mFireRnd > 650 And mFireRnd <= 1000 Then Fire_GetFireClass = 5  ' 35%
End Function

Private Function Fire_GetFirenBal(ByVal mFireClass As Single) As String
  Fire_GetFirenBal = ""
  '1 Clear out any current values
  FirePValue = 2
  Do Until Sheets("nBals_DynamicData").Cells(FirePValue, 1) = ""
    Sheets("nBals_DynamicData").Cells(FirePValue, 9) = ""
    FirePValue = FirePValue + 1
  Loop

  'Load in a new random ProbValue for the class selected of prob Fire Class (See "Fire_GetFireClass")
  'The highest value will be the 'seed' nbal for the ignition
  FirePValue = 2
  Do Until Sheets("nBals_StaticData").Cells(FirePValue, 1) = ""
    If Sheets("nBals_StaticData").Cells(FirePValue, 10) = mFireClass Then
      mFireProb = Application.WorksheetFunction.RandBetween(0, 1000) / 1000
      mBalRow = GetnBal_Row(Sheets("nBals_StaticData").Cells(FirePValue, 1), "nBals_DynamicData")
      Sheets("nBals_DynamicData").Cells(FirePValue, 9) = mFireProb
    End If
    FirePValue = FirePValue + 1
  Loop

  'Find the nBal the scored the Max Fire Probability
  mFireMax = Application.WorksheetFunction.Max(Sheets("nBals_DynamicData").Range("I2:I810"))
```

```
    FirePValue = 2
    Do Until Sheets("nBals_DynamicData").Cells(FirePValue, 1) = ""
        If Sheets("nBals_DynamicData").Cells(FirePValue, 9) = mFireMax Then
            Fire_GetFirenBal = Sheets("nBals_DynamicData").Cells(FirePValue, 1)
            Exit Do
        End If
        FirePValue = FirePValue + 1
    Loop
End Function

Private Function Fire_GetFireStatus(ByVal mFirenBal As String) As Boolean
    ' the Ignition will turn into a fire if:
    '1 Veld Age

    Fire_GetFireStatus = False
    'Set a random Variable for Veld Age Probability
    veldAgeP = Application.WorksheetFunction.RandBetween(0, 100)
    mVeldAge = Sheets("nBals_DynamicData").Cells(GetnBal_Row(mFirenBal, "nBals_DynamicData"), 8)

    If mVeldAge >= 25 Then Fire_GetFireStatus = True: Exit Function
    If mVeldAge >= 20 And veldAgeP >= 20 Then Fire_GetFireStatus = True: Exit Function
    If mVeldAge >= 15 And veldAgeP >= 40 Then Fire_GetFireStatus = True: Exit Function
    If mVeldAge >= 10 And veldAgeP >= 60 Then Fire_GetFireStatus = True: Exit Function
    If mVeldAge >= 5 And veldAgeP >= 80 Then Fire_GetFireStatus = True: Exit Function
End Function

Private Function Fire_Severity(ByVal iRndNum As Single) As Double
    Fire_Severity = 0
    Fire_Severity = Round(Sheets("Fire_FDI").Cells(iRndNum, 13), 2)
End Function

Private Function Fire_BurnIndFire(ByVal mFireArea As Double, ByVal inBal As String, ByVal iFire_Severity As
Double) As Double
    Fire_BurnIndFire = 0
    'Clear out the previous fire List
    Sheets("nBal_FireList").Range("A2:A500") = ""
    ' Application.StatusBar = "nBals Burning:" & inBal
    mAreaBurnt = 0
    mBalRowD = GetnBal_Row(inBal, "nBals_DynamicData")
    mBalRowS = GetnBal_Row(inBal, "nBals_StaticData")
    mAreaBurnt = mAreaBurnt + Sheets("nBals_StaticData").Cells(mBalRowS, 3)     'The Area Burnt in the
Individual Fire
    Sheets("nBals_DynamicData").Cells(mBalRowD, 8) = -1                    'VeldAge
    Sheets("nBals_DynamicData").Cells(mBalRowD, 10) = iFire_Severity
    Sheets("nBals_DynamicData").Cells(mBalRowD, 11) = -1                   'Tag to Allow AIA to decrease
    Fire_RemoveVegandSeed inBal, iFire_Severity, 1

    sCount = 2
    tCount = 1
    Sheets("nBal_FireList").Cells(sCount, 1) = inBal
    Do Until mAreaBurnt >= mFireArea Or Sheets("nBal_FireList").Cells(sCount, 1) = ""   'Fire larger than
expected area or no more nBals to burn
        ScnBal = Sheets("nBal_FireList").Cells(sCount, 1)
        'Find Target nBal, If Target is greater than 5 Years, The add to source list, get nBal ha and add to
mAreaBurnt
        fTgnBal = 2
        Do Until Sheets("nBal_Neighbours").Cells(fTgnBal, 1) = ""
```

```
        If Sheets("nBal_Neighbours").Cells(fTgnBal, 1) = ScnBal Then
          'Get nBal Size,  Tag Veld Age, Tag burn severity and Remove Plants and Seeds
          TgnBal = Sheets("nBal_Neighbours").Cells(fTgnBal, 2)
          mBalRowD = GetnBal_Row(TgnBal, "nBals_DynamicData")
          mBalRowS = GetnBal_Row(TgnBal, "nBals_StaticData")
          mnBalAge = Sheets("nBals_DynamicData").Cells(mBalRowD, 8)
          If mnBalAge > 5 Then
            ' Application.StatusBar = "nBals Burning:" & inBal & " - " & TgnBal
            mAreaBurnt = mAreaBurnt + Sheets("nBals_StaticData").Cells(mBalRowS, 3)     'The Area Burnt
            Sheets("nBals_DynamicData").Cells(mBalRowD, 8) = -1
            Sheets("nBals_DynamicData").Cells(mBalRowD, 10) = iFire_Severity
            Sheets("nBals_DynamicData").Cells(mBalRowD, 11) = -1              'Tag for Available Invaded
Area
            mBurntnBalID = Sheets("nBals_StaticData").Cells(mBalRowS, 1)
            'Fire_RemoveVegandSeed
            Fire_RemoveVegandSeed mBurntnBalID, iFire_Severity, 1
            'Add the TgnBal to the FireList
            Do Until Sheets("nBal_FireList").Cells(tCount, 1) = ""
              tCount = tCount + 1
            Loop
            Sheets("nBal_FireList").Cells(tCount, 1) = TgnBal
            If mAreaBurnt >= mFireArea Then Exit Do
          End If  'mnBalAge > 5
        End If  'Sheets("nBal_Neighbours")
        fTgnBal = fTgnBal + 1
      Loop
      sCount = sCount + 1
    Loop    'mAreaBurnt >= mFireArea

    Fire_BurnIndFire = mAreaBurnt

End Function

Private Sub Fire_RemoveVegandSeed(ByVal iBal As String, ByVal mFireSeverity As Double, ByVal iCalcType As
Integer)
    'The servity (FDI Calc) of the fire determins how many plants and seeds are destroyed
    'Alert Stages/ Colour codes, FDI, Fire Danger, Ratings
    'BLUE, 0-20, Low, Insignificant
    'GREEN, 21-45, Moderate, Low
    'YELLOW, 46-60, dangerous, Medium
    'ORANGE, 61-75, Very dangerous, high
    'RED, 76-100, Extremely dangerous, Extremely high
    FireBal = 2
    Do Until Sheets("M_Pop_All").Cells(FireBal, 1) = ""
      If Sheets("M_Pop_All").Cells(FireBal, 1) = iBal Then
        Sheets("M_Pop_All").Cells(FireBal, 1).Interior.ColorIndex = 38
        If mFireSeverity <= 45 Then
          mFireSeverityA = 1 - (mFireSeverity / 45)       ' turned into a proportion of 1
          'Litter Layer of Seeds
          Sheets("M_Pop_All").Cells(FireBal, 63) = Sheets("M_Pop_All").Cells(FireBal, 63) * mFireSeverityA
          mFireSeverityA = 1 - (mFireSeverity / 100)
          If iCalcType = 1 Then
            For f = 6 To 61
              Sheets("M_Pop_All").Cells(FireBal, f) = Sheets("M_Pop_All").Cells(FireBal, f) * mFireSeverityA
            Next f
          End If
        End If
```

```
            If mFireSeverity > 45 And mFireSeverity <= 60 Then
              mFireSeverityA = 1 - (mFireSeverity / 60)      ' turned into a proportion of 1
              Sheets("M_Pop_All").Cells(FireBal, 63) = 0
              Sheets("M_Pop_All").Cells(FireBal, 64) = Sheets("M_Pop_All").Cells(FireBal, 64) * mFireSeverityA
              mFireSeverityA = 1 - (mFireSeverity / 100)
              If iCalcType = 1 Then
                For f = 6 To 61
                  Sheets("M_Pop_All").Cells(FireBal, f) = Sheets("M_Pop_All").Cells(FireBal, f) * mFireSeverityA
                Next f
              End If
            End If

            If mFireSeverity > 60 And mFireSeverity <= 75 Then
              mFireSeverityA = 1 - (mFireSeverity / 75)      ' turned into a proportion of 1
              Sheets("M_Pop_All").Cells(FireBal, 63) = 0
              Sheets("M_Pop_All").Cells(FireBal, 64) = 0
              Sheets("M_Pop_All").Cells(FireBal, 65) = Sheets("M_Pop_All").Cells(FireBal, 65) * mFireSeverityA
              mFireSeverityA = 1 - (mFireSeverity / 100)
              If iCalcType = 1 Then
                For f = 6 To 61
                  Sheets("M_Pop_All").Cells(FireBal, f) = Sheets("M_Pop_All").Cells(FireBal, f) * mFireSeverityA
                Next f
              End If
            End If

            If mFireSeverity > 75 Then
              mFireSeverityA = 1 - (mFireSeverity / 100)      ' turned into a proportion of 1
              Sheets("M_Pop_All").Cells(FireBal, 63) = 0
              Sheets("M_Pop_All").Cells(FireBal, 64) = 0
              Sheets("M_Pop_All").Cells(FireBal, 65) = 0
              Sheets("M_Pop_All").Cells(FireBal, 66) = Sheets("M_Pop_All").Cells(FireBal, 66) * mFireSeverityA
              If iCalcType = 1 Then
                For f = 6 To 61
                  Sheets("M_Pop_All").Cells(FireBal, f) = Sheets("M_Pop_All").Cells(FireBal, f) * mFireSeverityA
                Next f
              End If
            End If
          End If
          FireBal = FireBal + 1
        Loop

End Sub

Private Function nBal_WasBurnt(inBalID As String) As Boolean
    nBal_WasBurnt = False
    iBal = 2
    Do Until Worksheets("nBals_DynamicData").Cells(iBal, 1) = ""
      If Worksheets("nBals_DynamicData").Cells(iBal, 1) = inBalID Then
        If Worksheets("nBals_DynamicData").Cells(iBal, 8) = 0 Then
          nBal_WasBurnt = True
        End If
        Exit Do
      End If
     iBal = iBal + 1
    Loop
End Function
```

```
Sub iQuater5()
' Called at the end of each model year to write date to the output sheets
   Application.StatusBar = "S:" & iModelSimulate & " Y:" & iModelYear + 1 & " Dat Output Q5"

'1. Add the plants per Ha
   mplot = 2 ' First row of the data
   Do Until Sheets("M_Pop_All").Cells(mplot, 1) = ""
      Sheets("M_Pop_All").Cells(mplot, 3) =
Application.WorksheetFunction.Sum(Range(Sheets("M_Pop_All").Cells(mplot, 5),
Sheets("M_Pop_All").Cells(mplot, 61)))
      mplot = mplot + 1
   Loop

'Plants
   nBal = 6: pTot = 0: pHa = 0: sTot = 0
   Do Until Sheets("DataOut_Plants").Cells(nBal, 1) = ""
      nBal_ID = Sheets("DataOut_Plants").Cells(nBal, 1)
      nBal_Ha = Sheets("DataOut_Plants").Cells(nBal, 2)
      Sheets("DataOut_Plants").Cells(nBal, iModelYear + 4) = GetnBal_PlantsHa(nBal_ID)
      pTot = pTot + (Sheets("DataOut_Plants").Cells(nBal, iModelYear + 4) * nBal_Ha)
      pHa = pHa + nBal_Ha
      nBal = nBal + 1
   Loop

'Add Totals at top of sheet
   mTime = mTimeQEnd - mTimeQStart
   mTime = Right(CStr(Format(mTime, "hh mm ss")), 5)
   Sheets("DataOut_Plants").Cells(1, iModelYear + 4) = mTime
   Sheets("DataOut_Plants").Cells(2, iModelYear + 4) = pTot              ' Total Plants
   Sheets("DataOut_Plants").Cells(3, iModelYear + 4) = pTot / pHa         ' Plants / ha
   Sheets("DataOut_Plants").Cells(4, iModelYear + 4) = Round((pTot / Sheets("DataOut_Plants").Cells(2, 3)) *
100, 2) ' Cumalitive Reduction %

'2. Add the Person Days Used
   pTot = 0: pHa = 0
   nBal = 2    ' First Row of Data
   Do Until Sheets("nBals_DynamicData").Cells(nBal, 1) = ""
      Sheets("DataOut_PD").Cells(nBal + 5, iModelYear + 4) = Sheets("nBals_DynamicData").Cells(nBal, 7)
      Sheets("nBals_DynamicData").Cells(nBal, 7) = 0                          ' reset the value for the next year
         pTot = pTot + Sheets("DataOut_PD").Cells(nBal + 5, iModelYear + 4)             ' Total pd
         If Sheets("DataOut_PD").Cells(nBal + 5, iModelYear + 4) > 0 Then
            pHa = pHa + Sheets("DataOut_PD").Cells(nBal + 5, 2)
         End If

      nBal = nBal + 1
   Loop
'Add Totals at top of sheet
   Sheets("DataOut_PD").Cells(2, iModelYear + 4) = pTot              ' Total PD
   Sheets("DataOut_PD").Cells(3, iModelYear + 4) = pHa              ' Total PD
   Sheets("DataOut_PD").Cells(4, iModelYear + 4) = pTot / pHa         ' PD / ha
   If iModelYear > 0 Then
      Sheets("DataOut_PD").Cells(5, iModelYear + 4) = Round(((pTot / pHa) / Sheets("DataOut_PD").Cells(4, 4))
* 100, 2) ' % Cumalitive Reduction in PD/HA
   Else
      Sheets("DataOut_PD").Cells(5, iModelYear + 4) = 1
```

```
    End If

'3. Add the Seeds per Ha
    mplot = 2 ' First row of the data
    Do Until Sheets("M_Pop_All").Cells(mplot, 1) = ""
        Sheets("M_Pop_All").Cells(mplot, 75) =
Application.WorksheetFunction.Sum(Range(Sheets("M_Pop_All").Cells(mplot, 63),
Sheets("M_Pop_All").Cells(mplot, 72)))
        mplot = mplot + 1
    Loop

    sTot = 0: sHa = 0
    nBal = 6    ' First Row of Data
    Do Until Sheets("DataOut_Seeds").Cells(nBal, 1) = ""
        nBal_ID = Sheets("DataOut_Seeds").Cells(nBal, 1)
        Sheets("DataOut_Seeds").Cells(nBal, iModelYear + 4) = GetnBal_SeedsHa(nBal_ID)
        sTot = sTot + (Sheets("DataOut_Seeds").Cells(nBal, 2) * Sheets("DataOut_Seeds").Cells(nBal, iModelYear +
4))
        sHa = sHa + Sheets("DataOut_Seeds").Cells(nBal, 2)
        nBal = nBal + 1
    Loop
'Add Totals at top of sheet
    mTime = mTimeQEnd - mTimeQStart
    mTime = Right(CStr(Format(mTime, "hh mm ss")), 5)
    Sheets("DataOut_Seeds").Cells(1, iModelYear + 4) = mTime
    Sheets("DataOut_Seeds").Cells(2, iModelYear + 4) = sTot              ' Total Plants
    Sheets("DataOut_Seeds").Cells(3, iModelYear + 4) = sTot / sHa         ' Seeds / ha
    Sheets("DataOut_Seeds").Cells(4, iModelYear + 4) = Round((sTot / Sheets("DataOut_Seeds").Cells(2, 3)) *
100, 2) ' Cumalive Reduction %

'Reset the number of plants cleared & increment Time since Cleared
    d = 2
    Do Until Sheets("nBals_DynamicData").Cells(d, 1) = ""
        Sheets("nBals_DynamicData").Cells(d, 4) = 0
        Sheets("nBals_DynamicData").Cells(d, 12) = Sheets("nBals_DynamicData").Cells(d, 12) + 1
        d = d + 1
    Loop

  ActiveWorkbook.Save

End Sub

Private Sub Write_PDused(ByVal iBal As String, ByVal iHa As Single)
    fBal = 7
    FoundBal = False

    Do Until Sheets("DataOut_PD").Cells(fBal, 1) = "" Or FoundBal = True
        If Sheets("DataOut_PD").Cells(fBal, 1) = iBal Then
            Sheets("DataOut_PD").Cells(fBal, iModelYear + 4) = mnBal_PdNeed        ' From the Common Variable
            FoundBal = True
        End If
        fBal = fBal + 1
    Loop

    If FoundBal = False Then
            Sheets("DataOut_PD").Cells(fBal, 1) = iBal
            Sheets("DataOut_PD").Cells(fBal, 2) = iHa
```

```
      Sheets("DataOut_PD").Cells(fBal, iModelYear + 4) = mnBal_PdNeed        ' From the Common Variable
   End If

End Sub

Sub nBal_ScheduleSort(ByVal mSortType As String)

   If mSortType = "Systematic" Then
      'Do Nothing as the list is already set
      Exit Sub
   End If

   If mSortType = "Random" Then
      Schedule_MakeRandomList
      Worksheets("M_nBal_Schedule").Sort.SortFields.Clear
      Worksheets("M_nBal_Schedule").Sort.SortFields.Add _
         Key:=Range("J2:J1000"), SortOn:=xlSortOnValues, Order:=xlAscending,
DataOption:=xlSortTextAsNumbers
      With Worksheets("M_nBal_Schedule").Sort
         .SetRange Range("A1:J1000"): .Header = xlYes: .MatchCase = False
         .Orientation = xlTopToBottom: .SortMethod = xlPinYin
         .Apply
      End With
      Exit Sub
   End If

   If mSortType = "Consensus" Then
      Schedule_MakePriorityList 1
   End If

   If mSortType = "Water production" Then
      Schedule_MakePriorityList 2
   End If

   If mSortType = "Maintain follow-ups" Then
      Schedule_MakePriorityList 3
   End If

   If mSortType = "Keep It Clean" Then
      Schedule_MakePriorityList 4
   End If

   Worksheets("M_nBal_Schedule").Sort.SortFields.Clear
   Worksheets("M_nBal_Schedule").Sort.SortFields.Add _
      Key:=Range("I2:I1000"), SortOn:=xlSortOnValues, Order:=xlDescending,
DataOption:=xlSortTextAsNumbers
   With Worksheets("M_nBal_Schedule").Sort
      .SetRange Range("A1:I1000"): .Header = xlYes: .MatchCase = False
      .Orientation = xlTopToBottom: .SortMethod = xlPinYin
      .Apply
   End With

End Sub

Sub Schedule_MakeRandomList()
   nBal = 2
   Do Until Sheets("M_nBal_Schedule").Cells(nBal, 1) = ""
```

```
        Sheets("M_nBal_Schedule").Cells(nBal, 10) = Application.WorksheetFunction.RandBetween(0, 3000)
        nBal = nBal + 1
    Loop
End Sub

Sub Schedule_MakePriorityList(iSchedule As Integer)
    mSchedule = iSchedule
    nBal = 2
    Do Until Sheets("M_nBal_Schedule").Cells(nBal, 1) = ""
        mnBal = Sheets("M_nBal_Schedule").Cells(nBal, 1)
        Sheets("M_nBal_Schedule").Cells(nBal, 2) = schLoad_AreaBurn(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 3) = schLoad_IPDensity(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 4) = schLoad_Topography(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 5) = schLoad_FireRisk(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 6) = schLoad_IPAgeClass(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 7) = schLoad_IPType(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 8) = schLoad_LastClear(mnBal, mSchedule)
        Sheets("M_nBal_Schedule").Cells(nBal, 9) = _
        Application.WorksheetFunction.Sum(Range(Sheets("M_nBal_Schedule").Cells(nBal, 2), _
        Sheets("M_nBal_Schedule").Cells(nBal, 8)))
        nBal = nBal + 1
    Loop
End Sub
Private Function schLoad_AreaBurn(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_AreaBurn = 0
    mVeldAge = GetnBal_VeldAge(iBal)
    If mVeldAge > 3 Then
        mVeldI = Sheets("Strat_SelecWeights").Cells(6, iSchedule + 1)
    Else
        mVeldI = Sheets("Strat_SelecWeights").Cells(5, iSchedule + 1)
    End If
    schLoad_AreaBurn = mVeldI * Sheets("Strat_SelecWeights").Cells(4, iSchedule + 1)

End Function

Private Function schLoad_IPDensity(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_IPDensity = 0
    IPDensity = GetnBal_PlantsHa(iBal)
        If IPDensity >= 56666 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(9, iSchedule + 1) 'close
        If IPDensity >= 31533 And IPDensity < 56666 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(10,
iSchedule + 1) 'dense
        If IPDensity >= 90667 And IPDensity < 31533 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(11,
iSchedule + 1) 'medium
        If IPDensity >= 1633 And IPDensity < 90667 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(12,
iSchedule + 1) 'scattered
        If IPDensity >= 180 And IPDensity < 1633 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(13,
iSchedule + 1) ' very scattered
        If IPDensity > 1 And IPDensity < 180 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(14, iSchedule +
1) ' occasional
        If IPDensity <= 1 Then IPDensityI = Sheets("Strat_SelecWeights").Cells(15, iSchedule + 1)  ' Rare

    schLoad_IPDensity = IPDensityI * Sheets("Strat_SelecWeights").Cells(8, iSchedule + 1)

End Function

Private Function schLoad_Topography(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_Topography = 0
```

```
    If iSchedule <> 2 Then
        TopographyI = GetnBal_Topo1(iBal)
    Else
        TopographyI = GetnBal_Topo2(iBal)
    End If
    schLoad_Topography = TopographyI * Sheets("Strat_SelecWeights").Cells(17, iSchedule + 1)
End Function

Private Function schLoad_FireRisk(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_FireRisk = 0
    mVeldAge = GetnBal_VeldAge(iBal)
    mCoastal_Scree = fnCoastalScree(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mCoastal_Scree

    mDune_Asteraceous_Fynbos = fnDuneAsteraceousFynbos(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mDune_Asteraceous_Fynbos

    mEricaceous_Fynbos = fnEricaceousFynbos(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mEricaceous_Fynbos

    mForest_Thicket = fnForestThicket(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mForest_Thicket

    mMesic_Mesotrophic_Proteoid = fnMesicMesotrophicProteoid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mMesic_Mesotrophic_Proteoid

    mMesic_Oligotrophic_Proteoid = fnMesicOligotrophicProteoid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mMesic_Oligotrophic_Proteoid

    mRenosterveld = fnRenosterveld(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mRenosterveld

    mSandplain_Proteoid = fnSandplainProteoid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mSandplain_Proteoid

    mCliff_Communities = fnCliffCommunities(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mCliff_Communities

    mUpland_Restioid = fnUplandRestioid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mUpland_Restioid

    mVlei = fnVlei(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mVlei

    mWet_Mesotrophic_Proteoid = fnWetMesotrophicProteoid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mWet_Mesotrophic_Proteoid

    mWet_Oligitrophic_Proteoid = fnWetOligitrophicProteoid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mWet_Oligitrophic_Proteoid

    mWet_Restioid = fnWetRestioid(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mWet_Restioid

    mWetlands = fnWetlands(iBal, mVeldAge)
    schLoad_FireRisk = schLoad_FireRisk + mWetlands

    If schLoad_FireRisk <= 1.333 Then FireRiskCat = 0.07
```

```
    If schLoad_FireRisk > 1.333 And schLoad_FireRisk <= 2.666 Then FireRiskCat = 0.28
    If schLoad_FireRisk > 2.666 Then FireRiskCat = 0.65

    schLoad_FireRisk = FireRiskCat * Sheets("Strat_SelecWeights").Cells(22, iSchedule + 1)

End Function

Private Function schLoad_IPAgeClass(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_IPAgeClass = 0

    mCoverSeedling = GetnBal_CoverSeedlings(iBal)
    mCoverYoung = GetnBal_CoverYoung(iBal)
    mCoverAdult = GetnBal_CoverAdult(iBal)

    mCoverMax = Application.WorksheetFunction.Max(mCoverSeedling, mCoverYoung, mCoverAdult)

    If mCoverMax = mCoverSeedling Then IPDensityClass = Sheets("Strat_SelecWeights").Cells(30, iSchedule + 1)
    If mCoverMax = mCoverYoung Then IPDensityClass = Sheets("Strat_SelecWeights").Cells(29, iSchedule + 1)
    If mCoverMax = mCoverAdult Then IPDensityClass = Sheets("Strat_SelecWeights").Cells(28, iSchedule + 1)

    schLoad_IPAgeClass = IPDensityClass * Sheets("Strat_SelecWeights").Cells(27, iSchedule + 1)

End Function

Private Function schLoad_IPType(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_IPType = Sheets("Strat_SelecWeights").Cells(34, iSchedule + 1)
    schLoad_IPType = schLoad_IPType * Sheets("Strat_SelecWeights").Cells(32, iSchedule + 1)
End Function

Private Function schLoad_LastClear(ByVal iBal As String, ByVal iSchedule As Integer) As Double
    schLoad_LastClear = 0
    mClearTime = GetnBal_ClearTime(iBal)
    mPlantsHA = GetnBal_PlantsHa(iBal)
    If mClearTime >= 99 Then mLastClear = Sheets("Strat_SelecWeights").Cells(38, iSchedule + 1)
    If mClearTime >= 6 Then mLastClear = Sheets("Strat_SelecWeights").Cells(39, iSchedule + 1)
    If mClearTime < 6 Then
        If mPlantsHA > 1 Then
            mLastClear = Sheets("Strat_SelecWeights").Cells(40, iSchedule + 1)
        Else
            mLastClear = Sheets("Strat_SelecWeights").Cells(41, iSchedule + 1)
        End If
    End If
    schLoad_LastClear = mLastClear * Sheets("Strat_SelecWeights").Cells(37, iSchedule + 1)

End Function

Sub Write_SimulationData()
    'This writes out the full files at the end of simulation
    mFileName = mFileLoc & "SIM " & iModelSimulate & " DataOut_Plants.txt"
    mSheet = "DataOut_Plants"
    Write_FileData mFileName, mSheet

    mFileName = mFileLoc & "SIM " & iModelSimulate & " DataOut_PD.txt"
    mSheet = "DataOut_PD"
    Write_FileData mFileName, mSheet

    mFileName = mFileLoc & "SIM " & iModelSimulate & " DataOut_Seeds.txt"
```

```
    mSheet = "DataOut_Seeds"
    Write_FileData mFileName, mSheet

    mFileName = mFileLoc & "SIM " & iModelSimulate & " DataOut_Fire.txt"
    mSheet = "DataOut_FireHA"
    Write_FileData mFileName, mSheet

    'This Writes out the Plant Totals
    mFileName = mFileLoc & "Plants.txt"
    mSheet = "DataOut_Plants"
    Write_FileTotals mFileName, mSheet, 2


    'This Writes out the PersonDays
    mFileName = mFileLoc & "PersonDays.txt"
    mSheet = "DataOut_PD"
    Write_FileTotals mFileName, mSheet, 2

    'This Writes out the Ha Cleared
    mFileName = mFileLoc & "HaCleared.txt"
    mSheet = "DataOut_PD"
    Write_FileTotals mFileName, mSheet, 3

    'This Writes out the Seeds Totals
    mFileName = mFileLoc & "Seeds.txt"
    mSheet = "DataOut_Seeds"
    Write_FileTotals mFileName, mSheet, 2

    'This Writes out the Ha Burnt Totals
    mFileName = mFileLoc & "HaBurnt.txt"
    mSheet = "DataOut_FireHA"
    Write_FileTotals mFileName, mSheet, 2

    'This makes a copy of the nBals Treated
    For nB = 2 To 811
        Sheets("DataOut_Treatements").Cells(nB, iModelSimulate + 1) = Sheets("nBals_DynamicData").Cells(nB -
1, 6)
    Next nB

End Sub

Sub Write_FileData(ByVal iFile As String, ByVal iSheet As String)

    Dim fso As New FileSystemObject
    Dim mTextStream As TextStream
    Dim mText As String
    'Create and Open the File (iFile)
    mFileName = iFile

    Set mTextStream = fso.OpenTextFile(mFileName, ForAppending, True)
    mText = Sheets(iSheet).Cells(1, 1) & vbTab
    mText = mText & Sheets(iSheet).Cells(1, 2) & vbTab

    mTextStream.WriteLine (mText)

        wrL = 2         'First Line of Real Data
        Do Until Sheets(iSheet).Cells(wrL, 1) = ""
```

```
        mText = ""                          ' Reset the Text
        For wrC = 1 To iModelYear + 4
          mText = mText & Sheets(iSheet).Cells(wrL, wrC) & vbTab
        Next wrC
        mTextStream.WriteLine (mText)           'Write the Data
        wrL = wrL + 1
      Loop

   mTextStream.Close

End Sub

Sub Write_FileTotals(ByVal iFile As String, ByVal iSheet As String, ByVal tRow As Single)

   Dim fso As New FileSystemObject
   Dim mTextStream As TextStream
   Dim mText As String
   'Create and Open the File (iFile)
   mFileName = iFile

   Set mTextStream = fso.OpenTextFile(mFileName, ForAppending, False)
   mText = ""
   mText = iModelSimulate & vbTab

   If iSheet = "DataOut_FireHA" Then
      ds = 2
   Else
      ds = 3
   End If

   For dc = ds To iModelYear + 3
     mText = mText & Sheets(iSheet).Cells(tRow, dc) & vbTab
   Next dc
   mTextStream.WriteLine (mText)

End Sub

Sub Model_ResetNextSimulate()

   iQuater0 False

End Sub

Private Function fnCoastalScree(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
   fnCoastalScree = 0
   fnCoastalScreeP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 2, False)
   fnCoastalScreeHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
   fnCoastalScreeP = fnCoastalScreeP / fnCoastalScreeHa
   If fnCoastalScreeP > 0 Then
      FireHaz = 0
      If mVeldAge < 2.1 Then FireHaz = 1
      If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
      If mVeldAge > 5.1 And mVeldAge < 11.1 Then FireHaz = 3
      If mVeldAge > 11.1 Then FireHaz = 4
   End If
```

```
   fnCoastalScree = FireHaz * fnCoastalScreeP
End Function

Private Function fnDuneAsteraceousFynbos(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
   fnDuneAsteraceousFynbos = 0
   fnDuneAsteraceousFynbosP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 3, False)
   fnDuneAsteraceousFynbosHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
   fnDuneAsteraceousFynbosP = fnDuneAsteraceousFynbosP / fnDuneAsteraceousFynbosHa
   If fnDuneAsteraceousFynbosP > 0 Then
      FireHaz = 0
      If mVeldAge < 2.1 Then FireHaz = 1
      If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
      If mVeldAge > 5.1 And mVeldAge < 11.1 Then FireHaz = 3
      If mVeldAge > 11.1 Then FireHaz = 4
   End If
   fnDuneAsteraceousFynbos = FireHaz * fnDuneAsteraceousFynbosP
End Function

Private Function fnEricaceousFynbos(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
   fnEricaceousFynbos = 0
   fnEricaceousFynbosP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 4, False)
   fnEricaceousFynbosHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
   fnEricaceousFynbosP = fnEricaceousFynbosP / fnEricaceousFynbosHa
   If fnEricaceousFynbosP > 0 Then
      FireHaz = 0
      If mVeldAge < 2.1 Then FireHaz = 1
      If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
      If mVeldAge > 5.1 And mVeldAge < 11.1 Then FireHaz = 3
      If mVeldAge > 11.1 Then FireHaz = 4
   End If
   fnEricaceousFynbos = FireHaz * fnEricaceousFynbosP
End Function

Private Function fnForestThicket(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
   fnForestThicket = 0
   fnForestThicketP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 5, False)
   fnForestThicketHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
   fnForestThicketP = fnForestThicketP / fnForestThicketHa
   If fnForestThicketP > 0 Then
      FireHaz = 0
      If mVeldAge Then FireHaz = 1
   End If
   fnForestThicket = FireHaz * fnForestThicketP
End Function

Private Function fnMesicMesotrophicProteoid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
   fnMesicMesotrophicProteoid = 0
   fnMesicMesotrophicProteoidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 6, False)
   fnMesicMesotrophicProteoidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
```

```
    fnMesicMesotrophicProteoidP = fnMesicMesotrophicProteoidP / fnMesicMesotrophicProteoidHa
    If fnMesicMesotrophicProteoidP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 2
        If mVeldAge > 8.1 And mVeldAge < 11.1 Then FireHaz = 3
        If mVeldAge > 11.1 Then FireHaz = 4
    End If
    fnMesicMesotrophicProteoid = FireHaz * fnMesicMesotrophicProteoidP
End Function

Private Function fnMesicOligotrophicProteoid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnMesicOligotrophicProteoid = 0
    fnMesicOligotrophicProteoidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 7, False)
    fnMesicOligotrophicProteoidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnMesicOligotrophicProteoidP = fnMesicOligotrophicProteoidP / fnMesicOligotrophicProteoidHa
    If fnMesicOligotrophicProteoidP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 2
        If mVeldAge > 8.1 And mVeldAge < 11.1 Then FireHaz = 3
        If mVeldAge > 11.1 Then FireHaz = 4
    End If
    fnMesicOligotrophicProteoid = FireHaz * fnMesicOligotrophicProteoidP
End Function

Private Function fnRenosterveld(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnRenosterveld = 0
    fnRenosterveldP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 8, False)
    fnRenosterveldHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnRenosterveldP = fnRenosterveldP / fnRenosterveldHa
    If fnRenosterveldP > 0 Then
        FireHaz = 0
        If mVeldAge < 2.1 Then FireHaz = 1
        If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 3
        If mVeldAge > 5.1 Then FireHaz = 4
    End If
    fnRenosterveld = FireHaz * fnRenosterveldP
End Function

Private Function fnSandplainProteoid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnSandplainProteoid = 0
    fnSandplainProteoidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 9, False)
    fnSandplainProteoidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnSandplainProteoidP = fnSandplainProteoidP / fnSandplainProteoidHa
    If fnSandplainProteoidP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 2
        If mVeldAge > 8.1 And mVeldAge < 14.1 Then FireHaz = 3
        If mVeldAge > 14.1 Then FireHaz = 4
```

```
    End If
    fnSandplainProteoid = FireHaz * fnSandplainProteoidP
End Function

Private Function fnCliffCommunities(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnCliffCommunities = 0
    fnCliffCommunitiesP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 10, False)
    fnCliffCommunitiesHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnCliffCommunitiesP = fnCliffCommunitiesP / fnCliffCommunitiesHa
    If fnCliffCommunitiesP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 14.1 Then FireHaz = 2
        If mVeldAge > 14.1 And mVeldAge < 24.1 Then FireHaz = 3
        If mVeldAge > 24.1 Then FireHaz = 4
    End If
    fnCliffCommunities = FireHaz * fnCliffCommunitiesP
End Function

Private Function fnUplandRestioid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnUplandRestioid = 0
    fnUplandRestioidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 11, False)
    fnUplandRestioidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnUplandRestioidP = fnUplandRestioidP / fnUplandRestioidHa
    If fnUplandRestioidP > 0 Then
        FireHaz = 0
        If mVeldAge < 2.1 Then FireHaz = 1
        If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 3
        If mVeldAge > 8.1 Then FireHaz = 4
    End If
    fnUplandRestioid = FireHaz * fnUplandRestioidP
End Function

Private Function fnVlei(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnVlei = 0
    fnVleiP = Application.WorksheetFunction.VLookup(iBal, Worksheets("nBal_VegTypes").Range("Veg_Types"),
12, False)
    fnVleiHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnVleiP = fnVleiP / fnVleiHa
    If fnVleiP > 0 Then
        FireHaz = 0
        If mVeldAge < 2.1 Then FireHaz = 1
        If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
        If mVeldAge > 5.1 Then FireHaz = 4
    End If
    fnVlei = FireHaz * fnVleiP
End Function

Private Function fnWetMesotrophicProteoid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnWetMesotrophicProteoid = 0
```

```
    fnWetMesotrophicProteoidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 13, False)
    fnWetMesotrophicProteoidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnWetMesotrophicProteoidP = fnWetMesotrophicProteoidP / fnWetMesotrophicProteoidHa
    If fnWetMesotrophicProteoidP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 2
        If mVeldAge > 8.1 And mVeldAge < 11.1 Then FireHaz = 3
        If mVeldAge > 11.1 Then FireHaz = 4
    End If
    fnWetMesotrophicProteoid = FireHaz * fnWetMesotrophicProteoidP
End Function

Private Function fnWetOligitrophicProteoid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnWetOligitrophicProteoid = 0
    fnWetOligitrophicProteoidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 14, False)
    fnWetOligitrophicProteoidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnWetOligitrophicProteoidP = fnWetOligitrophicProteoidP / fnWetOligitrophicProteoidHa
    If fnWetOligitrophicProteoidP > 0 Then
        FireHaz = 0
        If mVeldAge < 5.1 Then FireHaz = 1
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 2
        If mVeldAge > 8.1 And mVeldAge < 11.1 Then FireHaz = 3
        If mVeldAge > 11.1 Then FireHaz = 4
    End If
    fnWetOligitrophicProteoid = FireHaz * fnWetOligitrophicProteoidP
End Function

Private Function fnWetRestioid(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnWetRestioid = 0
    fnWetRestioidP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 15, False)
    fnWetRestioidHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnWetRestioidP = fnWetRestioidP / fnWetRestioidHa
    If fnWetRestioidP > 0 Then
        FireHaz = 0
        If mVeldAge < 2.1 Then FireHaz = 1
        If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
        If mVeldAge > 5.1 And mVeldAge < 8.1 Then FireHaz = 3
        If mVeldAge > 8.1 Then FireHaz = 4
    End If
    fnWetRestioid = FireHaz * fnWetRestioidP
End Function

Private Function fnWetlands(ByVal iBal As String, ByVal mVeldAge As Integer) As Double
    fnWetlands = 0
    fnWetlandsP = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 16, False)
    fnWetlandsHa = Application.WorksheetFunction.VLookup(iBal,
Worksheets("nBal_VegTypes").Range("Veg_Types"), 18, False)
    fnWetlandsP = fnWetlandsP / fnWetlandsHa
    If fnWetlandsP > 0 Then
```

```
      FireHaz = 0
      If mVeldAge < 2.1 Then FireHaz = 1
      If mVeldAge > 2.1 And mVeldAge < 5.1 Then FireHaz = 2
      If mVeldAge > 5.1 Then FireHaz = 4
   End If
   fnWetlands = FireHaz * fnWetlandsP
End Function
'The End... :)
```