Imperial College London

Faculty of Natural Sciences

How uncertainty affects conservation planning – a Florida case study

By

Paul De Ornellas

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Abstract

The need for sound decision making in conservation planning is as important today as it ever has been. To meet this need conservation practitioners have developed a range of tools to help make better use of the information at their disposal. Decision-theory, a structured approach involving explicit goals and objectives is now widely applied, most commonly in the field of systematic conservation planning. The planning process relies on data, information which is subject to bias and uncertainty. The need to understand how this might impact upon the decisions we make in conservation planning would seem evident. Few studies have sought to assess the impact of how data uncertainty affects planning method outputs in an applied scenario. In this study I conducted a sensitivity analysis on the Protection Index, a conservation metric based on the IUCN distributional indicators NOO, AOO and EOO, recently used as a planning tool in Florida. Using the Florida Natural Areas Inventory database I assessed species current conservation status in the managed area network and the benefit of adding the Nature Conservancy's portfolio of sites. Analysis of the database revealed significant taxonomic and threat rank biases in species occurrences. By deleting data from the database in the biased manner identified in the original data set we replicated a 'data poor' scenario, typical of many real situations. A sensitivity test was performed on the Protection Index using this biased deleted data and an unbiased deleted set. Comparing their effects on the Protection Indexes measure of conservation benefit and site performance allowed the effects of data loss and bias on planning priorities to be assessed. It was found that certain high performing sites with only a few 'high value' occurrences were more sensitive to data depletion than those with many occurrences. Planners should be aware that elsewhere in the world similar sites with real benefit might be missed by planning methods due to poor quality data. These findings also inform field work; to maximise benefit from surveys from a planning perspective it would be better to focus on poorly surveyed areas than adding to occurrences in already well represented sites. Similarly, identifying new populations of species is more important than intensively surveying those already known. This study has demonstrated the utility of sensitivity analysis for a conservation planning method in an applied scenario. In doing so it has shown that the effects of uncertainty and data quality on planning decisions can be significant and should not be ignored.

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1 Introduction

1.1 Decision making in conservation today

The pressures on biodiversity today are well documented (WWF 2006, MEA2005) and as a result the importance of making the best possible decisions about what to do, when and where (Wilson et al 2007) is clear. In many regions this means deciding where to allocate scarce resources to best maximise our goal of the persistence of biodiversity (Margules and Pressey 2000). The field of conservation planning has developed rapidly over the last 30 years, moving on from reserve design based on an ad-hoc or rule of thumb basis (Pressey 1994, Diamond 1975) to applying a decision theory approach, where goals and objectives are explicit (Shea et al 1998, Westphal and Possingham 2003, Nicholson & Possingham 2006). Although decision theory has been applied in a range of conservation scenarios its most common application has been in the field of systemic conservation planning; the design of protected areas or reserve design (Sarkar et al 2006, Margules and Pressey 2000). While the importance of defining goals and objectives has become generally accepted (Westphal & Possingham 2003, Nicholson & Possingham 2006), one key component of decision theory has been neglected in conservation planning, the quantification of uncertainty and its explicit consideration in the decision making process (Shea et al 1998).

1.2 The importance of data quality and uncertainty

All conservation decision making is based on information and is vulnerable to the uncertainty and bias inherent in all data (Pressey 2004, Wolman 2006). Data typically used in reserve planning includes; species distribution data either as occurrences, range maps or predictive models and habitat models. This information is prone to uncertainty and bias (Rondini et al 2006). This may take the form of sampling bias on taxonomic or spatial grounds, errors of omission due to the many problems in surveying and detecting all occurrences (Brown et al 2000) or errors of commission as old records are used even after populations are extirpated (Gaston & Rodrigues 2003, Rondini et al 2006). The scale at which data is collected can have an impact on decision making (Hulbert and Jetz 2007, Araujo 2004) as can the process by which it is analysed (Rae et al 2007). The acceptance of biological data at face value in the application of many conservation planning methods has been noted by Moilanen et al (2006).

This coupled with awareness of the uncertainty and biases inevitably present in all data gives us grounds for concern. How are uncertainties in input data impacting upon conservation planning decisions and ultimately implementation on the ground? It would seem crucial to try and explore this process as part of robust decision-making.

1.3 Data uncertainty in the literature

Sensitivity testing is the exploration of how variations in process output are due to variation in the inputs (Stoms et al 1992). Its utility as an approach is well accepted and it is has been used widely across a range of disciplines; including GIS (Crosetto & Tarantola 2001, Rae et al 2007), IUCN Red listing (Akcakaya et al 2000) and population viability analysis (McCarthy et al 1995, Dreschler 2004). Its application to assess the impacts of data uncertainty, bias and data quality in conservation planning is less well represented in the literature. A number of studies have directly tested the sensitivity of conservation planning tools to different habitat suitability models (Gaston & Rodrigues 2003, Hernandez et al 2006, Moilanen et al 2006, Rondinini et al 2006). Two studies by, Freitag & Van Jaarsveld (1998) and Grand et al (2007) conducted sensitivity analyses on site selection algorithms using South African species for theoretical rather than applied case studies. Both of these studies used data deletion on the basis of biases in the data to see how site selection varied. The lack of sensitivity testing to assess how data can affect outputs within the published literature in conservation planning is an omission and one which this study seeks to address.

1.4 Aims and Objectives

The overall goal of this study was to explore how uncertainty and data quality affects conservation planning decisions. To do this I applied the Protection Index (Turner et al (2006a), a metric for assessing conservation priorities, to a large and relatively comprehensive dataset in Florida. The Protection Index was developed by Turner et al (2006a) to measure conservation progress and identify priorities, based on the IUCN (2001, 2006) distributional criteria, AOO, EOO and NOO. The PI has been used in Florida to measure conservation progress in the managed area networks in the state and as a planning tool to assess the benefit of site acquisition portfolios (Nicholson et al 2007). I sought to expand upon this work and use the Protection Index as an example of a measure of conservation progress and perform a sensitivity analysis using the Florida Natural Areas Inventory (FNAI) dataset used by Nicholson et al (2007). This represented 181 species across the state, totalling almost 11,000 recorded occurrences.

1.4.1 The more specific aims and objectives of the study were:

1. To assess the performance of the Protection Index as it applies in the current managed area network in Florida, using the species records in the FNAI biodiversity database. I also assessed a real world planning scenario in the form of The Nature Conservancy's (TNC) acquisition portfolio (TNC2005). My focus here was to gain an understanding of how the Protection Index can guide conservation action in Florida through an assessment of current species protection and conservation priorities.

2. To conduct a sensitivity analysis of conservation priorities with changing data quality. This involved three main stages:

2.1 First by analysing existing biases in the FNAI dataset to allow us to better understand the data and to inform the main part of the analysis.

2.2 Secondly, by assessing the impact of spatial scale on the Protection Index. This involved developing new species habitat models and producing Area of Occurrence estimates for all species at a range of grid sizes. The significance of scale in distribution data and habitat models is well recognised (Araujo 2004, Hulbert & Jetz 2007) but the impact on planning at a fine scale is poorly studied. The study by Nicholson et al (2007) measured AOO at a 30m resolution so this study would also ensure it was assessed at the IUCN reference scale.

2.3 Finally, by conducting a sensitivity analysis of the Protection Index using a data depleted occurrence dataset. Two data depletion scenarios were explored; random deletion and biased random deletion of occurrences. The loss of data would replicate data poor scenarios, while the biased data mimics patterns of missing data that are found in real datasets: taxonomic bias and threat bias.

This study will provide a much needed example of an exploration of the impact of data quality and uncertainty on conservation planning decision in an applied scenario. The insights gained will help to understand the utility of the Protection Index as a conservation planning tool, and, more importantly, how limitations in our data impacts on the decision making process. What types of biases in the data are the metric most sensitive to? What does this mean for our application of its measure of progress? Most importantly what does this mean for our application to real world scenarios?

2 Background

In this section I seek to review decision making in conservation today, to include how we measure conservation success or progress before moving on to discuss how data uncertainty might affect this and introduce the topic of sensitivity analyses. I then discuss the Protection Index (Turner et al 2006a) and the important aspects of how the IUCN guidelines relate to the PI.

2.1 Decision making in conservation

Decisions have been made in natural resource allocation for as long as humans have interacted with the world. Historically, recorded land use decisions include such diverse objectives as reservation of private areas for hunting in Norman England (Hayman 2003), through to the development of sacred groves in India (Chandrashekara et al 1998). Over time the human induced pressure on the Earth's resources has increased (Diamond 2005), and is unlikely to diminish in the foreseeable future (Millennium Ecosystem Assessment 2005). The resulting 'biodiversity crisis' has been well documented (Balmford and Bond 2005) and champions of biodiversity must be aware that many natural areas are likely to be transformed.

In this environment, sound practices for reaching decisions about conserving biodiversity are essential. Since the mid 1990s, conservationists have been developing systems that assist in the targeting of efforts (Olsen & Dinerstein 1998, Myers et al 2000). Many identify priorities for action, often with a species bias (Leader-Williams & Dublin 2000). A number of these use ranks or scores to indicate which species are the most threatened (Master et al 2001,) or utilise quantitative criteria like the IUCN Redlist ((IUCN 2001) see section 2.2). However, whether high extinction risk should equate with high priority is hotly contested (Mace and Lande 1992, Possingham et al 2002) and many other factors such as feasibility, cost and urgency should be considered (Murdoch et al 2007). Other approaches focus on ecosystem services or communities but this too is not without problems (Chan et al 2006). In helping identify clear goals and objectives, a key development in conservation decision-making over the last two decades has been the use of decision theory as a structural framework to set conservation priorities (Shea et al 1998, Westphal and Possingham 2003, Nicholson and Possingham 2006, Mace 2006). Decision theory has been applied to many aspects of conservation science include optimal monitoring (e.g., Field et al 2005, Joseph et al 2006), how best to allocate funds (Wilson et al 2007), and adaptive species management (Maguire 1986, Milner-Guilland 1999).

Probably the most common application of decision theory has been in systematic conservation planning: the design of protected areas or reserve design. In the past reserves have often been situated in areas of little value for farming, forestry or resource extraction which have not always adequately represented biodiversity (Pressey 1994). Early reserve designs efforts focused on simple ecological ideas such as island biogeography (Diamond 1976) but moved to structured goal focused decision making based on species-specific distributional information in the 1980s (Kirkpatrick 1983, Margules et al 1988). By the 1990s Systematic Conservation Planning (SCP) had developed as its own field of conservation, along with a series of alogorithm-based software packages and the incorporation of structured levels of analysis of biological, environmental, socioeconomic and stakeholder factors (see Margules and Pressey 2000, Knight et al 2006 for a good applied review in the South African context). Increasingly, socio-economic as well as biodiversity concerns are included in conservation planning, including acquisition costs, ongoing management costs, feasibility, and opportunity (Naidoo et al 2006, McBride et al 2007).

Although the overarching goal in conservation planning is typically the persistence of biodiversity this has been difficult to tackle directly. Precisely which aspects of biodiversity should be targeted for conservation action has been the topic of at times heated debate, including the choice of species versus communities, environmental variables and different taxonomic groups (Brooks et al 2004, Pressey 2004, Cowling et al 2004). Regardless of target, the impossibility of having measures for all aspects of biodiversity is evident. The development of biodiversity surrogates, partial measures that represent biodiversity features has been an attempt to address this. A range of surrogates have been used, including taxonomic groups, environmental classes and species assemblages although much debate exists as to their efficacy at representing biodiversity (Gaston et al 2002, Faith 2003 and Cowling et al 2004).

Unfortunately, persistence is hard to measure as almost by definition, one is looking to assess the long term impacts of short term actions. Population viability analyses attempt to incorporate habitat and species population modelling to give an indication of extinction (Nicholson et al 2006). This process is data intensive, requiring much detail relating to population demographics and biology which are often not available and would not be feasible to conduct for many species (Akçakaya & Sjögren-Gulve 2000). Therefore many objectives have been used as proxies for achieving the goal of biodiversity persistence; from a target population or area for a species (Cowling et al 1999) to percentage targets for habitat 'preserved' (Rodrigues & Gaston 2002). Many other factors are also considered; including, landscape features such as connectivity and patch size (Moilanen & Nieminen 2002, McDonnell et al 2002), incorporating evolutionary processes and predicting the impacts of climate change (Forest et al 2007). The field of decision making and planning in conservation is rapidly developing, adapting to take into account a dynamic and uncertain world (Pressey et al 2007, Wilson et al 2007).

Conservation planning is dependent on a measure of conservation benefit with increasing conservation effort, known as the benefit function. For example, the probability that a population will persist increases with population size (e.g. Haight et al 2004). Many different benefit functions have been applied in conservation planning, from simple step functions (the species is either represented in the reserve network or not), to continuous functions to relate, for example, increasing area protected with biodiversity benefit (Arponen et al 2006). Without a basis in ecological theory any surrogate for species persistence such as habitat protected is arbitrary for example, 10% of area protected (Nicholson 2006). Many different functional forms have been used in conservation planning tools, including species-area curves (Desmet & Cowling 2004, Wilson et al 2005), and species persistence models (Haight et al 2004, Nicholson et al 2006). A recently developed metric for measuring conservation benefit is the Protection Index (Turner et al 2006a).

2.2 The Protection Index

The Protection Index (PI) was developed by Turner et al (2006) as a simple metric for measuring conservation benefit, utilising readily available data. It uses three distributional indicators of species viability; area of occupancy (AOO), extent of occurrence (EOO) and number of occurrences (NOO) (see below for definitions). The benefit function relies on thresholds used in the IUCN Red List criteria to designate species threat categories to produce a non-linear benefit function (see section 3.2.1.2 for calculation details) giving a measure of a species current protection status. The Protection Index can also be used to assess potential conservation benefit of new protected areas being added to a set of managed sites, by assessing the overall species benefit of adding a specific site to the current network.

The PI was originally applied in a study of thirty species in the Lake Wales Ridge area of Florida (Turner et al 2006). Subsequently, it was used to assess planning strategies statewide in Nicholson et al (2007). Nicholson et al (2007) used the Protection Index to assess the impact of a range of conservation scenarios as well as adapting the idea to assess the conservation status of ecological communities.

The IUCN Red List is one of the most important tools in conservation decision making (Akçakaya et al 2000). The Red List criteria cover a broad range of indications of species threat status and likely risk of extinction (IUCN 2006). Although originally designed to be applied at a global level the application of the criteria at a regional scale is accepted (Gardenfors et al 2003, Milner Guilland et al 2006, Miller et al 2007). It is the most widely applied measure of species threat and many countries maintain a national red list (over 100 of the CBD signatories national threatened species lists are based on IUCN guidelines). IUCN threat categories are also correlated with extinction risk (Keith et al 2004, O'Grady et al 2004). The IUCN Red List criteria have been used in the Red List Index to measure conservation progress with time (Buchart et al 2004) by tracking changes in species red list categories at a national or international level – naturally this will be quite a coarse assessment of change and focus only on red listed species. By contrast the Protection Index (Turner et al 2006) applies Red List metrics to local scale conservation planning and priority setting.

The protection index is based on three of the measures of geographical distribution from Red List criteria B, AOO, EOO and NOO (see table 3.1 for category thresholds). Each of these seeks to capture a different aspect of threat in relation to species distribution.

2.2.1 Extent of Occurrence

EOO is defined by the IUCN as, 'the area contained within the shortest continuous imaginary boundary that can be drawn to encompass all sites of present occurrence of a taxon'. It measures the spatial spread of the areas currently occupied by a taxon. It is not intended to provide an accurate estimation of a species range but to give an indication of its resilience to threat. A species with a small EOO will be more vulnerable to catastrophic local events. It can be estimated using the minimum convex polygon although this risks overestimating when discontinuities are present (Figure 2-1) and so the IUCN guidelines recommend using the α-hull (Burgman and Fox 2003).

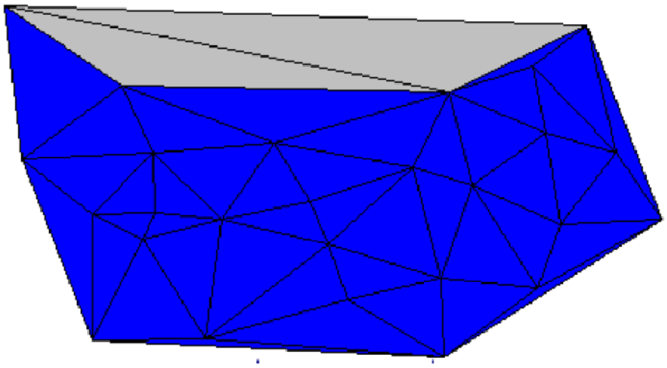

Figure 2-1 the shaded gray area shows the difference between EOO calculated using the α-hull compared to the minimum convex polygon. The apex of each triangle represents an occurrence. The mean convex polygon can include areas without occurrences. Image taken from IUCN (2006v3.1)

2.2.2 Area of Occupancy

The AOO is the area within the extent of occurrence occupied by the species. It should represent the habitat currently occupied by a species and is a function of the scale at which it is measured (Gaston et al 1991). The IUCN guide lines recommend that it is measured by overlaying a 2km by 2km grid over a map of species distribution and summing the area of the occupied cells. Many have found difficulties with adapting the scale at which many species distributions are mapped to that at which the IUCN guidelines are set (Hartley & Kunin 2003 and Nicholson et al 2007). It is vital that AOO is estimated at a suitable scale if the red list guidelines are to be used; finer scale underestimates whilst coarse scale overestimates AOO, with implications for a species threat listing. Recent work by Joseph & Possingham (2008) have found estimates of AOO to be a sub-optimal method for detecting species decline at a local level.

2.2.3 Number of Occurrences

The IUCN define a sub-population as, 'distinct groups within a population between which there is no genetic or demographic mixing'. A location is defined as, 'an area where a single event can rapidly affect all the members of a taxon' (IUCN 2001). It is important to note that the IUCN emphasise the location definition is related to threat. Two sub-populations at risk from the same threat should be classed as one location. This should be contrasted with the NatureServe definitions in Section 3.2.1.

2.3 Data uncertainty and Sensitivity Analyses

All measures of conservation progress and decision making are dependent on the data available, which is inevitably an incomplete inventory of biodiversity, with biases, assumptions and uncertainty (Margules and Pressey 2000; IUCN 2006). The acceptance of data at face value has been noted as a flaw in the application of many conservation planning methods (Moilanen et al 2006). At the same time uncertainty in ecological data and the intrinsically incomplete nature of much of the information that planners have to use has been documented (Wolman 2006, Pressey 2004, Possingham et al 2002). Crucial data on which many planning methods depend are species distributional data and habitat models. These are associated with a number of uncertainty and quality issues. Species distribution data can exhibit both errors of omission, failing to detect a presence, and commission, claiming presence when the species is not there. Omission errors can be attributable to the difficulty in being sure that a species is absent from a surveyed area. Wintle et al (2005) found that 18 visits were required to be 90% sure a forest owl was absent from an area, whilst Gaston and Rodrigues (2003) note that for restricted range species intensive surveying may be required to even identify species let alone estimate abundance. Other survey biases are inherent in distributional data such as spatial biases, as data points cluster at points of easy access and taxonomic biases as certain groups are over or under represented (Pressey et al 2004, Gaston & Rodrigues 2003). Using old data, particularly that associated with readily accessible herbarium or museum collections can also lead to commission errors as areas from which a species is no longer present are deemed occupied (Ponder et al 2001, Rondini et al 2006). The difficulty of maintaining up to date, detailed and accurate species distributional records for many species is evident. Alternatives such as range data are often associated with overestimates (Gaston 2003) and are a poor basis for quantitative analysis (Rodrigues et al 2004). Models derived from statistical methods rely on at least some raw data (Rondini et al 2006) whilst expert based models have been shown to be associated with high levels of variability between assessors (Johnson & Gillingham 2004) and less accurate than those based on statistics (Pearce et al 2001).

Sensitivity analysis is ‘how variations in output can be apportioned to different sources in variation in inputs’ (Stoms et al 1992). It has been used extensively in relation to GIS models were the processing method can have as significant an impact as the data itself in variation in outputs (Crosetto and Tarantola 2001, Rae et al 2007). The effect of uncertainty in data has also been explored using sensitivity analysis in population viability analysis (McCarthy et al 1995, Drechsler 2004), and IUCN Red Listing (Akcakaya et al 2000), but is relatively rarely used in the field of conservation planning. Several studies have assessed the impact of using different habitat suitability models in conservation planning (e.g.Fuller et al 2008, Gaston & Rodrigues 2003, Wilson et al 2005, Hernandez et al 2006, Moilanen et al 2006, Rondinini et al 2006) typically by assessing the impact of data quality on population modelling tools such as Marxan (Ball & Possingham 2000). Hernandez et al (2008) test the effect of data collected in a data poor scenario, contrasting well surveyed regions of Bolivia with those that have been less well studied. They found that models performed less well in data poor regions. Few studies however have directly tested the sensitivity of conservation planning tools to data quality, bias and uncertainty. Freitag and Van Jaarsveld (1998) looked at sensitivity of selection procedures to survey effort, survey intensity and taxonomic knowledge. Using a data set of South African mammals they carried out systematic deletions and assessed its impact on a site selection algorithm. The deletions were based on actual grid cell removal to try and replicate limitations in survey extent and data exclusions to replicate lack of knowledge or survey effort. The deletions were done in a random manner and found marked effects on site selection, variability and representiveness with increasing lack of data. The study by Grand et al (2007), again in South Africa used the Proteacae data set to investigate how biased data impacts on conservation reserve network selection. They carried out biased subsampling on the data set in the form of proximity to roads, removing proportionally more of the inaccessible records and sites. They also subsampled on the basis of abundance, removing more data from smaller populations in an attempt to replicate those populations likely to go undetected. These subsamples were contrasted with random deletions of an equal number of records. Like Freitag and Van Jaarsveld they tested the impact on areas selected by a site selection algorithm and found both an increase in variability in sites selected and the number of sites needed to meet predefined targets. These studies were theoretical in application and no studies appear in the literature conducting a sensitivity analysis of site selection techniques in practice.

3 Method

The aim of the study was to examine how data quality affects conservation planning decisions. This involved two main stages; firstly, following on from the work of Nicholson et al (2007) with respect to the scale of analysis and secondly, a sensitivity analysis of the Protection Index metric (Turner 2006a) (see section 2.2.1.) I will first briefly describe the study area before moving on to the data used and the steps involved in the process.

3.1 The study area

Florida has been the focus of the two studies to apply the Protection Index in the field (Turner et al 2006a and Nicholson et al 2007). As an area both of high biodiversity value as measured by endemicity (Endries et al 2007) and an area threatened by Human development (TNC 2005) it has been a focus of much conservation activity. Many planning activities have been implemented there including Gap analyses (Cox et al 1994), PVAs (Endries et al 2007) and the application of reserve design tools (Oetting et al 2006). The managed area network currently covers over 27% of the land and major conservation initiatives are ongoing. The Florida Forever scheme is spending $300 annually on land purchases for a range of uses of which conserving biodiversity is a major beneficiary. The Nature Conservancy (TNC) has developed a detailed ecoregional plan for the area based on Groves et al (2002) dividing the state into three main regions. From this a comprehensive site acquisition portfolio for the central Florida Peninsula ecoregion was developed (TNC 2005). This was based on the objective of protecting 10 occurrences for a suite of 301 species and 56 ecological communities. Interestingly despite including over 54% of the 76,460 km^2 within a region containing two large conurbations, Tampa and Orlando, fewer than half their targets were met by full acquisition.

3.2 Data

3.2.1 Species Data

The Florida Natural Areas Inventory (FNAI) is an organisation dedicated to collecting and maintaining ecological information on the biodiversity of the state of Florida. They track over 1,100 species across the state, of which 248 are deemed to be a priority. A species' Grank (NatureServe 2004) is the primary factor in prioritizing although others such as federal and state legal status may be important. Of these 248 species, 181 were included in the data set for analysis. Only observations made since 1980 were used, to minimise the likelihood of using data from populations that no longer exist. In addition fish and aquatic invertebrates were also excluded due to problems in calculating PI for species inhabiting linear environments (see Nicholson et al 2007 for more detail).

The species data set was derived from FNAIs' Element Occurrence (EO) database (NatureServe 2004). An 'Element' is a unit of conservation interest, ranging from individuals to metapopulations and encompassing species and ecological communities. An EO is the reported occurrence describing where the element occurs. It is a planning tool and should contain detailed descriptive information and a spatial component, typically a map. The observation that makes up an EO can vary in nature from museum collection, dedicated survey through to casual observation although unsupported these should not form the basis for the record.

The mapping of EOs attempts to capture both viability and locational uncertainty. As such the point representation is an abstraction of the 'on-the-ground' observation data. The FNAI are currently working to produce a complete set of polygons that describe the estimated occupied habitat. At the moment some species have been mapped in this way whilst other polygons are simply the points with uncertainty buffers. The maps of polygon and point EO distributions were presented as vector shapefiles with an abundance of extra information. There were 10924 recorded EOs post 1980 for the 181 target species.

3.2.2 Site data:

The FNAI also maintains a database of protected areas or managed sites (MAs) across the state. There are currently almost 1850 sites ranging in size from 0.008km^2 to 6222 km^2 and covering over 26% (47500 km^2) of the state (Figure 3-1).

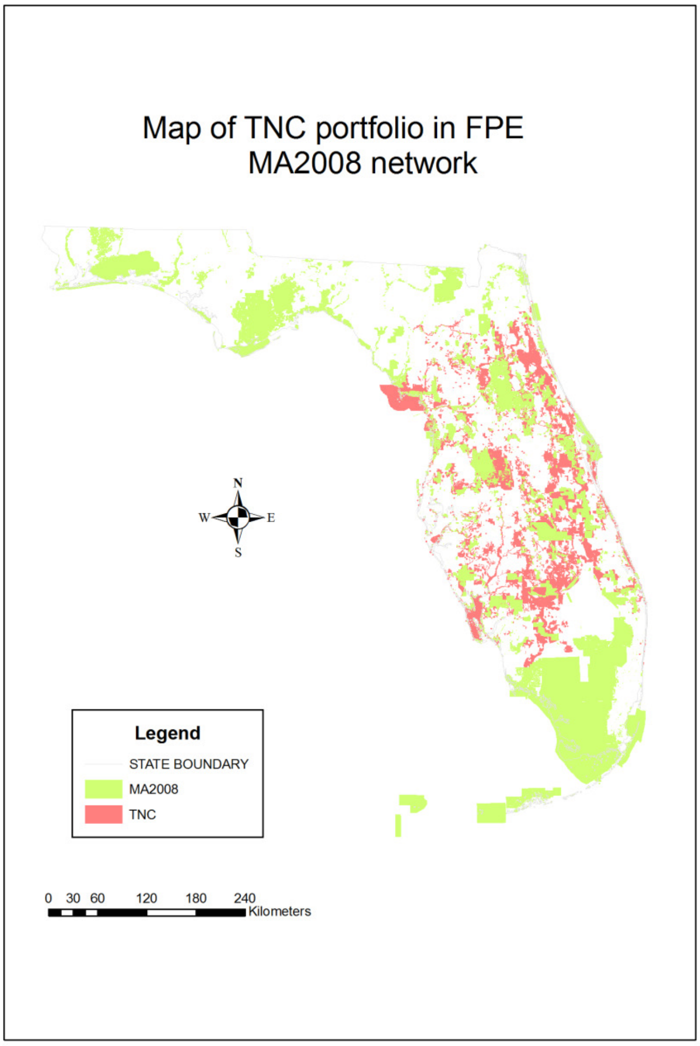

Figure 3-1 A map of the current managed area network (MA2008) and the proposed TNC portfolio (TNC)

We also looked at the proposed acquisition portfolio of the Nature Conservancy. The TNC suite of proposed sites is restricted to the Florida Peninsula Ecoregion(FPE) and is detailed in the TNC's ecoregional plan (2005). The FPE is one of sixty three North American ecoregions and is 76,200km^2 in area of which 41,416km^2, over 54% of the ecoregion, is proposed for acquisition (Figure 3-1). The portfolio is made up of 186 sites ranging in size from 0.01-1960 km^2. For this study only those sites not already protected were used for analysis, adding conservation 'value' over and above the current MA network. All the site maps were provided as vector shapefiles with associated database information.

3.2.3 Habitat Data:

The species habitat data were provided as 30m by 30m grid files, with each grid cell indicating occupied/unoccupied habitat. Six different types of models were used, varying in both their quality and conservatism and many species have multiple models available. Given the number available the same hierarchy of models used in Nicholson et al (2007) developed in conjunction with FNAI was used here:

i. FNAI habitat maps (FNAI 2006) attempt to map only occupied habitat. They match occurrences as EOs with suitable habitat maps. These maps are derived from both 1995-2000 WMD landcover data and the most recent FWC landsat data. These are then subject to expert review before producing the final and most conservative habitat models;

ii. FWC 2007 potential habitat maps which are developed from the Strategic Habitat Conservation Areas review by the Florida Fish and Wildlife Commission (Endries et al 2007; Root & Barnes 2007);

iii. FNAI range or potential habitat maps, developed using DOMAIN software modelling species occurrence based on biophysical attributes where species occur (FNAI 2006);

iv. FWC 2000 potential habitat maps (Cox & Kautz 2000);

v. FWC 1994 potential habitat maps (Cox et al 1994);

vi. Expert associations with habitat types.

These layers are derived from a combination of remote imaging data, observation and expert knowledge.

3.3 Process

There were 3 main stages to the analysis

1. Updating the work done in Nicholson et al (2007) with the most recent 2008 dataset and producing the PI calculations for the current managed area network and TNC portfolio.

2. Assessing the effects of scale on the analysis and producing area of occupancy figures at the IUCN standard 2km grid size.

3. Sensitivity analysis in two parts. An initial investigation into the potential biases within the dataset was carried out. Following directly from this a sensitivity analysis was performed to assess the impact of data quality on the PI. This involved depleting the dataset to test the robustness of the metric and replicate data poor scenarios.

3.3.1 Producing the Protection Index

The PI is a conservation benefit function based on the distributional indicators used in the IUCN guidelines, number of occurrences (NOO), area of occupancy (AOO) and extent of occurrence (EOO). For a given species it is only those portions of these values that fall within a protected area that contribute to the PI, being deemed to contribute to the species survival.

Both the Turner et al (2006) study and the Nicholson et al (2007) applied NatureServe definitions of occurrences to IUCN thresholds which is not without possible problems (as acknowledged in Nicholson et al 2007). It is important to understand the nature of the IUCN distributional indicators and how the guidelines between the two systems differ. Although NatureServe are currently updating their ranking processes (Masters et al in press) they differ from the IUCN guidelines in a number of ways. It is a ranking system partly quantitative based on occurrences but also scoring, weighted by threat, rarity and trends. They are measured at a global (G) and subnational (S) level and species can be allocated a joint rank with many combinations possible (Table 3-1).

Table 3-1 Table showing the main Granks from the NatureServe threat ranking system

Rank	Definition
GX	Presumed extinct – no hope of discovery
GH	Possibly extinct – some hope of discovery
G1	Critically Imperiled – high risk of extinction
G2	Imperilled – High risk of extinction
G3	Vulnerable – moderate risk of extinction
G4	Apparently Secure
G5	Secure

IUCN guidelines define a subpopulation as based not on any set distance but by absence of demographic or genetic mixing. They also define a location as any distinct area vulnerable to a single threatening event which will affect all members of the taxon present IUCN (2006). This contrasts with the NatureServe guidelines which define populations as groups separated by 0.5-3.5km (NatureServe 2006) with the assessor defining the exact limits. Thus an estimate of occurrences made under the NatureServe guidelines will likely be inflated compared to one made under IUCN criteria for which the threshold guidelines were designed with significance for Turner et al (2006a) and Nicholson et al (2007)

Measuring the NOO and EOO involves accurate spatial representation of EOs whilst AOO involves the spatial matching of the species habitat maps with sites map to produce protected occupied habitat. The preparation, manipulation and analysis of data was carried out using excel (Microsoft Office 2007), ArcGIS 9.2 with the Spatial Analyst extension (ESRI, Redlands, USA) and R(Cran@R-project.org).

3.3.1.1 Data Preparation

Data preparation was intensive to ensure the spatial accuracy of the analysis. Each EO has X and Y co-ordinates as well as a managed area name given in the database if the occurrence was recorded in an MA. Using the extract tool in the spatial analyst extension of ArcGIS these coordinates were used to allocate EOs to either; the MA or TNC site network, or given a No site designation. 1190 EOs were recorded as being in an MA whilst their co-ordinates had them positioned just outside. The polygon EO vector could be used to match those species whose estimated occurrence polygon (not just an uncertainty buffer) overlapped with an MA and on this basis 33 were allocated to the overlapped site. Additionally a lookup and match function was able to allocate another 652 EOs in a named MA for which co-ordinates didn't match. In total 7826 EOs were found to be in either an MA or not currently protected TNC sites out of an original database of 10924 and could be used for analysis.

For the purposes of assessing the PIaoo, the AOO was defined as the area of suitable habitat occupied by the species within sites. This involved combining the species habitat model maps with the maps of the sites:

Site maps were supplied originally as vectors with features represented as polygons, a more faithful representation but difficult to use for calculations. For processing, raster grids of these were produced from conversion tools in Spatial Analyst to allow precise overlay of site maps with the species habitat model. The raster grids needed to be at the same cell size, 'snapped' to the same bottom left cell and at the same extent to ensure exact grid overlay.

A problem arose in conversion as small, linear or embedded sites were lost during the process, regardless of sampling technique. Consequently, some small sites were merged with adjacent larger sites (this was important to ensure consistent representation of sites during the production of site map grids at varying scales described below). Therefore the number of sites in the current managed network dropped from 1844 to 1652. The TNC site file was provided as both a 30m raster grid and a vector meaning this process was not needed. The conditional tool of the spatial analyst extension of ArcGIS could then be used to produce an output raster representing species habitat within MA or TNC network. The cell count, in this case 900m2 per cell could be used for subsequent analysis.

To try and avoid overestimating AOO we decided to use only habitat associated with known occurrences. This meant the production of a new set of grids for the 95 species without ‘FNAI habitat’ standard models i.e. those species with models based on potential occupied habitat rather than known occupied habitat. This was done by introducing another two stages in the above process. Using the extract tool from spatial analyst extension of ArcGIS, a grid of species presence in a site was produced for each of the 95 species which represented only those MA and TNC sites with known EOs. The species habitat model grids were then compared with these presence-site rasters in the same manner as the FNAI habitat model species. This approach contrasts with that taken in Nicholson et al were the AOO with integrated with occurrences in subsequent analysis.

The EOO was calculated using the minimum convex polygon (MCP) technique (Figure 3-2). This was chosen rather than the recommended α-hull due to the nature of the PI calculation. The α-hull polygon, although a more conservative representation of EOO, can decrease in area as additional occurrences are added (Burgman & Fox 2003). This could result in the counterintuitive situation where the conservation status of a species worsened as a result of a new occurrence being added. As a result it was decided to use the MCP for those species with less than three occurrences, for which drawing a polygon would be impossible, the AOO was taken as the default. By definition EOO is the same as or larger than the AOO and to ensure this we added the condition that EOO≥ AOO within the code that calculated EOO.

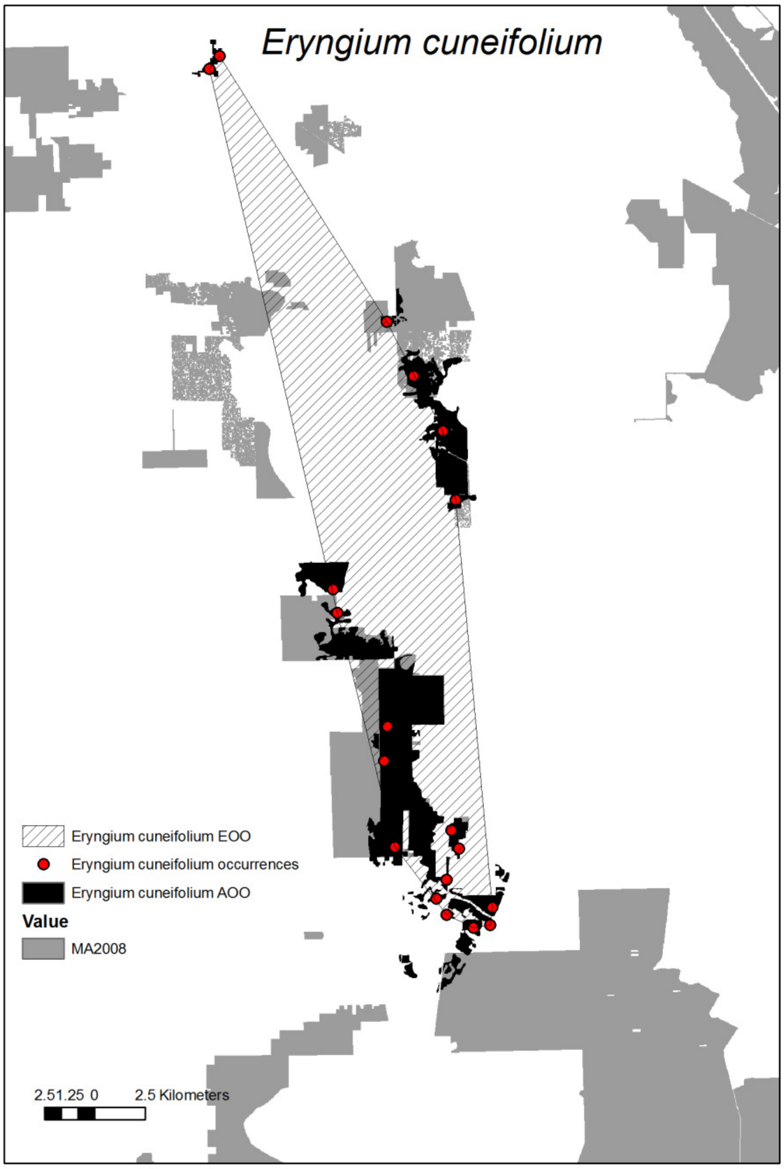

Figure 3-2 Image showing representing the EOO, AOO and NOO for the species *Eryngium cuneifolium* NOO = 19, PInoo= 3.225, AOO = 56.43km^2 , PIaoo=1.094, EOO=395.18 km^2 ,PIeoo=1.060 and PImin = 1.06

3.3.1.2 PI calculation*:*

The PI uses the IUCN thresholds as the basis for a continuous non-linear function ranging from 0 to 4 to capture incremental changes in threat rather than jumps between threat categories. PI=1 is set at the threshold for Critically Endangered, PI=2 at the threshold for Endangered, PI=3 at the threshold for Vulnerable and PI=4 for Near Threatened. Values for PI = 1,2 and 3 are taken directly from the IUCN (2006) red list guidance as indicated below (Table 3-2). No values are provided for Near Threatened by the IUCN and the threshold for PI=4 was set by Turner et al (2006a) as being five times the threshold for the next category, vulnerable. Linear interpolation between the points for a given criteria allows a conservation benefit function to be derived. For example if a given species is known to have 8 occurrences, it falls within the vulnerable category (5>occs<10) and a corresponding PI range of 2.0<PInoo≤3.0. The simple calculation PInoo=2.0 +(8-5)/10-5)=2.6 allows the PI value to be assigned (Figure 3-3).

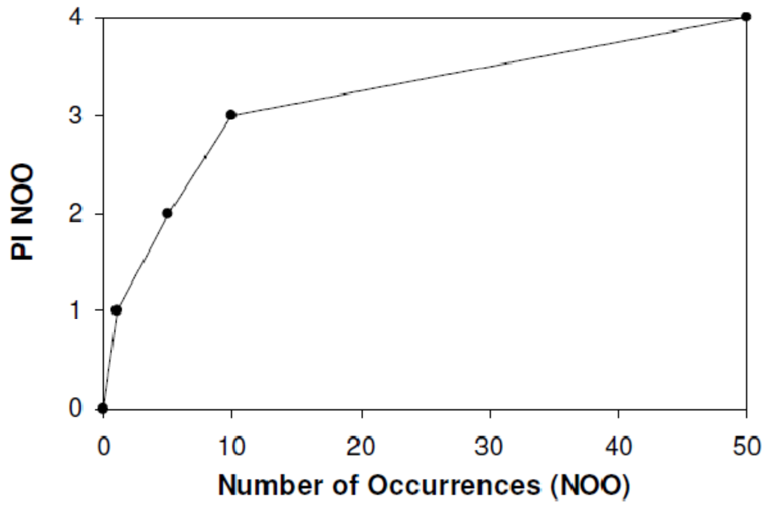

Figure 3-3 Plot illustrating how the Protection Index indice, PInoo relates to the Number of Occurrences (NOO). (adapted from Nicholson et al 2007)

Table 3-2 IUCN criteria thresholds

IUCN	NOO	AOO(km2)	EOO(km2)
Extinct	0	0	0
Critically Endangered	1	10	100
Endangered	5	500	5,000
Vulnerable	10	2,000	20,000
Near Threatened	50	10,000	100,000

This process is carried out using the data derived from GIS analysis plus site and species lists. Adapting a program written in R from the Nicholson et al (2007) study allowed the PIaoo, PInoo and PIeoo for each species to be calculated. A forth metric the PImin captures the IUCN usage of the worst performing indicator to represent a species classification and highlight its vulnerability.

PImin = min(PInoo,PIeoo,PIaoo)

It was felt that the metric PImean used in Turner et al (2006a) did not provide any extra utility as each of PI aoo/eoo and noo captured a different component of extinction risk that was perhaps obscured by taking an average of the three.

I sought to calculate the PI of the current Florida MA network (MA2008) and the potential conservation benefit of fulfilling the TNC portfolio in the FPE.

We also looked at what each site added to the overall PI for a species. I used the schema developed in Turner et al (2006a) and applied in Nicholson et al (2007) for dPI whereby the current PI for a species within the current MA network is measured and then each potential site is added and the PI recalculated. The difference between the two gives the dPI and represents the potential benefit in terms of PI, for a given species of adding the site to the portfolio. ∑dPI for a site, summed across all species is the measure of site performance.

In summary the results obtained will include:

- PI for each of the 181 species broken down into PInoo, PIaoo, PIeoo and PImin

- dPI for each proposed TNC site broken down into dPInoo, dPIaoo, dPIeoo and PImin

3.4 The effect of scale

AOO represents the habitat currently occupied by a species. Species with a low AOO are typically restricted range, habitat specialists and as such under a greater risk of extinction. AOO is a function of the scale at which it is measured and the scale chosen should be appropriate for the taxon given the nature of the threats involved (IUCN 2001). IUCN guidelines state,

"The finer the scale at which...habitats of taxa are mapped, the smaller the area will be that they are found to occupy..."

Different techniques exist for the assessment of AOO but the IUCN advises counting occupied cells in a grid overlaid over the whole species range. This is in effect what happens with raster grids within ArcGIS. The IUCN recommended grid size is 2km (cell area $4km^2$) and to use a finer scale the assessor should be sure that areas defined as being unoccupied represent true absences rather than simply undetected presences. Given the range of sources and techniques used to provide occurrence data and habitat models it was not justified to use a finer scale for assessment of the species in this study. In the study by Nicholson et al (2007) the AOO was estimated at a 30m grid size meaning that many species AOO values were potentially lower than would be obtained if measured at the reference cell size. A species might on this basis fall within a higher threat category and therefore a lower PIaoo. This may have serious implications for the PImin and therefore any decisions made on this basis.

This study sought to correct this anomaly by measuring AOO at the 2km cell size. This analysis proved more difficult than it originally appeared. It had been planned to carry out the AOO calculations at 30m, 500m, 1km and 2km cell size. A number of analysis problems occurred in analysing at coarser scales.

It is inappropriate to compare raster grids of different cell sizes as cells must exactly overlap to allow cell by cell calculation. Conversion from a fine scale to a coarser one can cause loss of detail. This can be accommodated for grids in which cells represent only presence/absence. The species habitat models were resized from the original 30m grids using the generalization tool of the spatial analyst extension of Arc GIS. This tool allowed raster cells to be scaled up by whole numbers only, hence output raster grids of 510m, 990m and 2010m were produced from the 30m originals.

The intention was to follow the same process for deriving AOO as described at the coarser scales i.e. using species habitat rasters at 2010m with the site map raster at 2010m. A major problem was encountered using coarse scale rasters combined by the same analysis method. The overall occupied habitat increases as one might expect with increasing grid size. However, sites which have no occupied habitat at the original measured 30m scale now appear have occupied habitat at the coarser scale. This is an unacceptable artefact of the analysis technique that could significantly alter the ΔPI for a site. It was decided that using this raster combination technique was therefore unsuitable for TNC site analysis.

For managed area analysis preserving site integrity was not important, we were less concerned with the value of each site than the overall contribution of the managed area network. On this basis the raster combination technique was done for the 181 spp. at both 30m and 2010m cell width. These values for AOO where then used to work out the scaling coefficient C for each species following IUCN guidelines (2006):

$C = (\log_{10}(AOO_2/AOO_1)/ \log_{10}(Ag_2/Ag_1))$

where AOO_1 is the AOO from the grids of area Ag_1 a size smaller than the reference scale and AOO_2 is the estimated AOO from grids of area Ag_2.

An estimate of the reference AOO, AOO_R may be calculated using:

$AOO_R = AOO_1*^{10C*10(AgR/Ag1)}$

In this study $Ag_1 = 0.0009km^2$, $Ag_2 = 4.04km^2$ and $Ag_r = 4\ km^2$

This allowed the AOO to be assessed at the reference 2km grid size for all species without any loss of sites or any artifactual increase in site representation.

3.5 Sensitivity Analysis

In this study I used the PI metric as the tool to assess the impact of input data on conservation decision making. The PI calculation outputs of PI for each species and the potential contribution of each site dPI for each site were the units that would be monitored in response to input changes. The effect of both poor data quality is simulated by disrupting the data set in both an unbiased and biased fashion.

3.5.1 Analysis of biases in FNAI dataset

The first step was to identify possible biases involved in the representation of EOs in the FNAI database to help inform the biased deletions. The data set was broken down on the basis of number of occurrences by species and examined comparing a number of factors that may reflect biases such as taxonomic group and threat ranking.

To make analysis of threat levels easier the Granks were converted to integers between 1 and 5 with 1 being the highest threat level. NatureServe threat rankings include many intermediate levels, queries and designations for different geographical scale (Table 3-1). These needed to be simplified; we took a conservative approach so that each species received the lowest threat category for which it was qualified. This was done to reflect the basis on which FNAI tracked species and how they are represented in the database.

3.5.2 Data depletion algorithms

The results of these preliminary analyses are detailed in the first part of the results section. On the basis of analyses of biases, I performed three main analyses of the effects of data loss:

3.5.2.1 Unbiased

Unbiased deletions were carried out to replicate the data poor situation. The FNAI database represents a well maintained and updated inventory in a wealthy country. Many situations faced by conservationists are not so well endowed. If there are no biases within the data set then simply depleting the data set by removing EOs in a random fashion will replicate these scenarios. The deletions were made by adapting the PI calculation program in R with the program set up to run for n deletions which would delete between 1 and 50% of the overall EO database.

3.5.2.2 Taxonomic Bias

The results of the analysis of biases suggest that the EO representation within the FNAI database is not unbiased. It was found that there was a marked bias towards birds and hepatofauna and against plants and invertebrates with little effect on mammals. By comparing the mean EO per species by taxonomic group I was able to allocate proportions to be deleted on the basis of taxa (Table 3-3)

Table 3-3 Table showing the proportions deleted on the basis of taxonomic bias. A value of 1.0 would represent no change, <1 a positive bias, >1 a negative bias. For programming reasons the value sums to 5.

Taxon	Herp	Bird	Mammal	Plant	Invert
Proportional Factor	0.22	0.26	0.84	1.69	1.99

This was done to try and replicate the biases found within the database. Not only would a data poor situation have less EOs overall but would have less on the basis of typical biases as found here. Conveniently there were five subdivisions within both chosen deletion sets each with an allocated deleted proportion that summed to 5.0 for all five. If the proportions were left at 1.0 for each subdivision, then the relative proportion deleted in each iteration was unchanged. When the proportion was less than 1.0 for a subdivision then a lower proportion would be deleted, replicating a positive bias. Similarly the converse was true for a proportion greater than 1.0. In total the proportions for the five subdivisions still totalled five. EOs were then deleted in random fashion on the basis of the allocated proportions.

3.5.2.3 Grank bias

The FNAI track species largely on the basis of G ranks, focusing on the higher ranked G1-3 species. From the biases analysis it appears that these G1-3 species are actually overrepresented, indeed many G1 and G2 species number of occurrences exceeds the NatureServe guidelines. Conversely the G4 and G5 species are underrepresented. On this basis it was decided to perform deletions by deleting a given proportion in a similar manner to that described above with different proportions removed for each Grank. The NatureServe guidelines were used to set a threshold for each Grank as detailed in Fig.4.1. This was compared with the mean number of EOs for a given species within each rank. The relative proportion by which each G rank mean EOs differed from nearest threshold boundary was used as the basis for the deletions (Table 3-4). This was in an attempt to ensure that the biases reflected in the FNAI dataset would be amplified as data was lost, mimicking a data poor scenario.

Table 3-4 Table showing the proportions deleted on the basis of Grank. A value of 1.0 would represent no change, <1 a positive bias, >1 a negative bias. For programming reasons the value sums to 5.

Grank	G1	G2	G3	G4	G5
Proportional Factor	0.7	0.75	0.93	1.2	1.42

3.5.3 Other scenarios

To attempt to replicate the impact of data quality in terms of the models, the PI was calculated for all species and MA/TNC with only the EOs from the G1-3 species used which were also the species with the better habitat models. This would also illustrate the scenario if the FNAI focused only on those species deemed threatened to the exclusion of G4 and G5 species.

The effect of scale will also be assessed, by using the AOO values measured at 30m, for its impact on how the current managed area network is performing and the conservation benefit of adding the TNC portfolio.

3.5.4 Analyzing output of sensitivity analyses

It was decided to focus on the measure of conservation coverage achieved or species protected PI and particularly PImin. This gives the poorest performing indicator and most significant measure of extinction risk. How the PImin changed for species with each disruption to the data set would be important. We were also interested in conservation priorities, identifying the most beneficial sites by how they contributed to the overall PImin, using the metric dPImin. This was the measure that would have most impact on conservation planning recommendations from the perspective of prioritising purchases. In addition this was further refined by focusing on those sites that were;

i) Highest priority in the current scenario with the full dataset as these were the sites of conservation planning interest, and

ii) Identifying which of those sites that were most sensitive to the deletion process and trying to understand what factors make them sensitive.

4 Results

The results section is broken into five main sections. The first part deals with the initial exploration of the data to identify any underlying biases and inform the sensitivity analysis. The second section presents the results relating to the effects of spatial scale, although aspects of scale relating to the sensitivity analysis and its impact on the Protection Index are in the final section. The baseline Protection Index results as they relate to both the current MA2008 sites and the TNC portfolio are detailed in the forth section before moving on to the sensitivity analysis. The final section presents the impact on the Protection Index of the effects of spatial scale and data deletion.

4.1 Data Exploration

4.1.1 Threat Rank:

Biases in the data relating to threat ranking were examined by looking at the species level representation of EOs grouped by Grank (Figure 4-1). The number of EOs per species shows a bell-shaped distribution; with an increase in the number of EOs per species as G rank increases up to G3 but fewer EOs than would be expected by Grank for low threat species (G4 and G5). To test this pattern, the number of EOs was fitted as a linear function of Grank, the explanatory variable was designated as a factor with the five ranks as levels. EOs, the response variable, are count data and so a linear model was fitted with a poisson error distribution. The results (Adjusted R^2 = 0.1475, F-statistic = 8.611 (4 and 172 df), p-value<0.001) confirmed the model as a reasonable fit for describing the data in these terms.

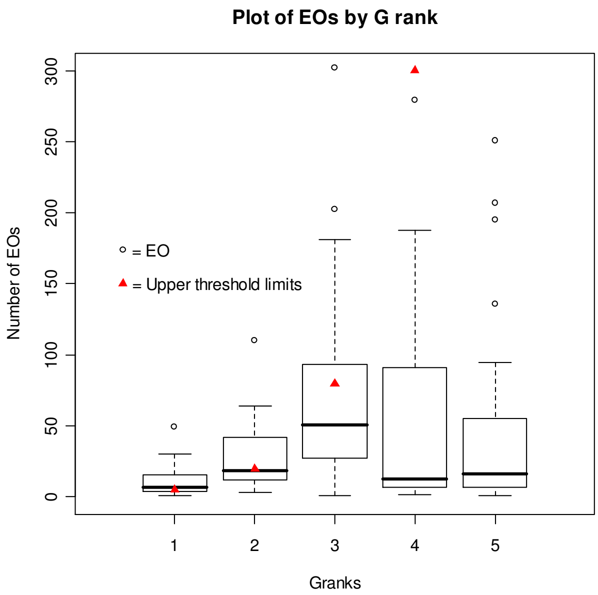

Figure 4-1 Plot of EOs by species grouped by Grank. The NatureServe Grank upper threshold boundaries are indicated by the red triangles

Three species are not displayed in Figure 4-1 or included in the statistical analyses as they have substantially more EOs than other species and represent extreme outliers.

- *Aphelocoma coerulescens,* the Florida Scrub Jay, has 444 EOs accounting for almost 32% of the EOs for the 36 Grank 2 species.

- *Haliaeetus leucocephalus,* the Bald Eagle, has 1610 EOs, over 56% of the EOs for the 28 Grank 5 species and almost 15% of the EOs in the whole post 1980 database.

- *Gopherus Polyphemus,* the gopher tortoise is one of 55 Grank 3 species and accounts for just under 8% (961) of the total post 1980 database EOs.

It is likely that a number of species in the two highest threat categories (G1 and G2) were over represented in the dataset as the number of occurrences exceeded the NatureServe thresholds for their Granking. Note, that although NatureServes' Granking protocol at the time these species were assessed depends predominantly on the number of occurrences, the overall Grank may be influenced by other factors such as decline in distribution or number of individuals. Table 4-1 shows the thresholds and actual means and medians per species within the group. 24 of the 'critically imperilled' G1 species had a number of EOs in excess of the threshold for that Grank. For each of the G1 and G2 ranks, the predicted mean number of EOs is greater than the upper threshold boundary for the category.

Table 4-1 Element Occurrence summary by Grank, including thresholds used in assigning Grank

GRanking	NatureServe thresholds for EOs	Mean EOs per species(range)	Median EOs per species
G1	<5	11.4 (1-49)	7
G2	6-20	40.73 (3-444)	18.5
G3	21-80	94.93 (1-961)	51
G4	81-300	54.45 (2-279)	13
G5	>300	78.67 (1-1610)	16

The lower threat categories, species ranked at G4 and G5, were underrepresented within the FNAI database in comparison with the expected number of occurrences. Grank appeared to be a significant factor in the representation of occurrences in the FNAI database, which is to be expected as this is one of the main guideline factors in whether or not a species is tracked. However, a clear pattern emerged of over-representation of the more threatened species and a corresponding under-representation of the less threatened species.

The weighting used in the biased deletion of EOs for a given Grank is a function of the degree to which a Grank is over or under-represented in the EO database. The average proportional over-representation of the species within each Grank is given by the ratio of the mean number of EOs per species within each Grank (μ_G) and NatureServe's threshold guidelines (T_G): μ_G / T_G. This ratio was normalised by the sum across Granks of the over-representation. As the weightings for the species used in the random deletion seek to over-exaggerate under-representation, the inverse of the proportional over-representation was used to give the final weighting the biased deletion of EOs for a given Grank (W_G) of :

$$W_G = \left(\frac{\mu_G / T_G}{\sum_{G=1}^{5} \mu_G / T_G} \right)^{-1} = \frac{\sum_{G=1}^{5} \mu_G / T_G}{\mu_G / T_G}$$

4.1.2 Effect Of Taxon

To investigate how biological factors might bias representation in the database I looked at how the number of EOs related to species by taxonomic group (birds, herpatofauna, mammals, invertebrates and plants). Plants made up the large part of the 181 species in the study at over 65% (Table 4-2). In terms of element occurrences the three groups of plant, bird and herpatofauna made up almost all the EOs in the database. Mammals, often cited as being an over-represented 'charismatic' group, were surprisingly low in number, both in terms of the number of species tracked and the number of EOs. A small number of species, particularly herpatofauna and birds were responsible for a large number of EOs. The bald eagle *Haliaeetus leucocephalus* alone comprised almost 15% of the database. By contrast a substantial number of plant species had only a handful of EOs.

Table 4-2 Element Occurrence summary by Taxonomic group

Taxonomic Group	Total EOs (%)	Number of species (%)	Mean per species in group
Bird	4411(0.4030)	33(0.182)	133
Herp	2744(0.4197)	17(0.194)	161
Invert	17(0.0045)	1 (0.006)	17
Mammal	440(0.1164)	11(0.061)	40
Plant	3337(0.3040)	119(0.657)	28

The invertebrate group was represented by only one species, *Cicindela highlandensis,* which may well be a typical pattern for this group in many biodiversity inventories, causing problems in fitting a model on the basis of taxon. For this reason it was excluded from the model. I fitted a linear model with poisson errors to the data (R^2 =0.1715, F-statistic = 13.08 (3 and 172 DF), p-value<0.001).

The weighting used for each taxonomic group (W_T) in the Taxonomic bias deletion was calculated as the inverse of the mean EO per species within each group (μ_T) with the overall mean EO per species (μ_{all}):

$$W_T = (\mu_T/\mu_{all})^{-1} = \mu_{all}/\mu_T$$

4.2 Effect Of Spatial Scale

AOO was calculated using the IUCN recommended scaling correction method. Typically this causes a proportionally larger increase in AOO for narrow range species than for those species with a wider distribution. The scaling coefficient C is typically close to 0 for wider ranging species and closer to 1 for narrow range, habitat specialists.

Figure 4-2 AOO in Km^2 measured at different grid cell size for 5 species. *Mustela frenata peninsulae* (C = 0.03), a habitat generalist and *Polyrrhiza lindenii* (C=0.04), a widespread orchid both have low values for the scaling coefficient whilst restricted range species like *Asplenium dentatum* (C= 0.56) and *Cheilanthes microphylla* (C=0.65) have typically higher values. The sea turtle *Caretta caretta* (C= 0.49) has a high scaling coefficient despite being a wide ranging species. shows graphically the change in AOO when measured at different scale and how this varies for species with different characteristics. *Mustela frenata peninsulae* (C = 0.03),a habitat generalist and *Polyrrhiza lindenii* (C=0.04), a relatively widespread orchid, both have low values for the scaling coefficient and it can be seen that the change in AOO from 30m to 2010m is proportionally less than for restricted range species like *Asplenium dentatum* (C= 0.56) and *Cheilanthes microphylla* (C=0.65). It is worth noting the wide ranging Loggerhead turtle *Caretta caretta* (C= 0.49) shows a similar pattern to a species like *Asplenium dentatum.* As measured at the Florida state scale, sea turtles are restricted range species, confined to narrow coastal strips on nesting beaches.

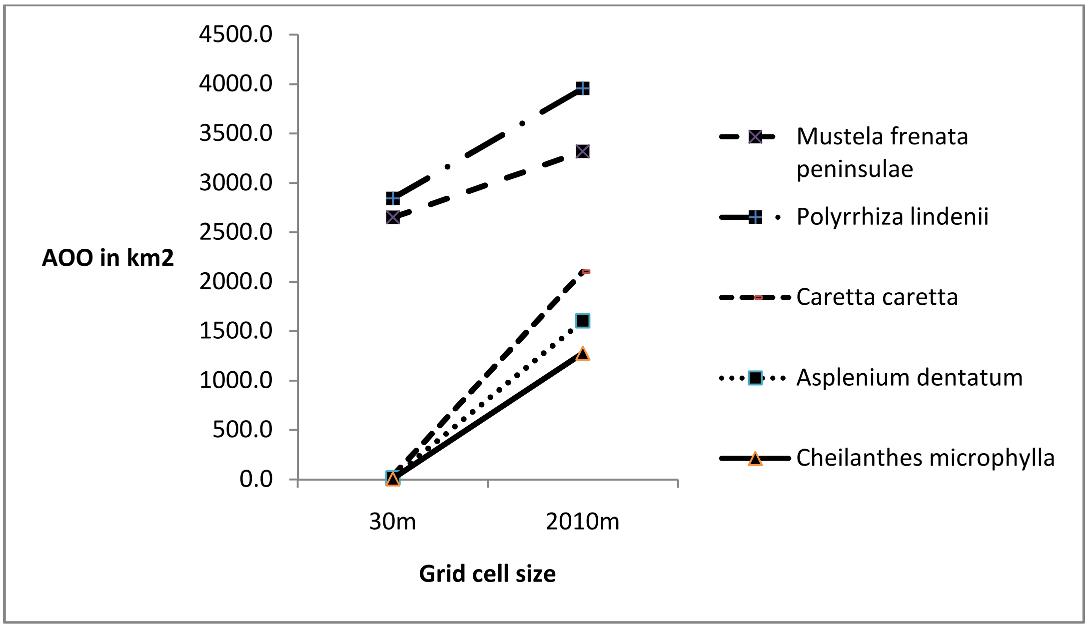

Figure 4-2 AOO in Km^2 measured at different grid cell size for 5 species. *Mustela frenata peninsulae* (C = 0.03), a habitat generalist and *Polyrrhiza lindenii* (C=0.04), a widespread orchid both have low values for the scaling coefficient whilst

restricted range species like *Asplenium dentatum* (C= 0.56) and *Cheilanthes microphylla* (C=0.65) have typically higher values. The sea turtle *Caretta caretta* (C= 0.49) has a high scaling coefficient despite being a wide ranging species.

4.3 The Protection Index

Conservation in this project was measured primarily by the overall protection status of the species as measured by PImin. I focussed on those species which receive most benefit as measured by greatest improvement in PImin by the addition of the TNC portfolio (Figure 4-3 and Table 4-3). A number of species that would benefit most from the acquisition of the full TNC portfolio were those with no occurrences within the current managed area system. For these species a few occurrences caused a bigger change in the PImin than for those species already well represented.

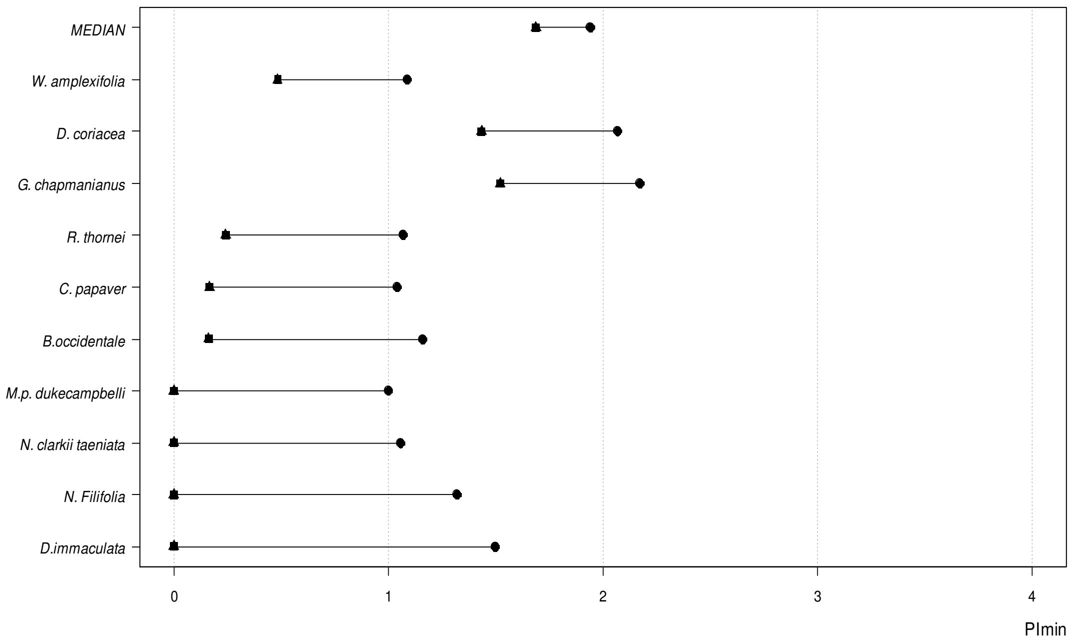

Figure 4-3 shows the 10 species for which the acquisition of the TNC portfolio will have the biggest impact in terms of change in PImin. The overall species median is also shown. ▲ = PImin in current MA2008 network ● = PImin with full acquisition of TNC portfolio.

Table 4-3 Top ten performing species measured by improvement in PImin from the current MA2008 network with the addition of the TNC portfolio. The limiting factor and number of EOs are also given.

Species	Grank	Taxon	EO in MA2008	PImin MA	EO in TNC	PImin TNC
Dicerandra immaculata	G1	Plant	0	NOO	3	NOO
Najas filifolia	G1	Plant	0	NOO	5	EOO
Nerodia clarkii taeniata	G1	Herp	0	NOO	3	EOO
Microtus penn. dukecampbelli	G1	Mam	0	NOO	1	NOO
Blechnum occidentale	G5	Plant	1	EOO	3	EOO
Callirhoe papaver	G5	Plant	1	EOO	2	AOO
Rhynchospora thornei	G3	Plant	1	EOO	3	AOO
Gymnopogon chapmanianus	G3	Plant	21	EOO	2	EOO
Dermochelys coriacea	G2	Herp	5	EOO	7	EOO
Warea amplexifolia	G1	Plant	2	EOO	18	EOO

The improvement seen for highly threatened plants with no occurrences within the current MA network is not surprising but there are some other patterns of note. The addition of just two EOs greatly improved the PImin for *G.chapmanianus* by virtue of being further away from a cluster of other occurrences and thereby pushing its EOO into the next category. Certain species such as *B.occidentale* and *C. Papaver* are very poorly represented but are also of low threat level. They may be poorly represented in the current MA network on this basis.

We also wanted to know how to gain the best conservation benefit from within the site portfolio, in addition to the current managed area network. The TNC portfolio is very comprehensive and is unlikely to ever be aquired in full. To know which sites to prioritise would be useful. The increase in PImin for each species provided by each site, dPImin gives a measure of value for species. By summing this across species ∑dPI, we gain a measure of conservation benefit acquired from this site. Many sites contributed little benefit measured by the ∑dPI and thus we focussed on a set of top performing sites, shown in Table 4-4 . This process best mirrored real world conservation actions. Many are centred on Lake Wales Ridge, a site well known for its endemic specis and imperilled status.

The number of occurrences per site, important to all three metrics (NOO, AOO and EOO) varied greatly. The particular species present was also important; for example the Green Swamp site has relatively few EOs but these are species to which a lot of value can be added (Table 4-4). Sites with fewer EOs may be more sensitive to data loss.

Table 4-4 Top 10 performing sites from TNC portfolio as measured by the conservation benefit function ∑dPImin

SITE NAME	Rank	∑dPImin	EOs
Southern Lake Wales Ridge Macrosite	1	4.55	273
Lake Wales Ridge State Forest Conservation Complex	2	3.41	182
Charlie Creek Watershed-Highlands Hammock-LWR Conservation Complex	3	2.90	113
Reedy Creek-Kissimmee Chain of Lakes Macrosite	4	2.88	110
Green Swamp	5	2.79	26
Lake County-North Lake Wales Ridge Warea Complex	6	2.73	84
Gum Slough-Withlacoochee River Conservation Complex	7	2.23	13
Lake Apopka Buffer	8	1.94	18
Withlacoochee State Forest Macrosite	9	1.67	21
Crooked Lake-Habitat Mosaic	10	1.63	101

4.4 Sensitivity Analysis

Four main types of disruption to the data set were carried out, reflecting different scenarios:

- The impact of spatial scale on the measurement of PI contrasting the AOO measured at the 2km reference scale with that measured at 30m.

- Using only the higher threat ranked (G1-G3) EOs, which has the effect of removing the poorer quality habitat models from the analysis.

- Unbiased random deletions of EOs from the dataset.

- Biased random deletions from the dataset, based on increasing the biases inherent in the data based on taxonomic group and threat ranking.

For all of these scenarios attention focused on the worst performing indicator of protection (PImin), and the sites that emerged as high priority (∑dPImin) and how these differ from analyses with the full data set.

4.4.1 Impact of scale:

Figure 4-4 shows the effect of using the AOO measured at the 30m grid size; unsurprisingly this resulted in smaller estimates of AOO compared to a 2km grid. This was reflected in the low PIaoo and corresponding impact on the lowest protection indicator PImin. The effect of this was to have lower overall conservation performance of current and potential future conservation scenarios, when compared with AOO measured at 2km. The values for PInoo and PIeoo remained constant across the two sets.

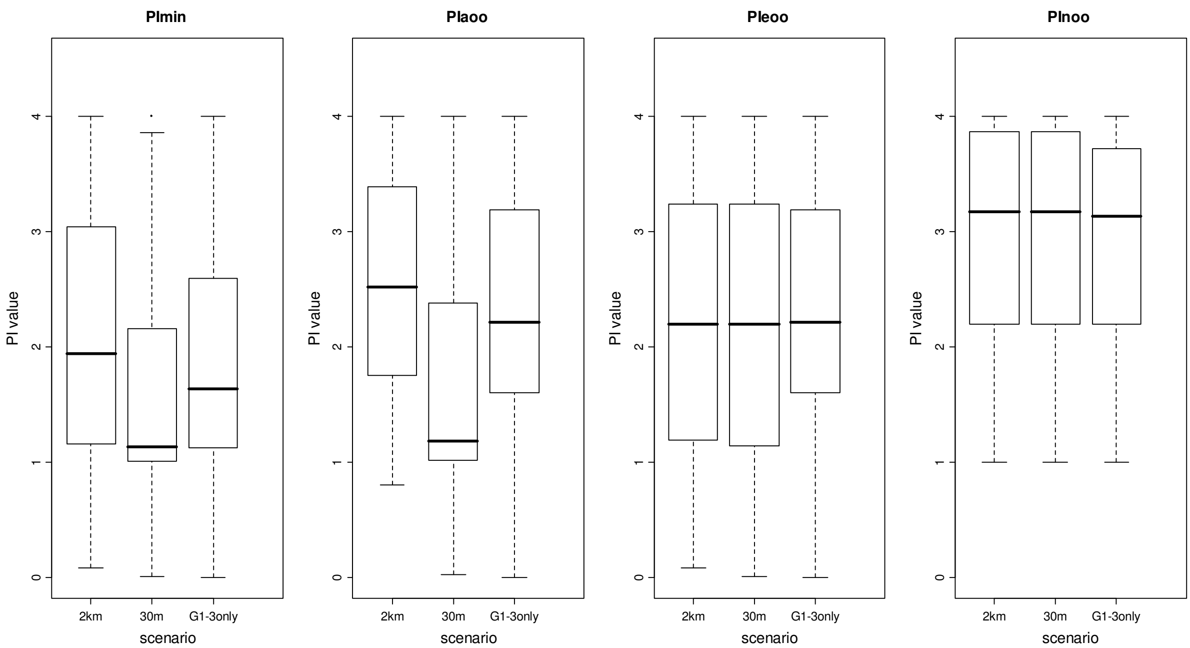

Figure 4-4 Conservation performance parameters, PIaoo, PIeoo, PInoo and PImin in the MA2008 network, for species in three different scenarios; AOO measured at 30m, AOO measured at 2km and with all G4 and G5 species removed

What is the impact of this fall in AOO in terms of species protected and priority sites? The change in AOO meant that the species that benefited most from the TNC portfolio (PImin) was quite different when calculated with AOO measured at 30m than with AOO measured at 2km.

There was less change to the highest priority sites caused by the use of a different scale to estimate AOO. Sites that lost conservation benefit ranking were the smaller sites Table 4-5. This mirrored the increasing influence of AOO as the lowest performing factor (PImin) for many species. The EOO falls for a number of species this is because for species with fewer than 3 EOs, EOO could not be calculated and AOO was used instead.

Table 4-5 Effect of scale at which AOO measured on Top 10 performing TNC sites measured by ∑dPImin

Site Name	Rank 2km	Rank 30m	Area Km^2
Southern Lake Wales Ridge Macrosite	1	2	171.87
Lake Wales Ridge State Forest Conservation Complex	2	6	92.53
Charlie Creek Watershed-Highlands Hammock-LWR Conservation Complex	3	7	270.54
Reedy Creek-Kissimmee Chain of Lakes Macrosite	4	3	412.80
Green Swamp	5	5	930.23
Lake County-North Lake Wales Ridge Warea Complex	6	35	42.76
Gum Slough-Withlacoochee River Conservation Complex	7	1	161.61
Lake Apopka Buffer	8	66	20.39
Withlacoochee State Forest Macrosite	9	4	192.98
Crooked Lake Habitat Mosaic	10	42	74.05

4.4.2 Excluding the G4 and G5 species

This deletion removed all those species associated with the poorer quality habitat models. This had remarkably little impact upon the species that benefited most from the TNC portfolio (PImin). As regards priority sites as measured by benefit added, ∑dPI, all of the top 10 performing sites based on the full set of species are still in the top 10 with the exception of two; Withlacoochee State Forest-Macrosite, which drops to 45 and Gum Slough-Withlacoochee River Conservation Complex which falls to 15. The WSF-Macrosite contained a relatively small number of EOs (21) making it vulnerable to missing data while much of its added value comes from representing species not already present in the MA network which are G4 or G5 species such as *Blechnum occidentale.* A similar pattern was seen for the Gum Slough site with a small number of EOs (18) seven of which were G4 or G5 species removed from this calculation. The remaining sites and the process by which they have been selected were remarkably insensitive to the removal of the less threatened species.

4.4.3 Unbiased deletions

EOs were deleted in random fashion from the EO dataset across a range of percentages from 0-50%. The Protection Index for a given species would be expected to fall with increasing loss of data as EOs are removed with corresponding reductions in NOO, EOO and AOO. However the added value of a site (∑dPI) and thus the identity of priority sites may change.

Figure 4-5 shows the PImin across all species at sequential deletions from 0 to 50% over forty iterations. As data is removed from the database the PImin declines, although the pattern of decline varied greatly across species.

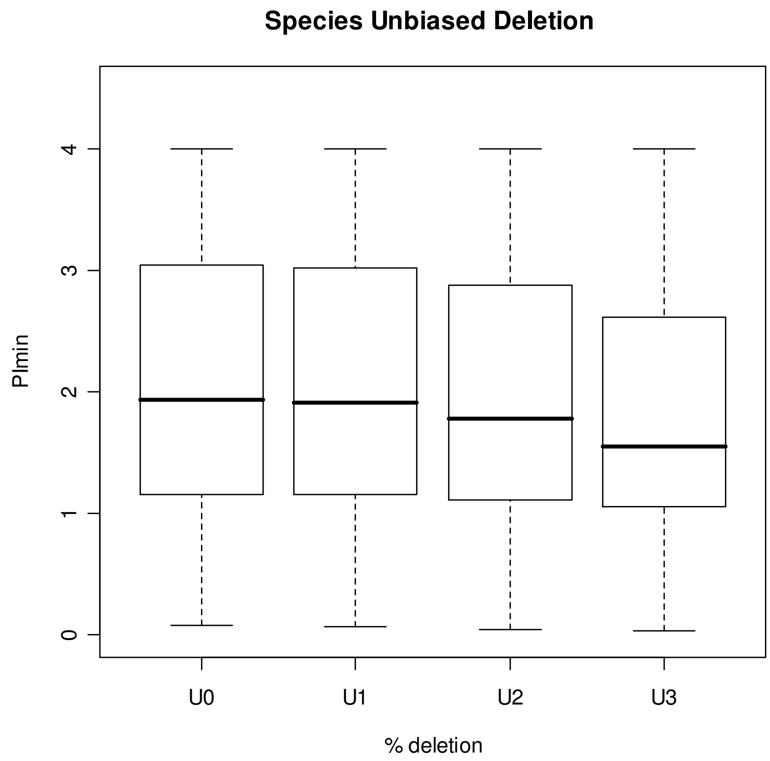

Figure 4-5 plot of species PImin over a series of unbiased deletions U0=0%, U1=8-12%, U2=18-22% and U3=28-32%

Some species, such as *Warea amplexifolia* showed little variation as data was removed (Figure 4-6); these species had a relatively large number of EOs (18) and proved resilient to the effect of data loss.

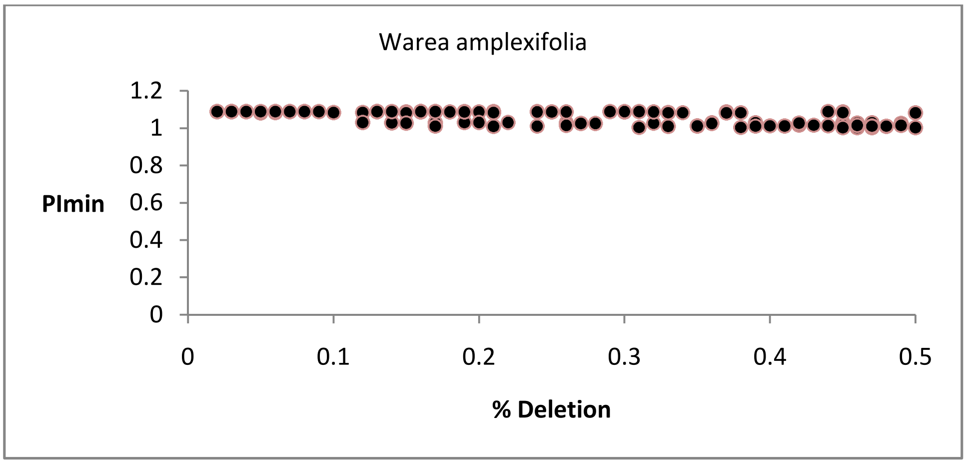

Figure 4-6 A plot showing the lack of change in PImin for the species *Warea amplexifolia* in response to removal of data in a series of unbiased deletions.

However species whose protection status was dependant on one or two EOs, due to either a limited number of occurrences or because of an unusual distribution rendering EOO dependant on a few outlier occurrences, were highly sensitive to data loss. For example, *Gymnopogon chapmanianus* was relatively well protected in terms of number of occurrences, but most of these were clustered, with two EOs contributing greatly to its poorest performing parameter, PIeoo. If these are deleted the PImin drops quite markedly (Figure 4-7), despite its good performance by other indicators.

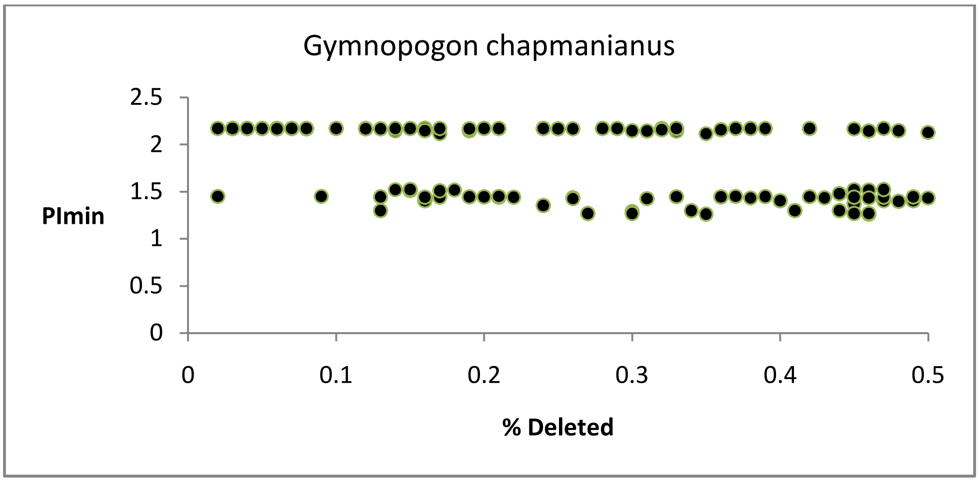

Figure 4-7 A plot showing the drop in PImin for species *Gymnopogon chapmanianus* in response to removal of data in a series of unbiased deletions

Of great importance when setting conservation priorities is how robust a priority site is to data loss. Note that because dPImin is influenced by the performance of other sites, a loss of species protection in another site could cause a site to become more important for that species' protection.

Because the Lake Apopka site has only a 18 EOs (Table 4-4) it is highly sensitive to data loss, observe the drop in ∑dPI at less than 5% data lost (Figure 4-8).

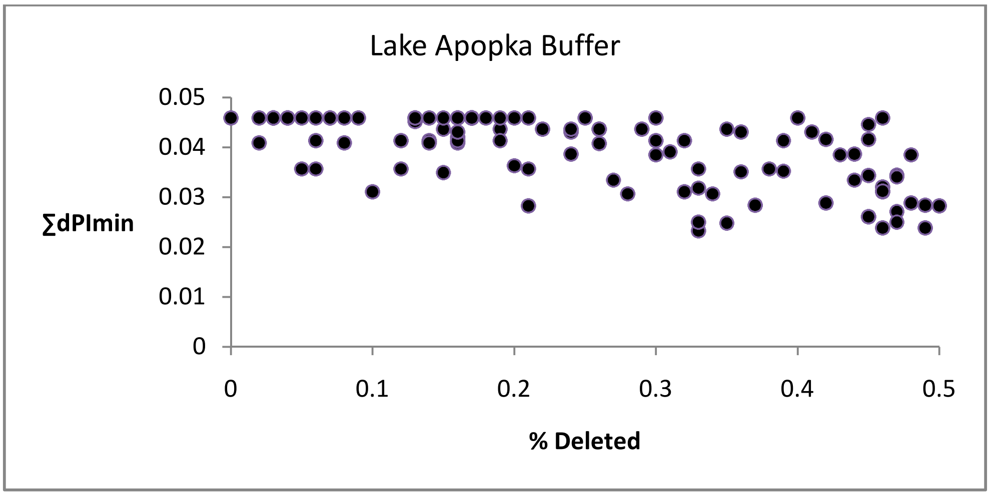

Figure 4-8 A plot showing fall and increased variability in the ∑PImin for the Lake Apopka Buffer site in response to removal of data in a series of unbiased deletions.

Data loss can cause dPImin to go up as well as down. This is well illustrated by the Withlacoochee site (Figure 4-9), although this site also has only 21 EOs, it included species like *Blechnum occidentale* with only 3 EOs.

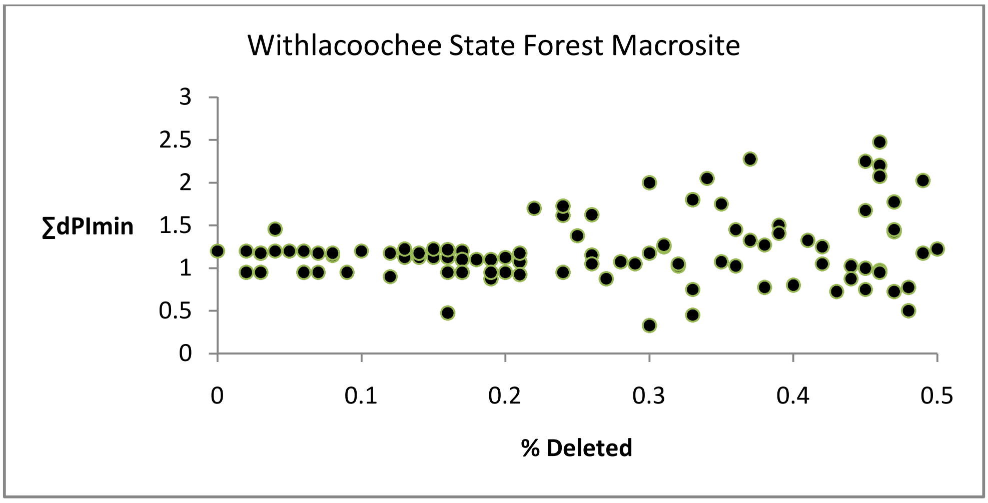

Figure 4-9 A plot showing how the ∑PImin for the Withlacoochee State Forest Macrosite varied, both increasing and decreasing in response to removal of data in a series of unbiased deletions

The highest priority site was the Southern Lake Wales Ridge site which had 273 EOs and was very robust to data depletion (Figure 4-10).

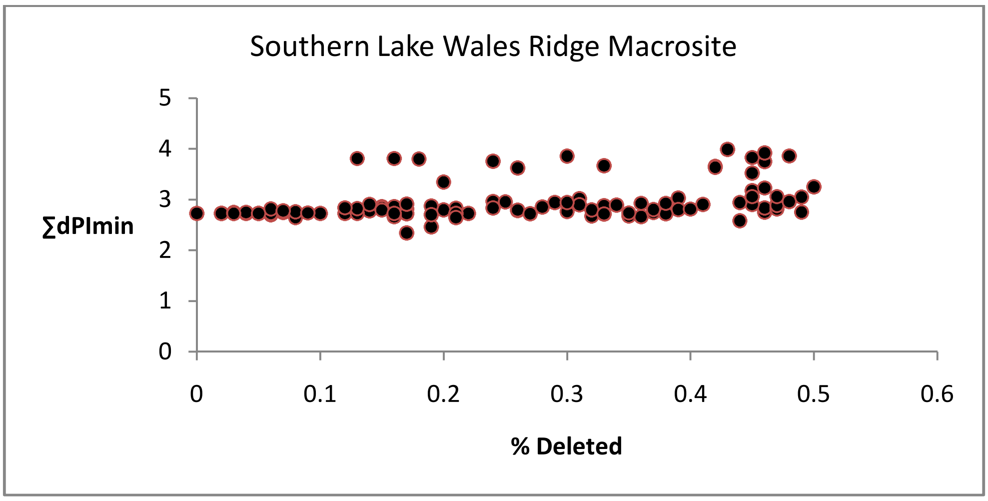

Figure 4-10 A plot showing how the relative lack of variation in ∑PImin for the Southern Lake Wales Ridge Macrosite in response to removal of data in a series of unbiased deletions

4.4.4 Biased deletions

This set of deletions was carried out to increase the existing data bias on the basis of Grank and Taxonomic group. Although different proportions of a given Grank or taxonomic group were set to be deleted, the EOs were deleted on a random basis in similar fashion to the random deletions sequence.

4.4.4.1 Taxonomic Bias

It can be seen from Figure 4-11 that Plants were more affected, in terms of PImin, by the taxonomic biased deletion suggesting that as a group they were more sensitive to this scenario (the single invertebrate species is not represented). All three of the other groups were deleted from the database proportionally less in this scenario.

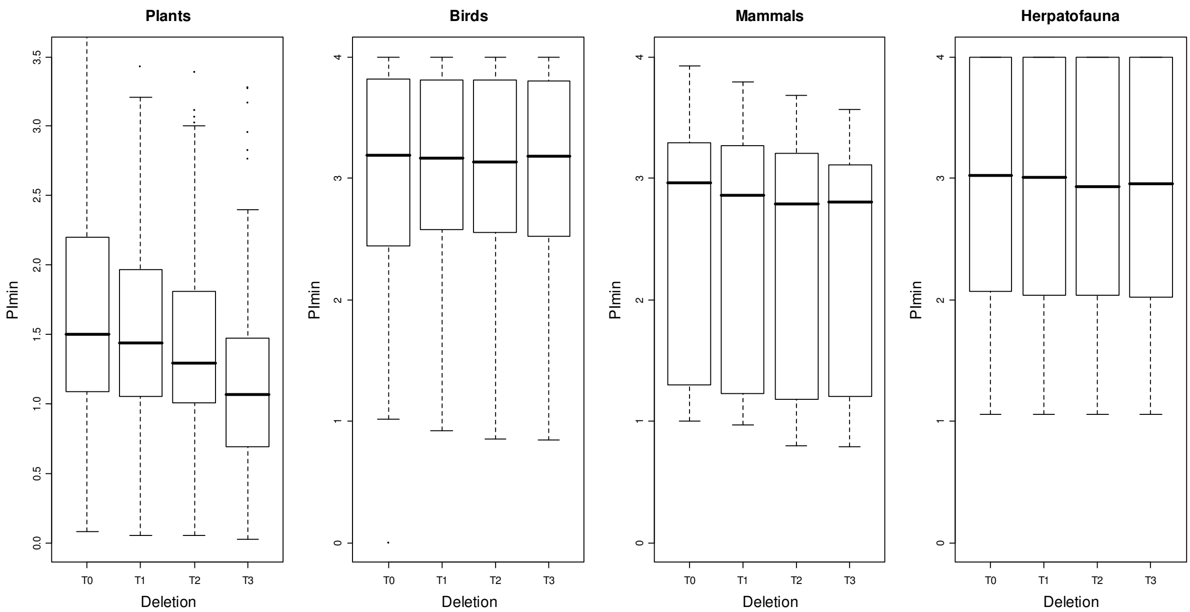

Figure 4-11 Boxplot showing how species from each taxonomic group performed measured by change in PImin as data was depleted on the basis of taxonomic bias. Overall % deleted from dataset given by T0= 0% deleted, T1=8-12% deleted, T2=18-22% deleted and T=3=28-32% deleted. The group Plants shows a fall in PImin whilst the other groups are little affected.

Figure 4-12 shows that the effects of the taxonomic biased deletion are more marked when broken down by Grank. All Granks showed a drop in PImin across the species with increasing removal of data. This is particularly marked for the lower 75% of each Grank. The top performing 25% were resilient in the face of the data lost in this scenario. This shows the significance of the larger number of plants species in each group. Because they were deleted in greater proportion they had fewer EOs compared with other groups and correspondingly lower PImins. This effect is illustrated by the finding that Plants were the only group more sensitive to the biased deletions than an unbiased deletion of the same number of occurrences (Figure 4-13).

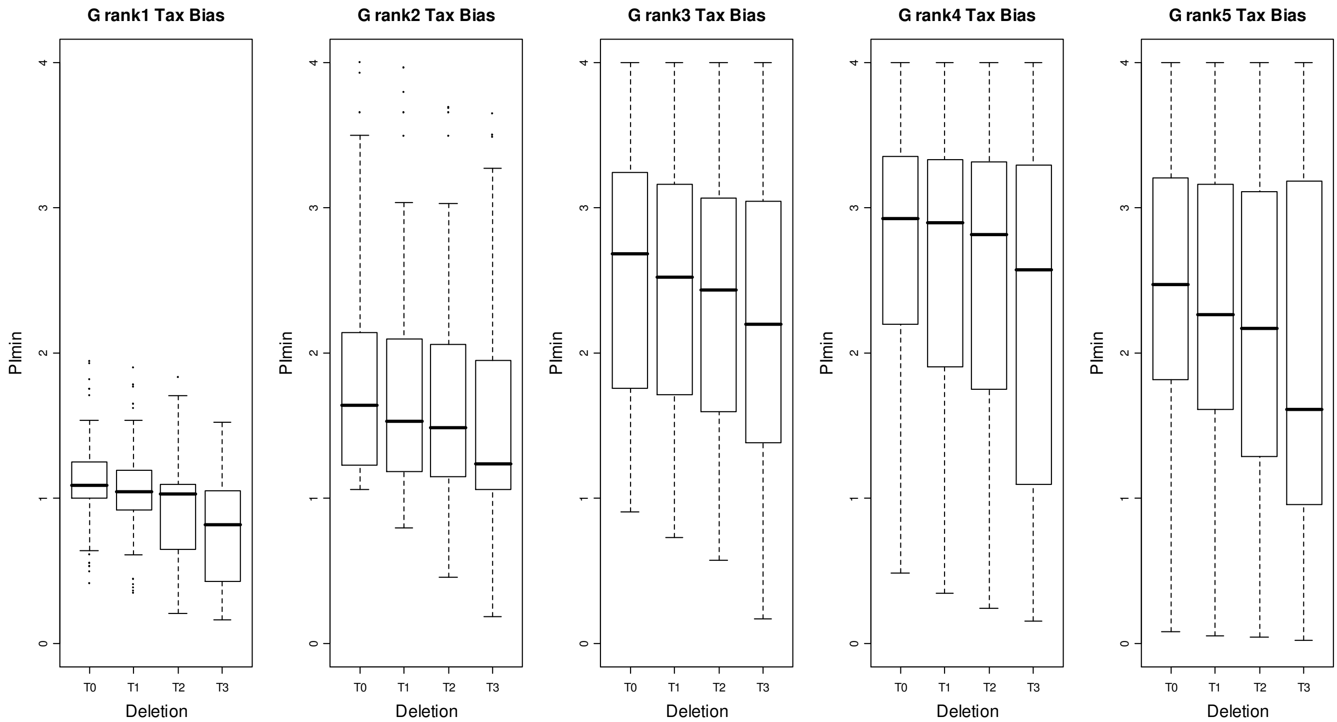

Figure 4-12 Boxplot showing how species from each Grank performed measured by change in PImin as data was depleted on the basis of taxonomic bias. Overall % deleted from dataset given by T0= 0% deleted, T1=8-12% deleted, T2=18-22% deleted and T3=28-32% deleted. There is a marked fall in median values with increasing % deletion.

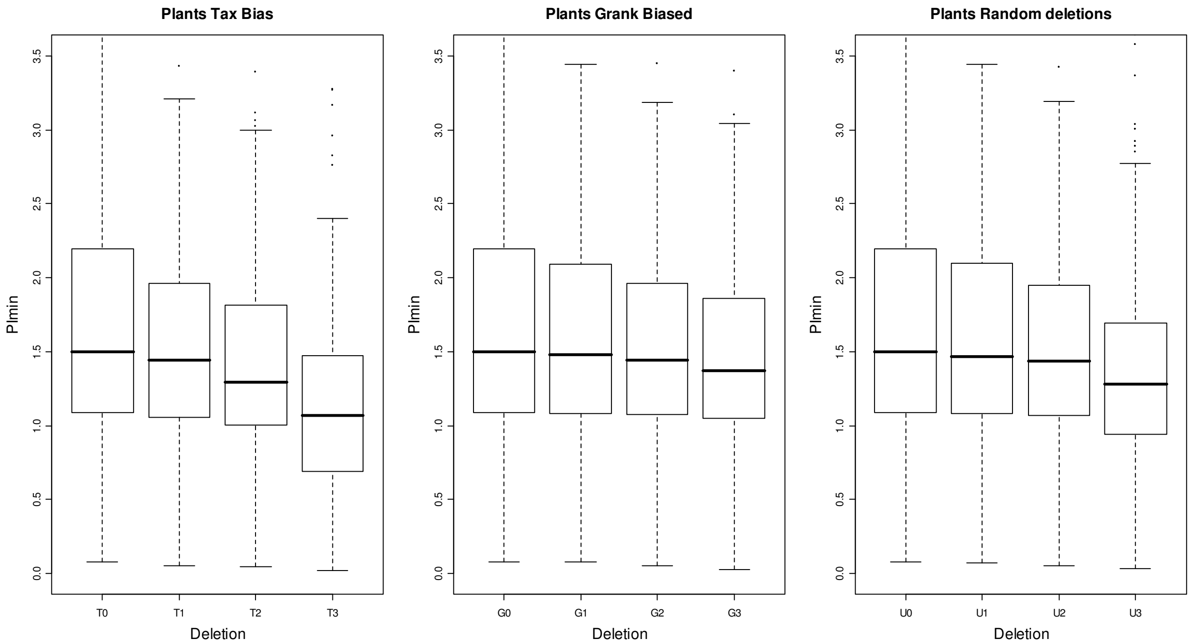

Figure 4-13 Boxplots comparing the effects of the three deletions on the group Plants measured by PImin. This demonstrates the greater effect of the taxonomic bias deletion compared to a random deletion of the same total number of occurrences. Overall % deleted from dataset given by G0/T0= 0% deleted, G1/T1=8-12% deleted, T1/T2=18-22% deleted and G3/T3=28-32% deleted

4.4.4.2 Grank Bias

The Grank bias deletion had the most pronounced effect on the less threatened G4 and G5 species which were deleted in greater proportion to the other Granks (Figure 4-14).

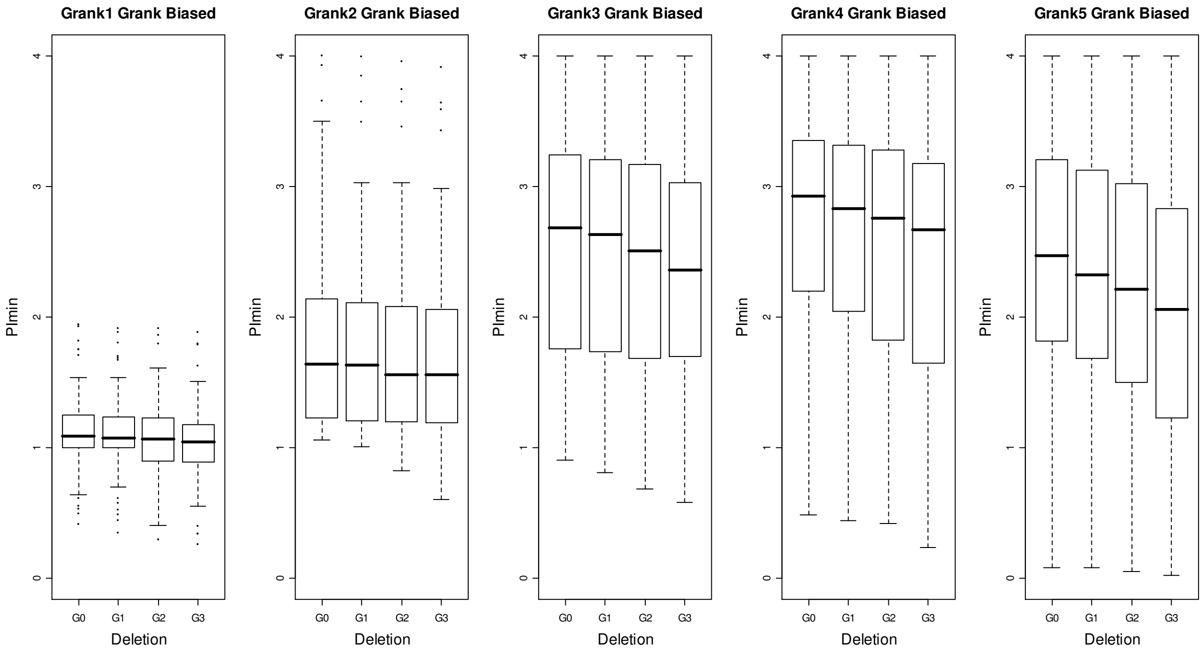

Figure 4-14 Boxplot showing how species from each Grank performed measured by change in mean PImin as data was depleted on the basis of Grank bias. Overall % deleted from dataset given by G0= 0% deleted, G1=8-12% deleted, G2=18-22% deleted and G3=28-32% deleted. There is a marked fall in median values with increasing % deletion for the lower threat ranks G4 and G5.

A more general trend was seen across the taxonomic groups in the Grank deletion with a moderate fall in PImin with increasing removal of data (Figure 4-15). This reflects to some degree the spread of Granks across each group.

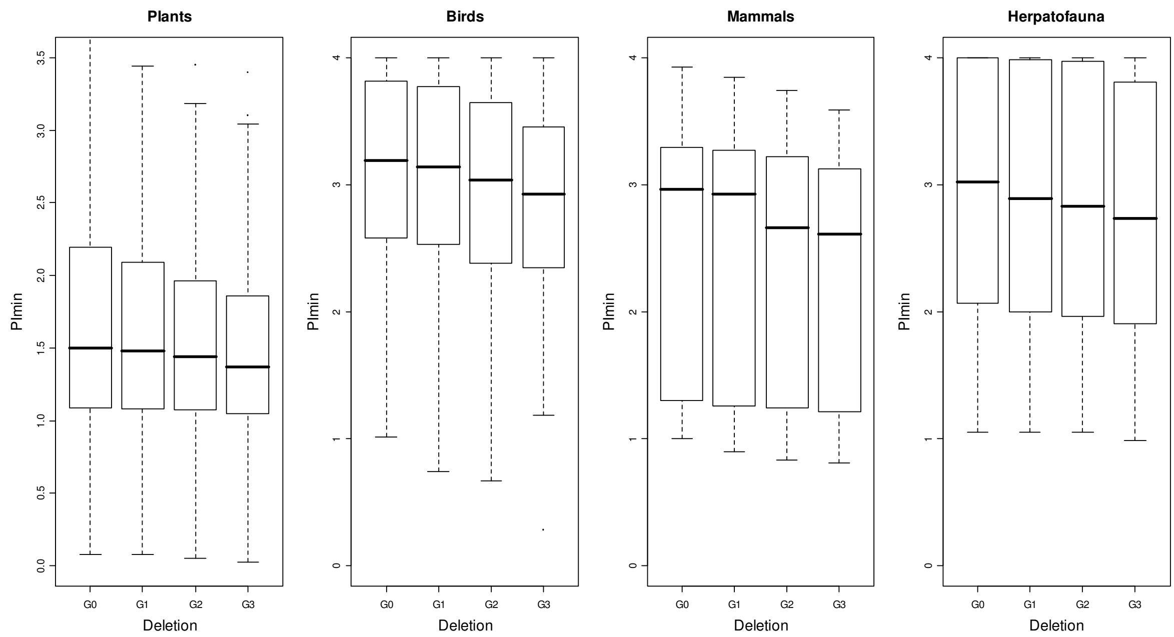

Figure 4-15 Boxplot showing how species from each Taxonomic Group performed measured by change in mean PImin as data was depleted on the basis of Grank bias. Overall % deleted from dataset given by G0= 0% deleted, G1=8-12% deleted, G2=18-22% deleted and G3=28-32% deleted. There is a moderate fall in median values with increasing % deletion for all groups G4 and G5

4.4.4.3 How do the sensitivity analyses affect site performance?

For many of the original top performing sites the sensitivity analyses had little impact on performance as measured by ∑dPI. This was not true for all sites and Figure 4-16 shows an example in Green swamp, a site which was particularly sensitive to the taxonnomic biased deletion. This reflects the fact that much of its 'value'came from a small number of plant occurrences which were more likely to be deleted in that scenario.

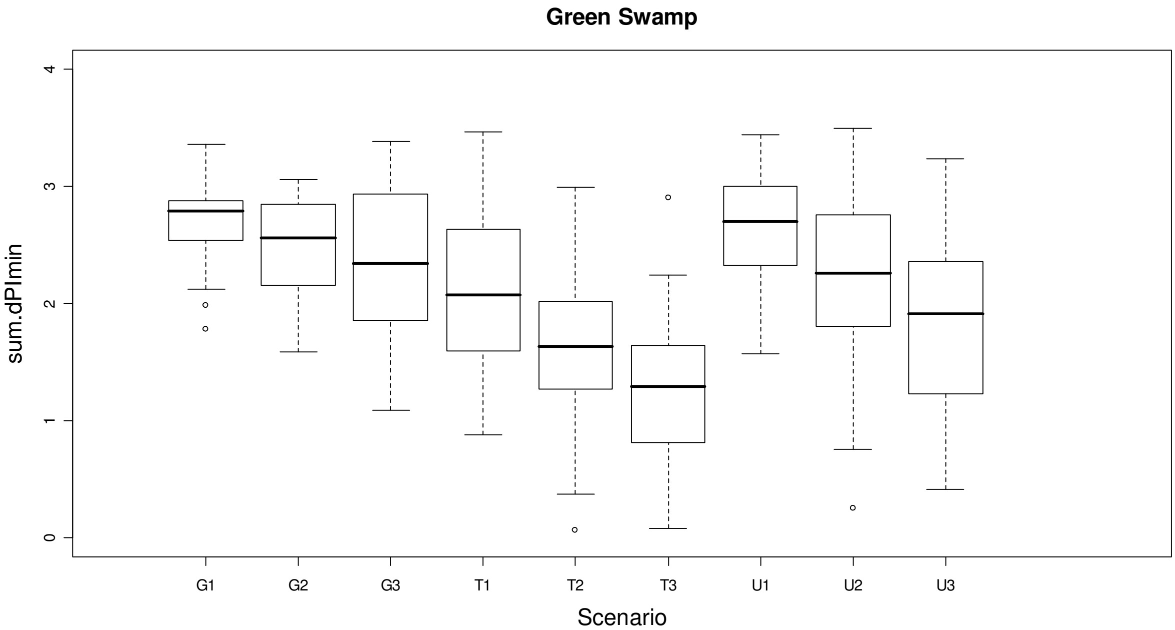

Figure 4-16 Boxplot for the Green Swamp site of how ∑dPI varied with each scenario. This site was sensitive to the taxonomic bias whilst it was little affected by the Grank bias. G=Grank bias, T=taxonomic bias, and U=unbiased. 1=8-12% deleted, 2=18-22% deleted and 3 =28-32% deleted.

It is noteworthy that no site showed a greater sensitivity to Grank biased deletion than either the random or taxonomic biased scenario. Overall, the top 10 performing sites measured currently, apart from the exceptions mentioned above, tended to perform as well across all the scenarios of the sensitivity analysis.

5. Discussion

The overall aim of this study was to investigate how conservation planning and ultimately decision making is affected by data quality and uncertainty. Strategic conservation planning tools are used by most conservation groups and natural resource managers (Meir et al 2004). All planning methods, whatever decision making tool they use, rely on input data to help produce useful outputs. Many authors have reported on the potential significance of data quality and uncertainty in conservation planning (Moilanen et al 2006, Wolman 2006, Ponder et al 2001, Pressey 2004) whilst at the same time noting that little work has been done to explore the impacts of this on decision making (Araújo 2004). In fact there is very little in the literature exploring the effect of data quality on decision making outputs in conservation planning (see Grand et al 2007 and Freitag & van Jaarsveld 1998 for rare examples).

The lack of analyses on the impact of data quality gives grounds for concern with regard to its effect on planning decisions and ultimately implementation. It would seem crucial to try and understand how our planning tools perform in the face of this uncertainty. To do this I performed a sensitivity analysis of the recently developed metric, the Protection Index (Turner et al 2006a) a conservation benefit function based on the IUCN guidelines that has been used as a measure of conservation progress in the field (Turner et al 2006b and Nicholson et al 2007).

The FNAI database used in this study is well maintained and benefits from existing in a well funded environment in a wealthy, developed nation (Nicholson et al 2007, Turner et al 2006). In other areas of the world data sets will be less complete, particularly in the developing nations where similar time and resources cannot be spared (Hernandez et al 2008). It has been well documented that these countries are often the location of many of the worlds' biodiversity hotspots (Myers et al 2000, Balmford et al 2003, Olsen & Dinerstein 2002). Data will always be incomplete (Wolman 2006) but sound decisions still need to be made, even in these circumstances. The findings on how data depletion affects the Protection Index provide insights into the factors that can influence how a planning tool performs in such data poor environments.

From the results it is very clear that as data is depleted two things happen. Firstly, our understanding of conservation progress and managed area coverage of species is not as comprehensive and thus priority species for conservation can change. Secondly, our priorities in terms of best sites for acquisition can change. I found that sites are varyingly sensitive to loss of data. Predictably, sites with many species occurrences consistently perform better than others (Figure 4-11). As data is depleted, however, some sites fared worse than others. This tended to be sites for which the measure of conservation benefit (∑dPImin) was boosted by a small number of occurrences. If these occurrences represent a priority species not currently represented in the managed area network then it is important that this site is identified. The metric does not differentiate between species by threat status, only whether the species is represented in the current managed area network or not. Therefore a site can gain its value by adding a few occurrences of any species, threatened or not as long as it ‘adds value’. Thus the definition of what constitutes ‘value’ is vital, the setting of conservation goals and objectives (Nicholson & Possingham 2006, Wilson et al 2006) and the important question, what are we looking to achieve? In common with many measures of conservation benefit, species distribution information is the currency for PI. Therefore it must be ensured that representation within the data set reflects their real world occurrence, i.e. rare in the database should equal rare in reality.

An important finding was that the current top 10 priority sites identified by the metric ∑dPImin were relatively robust throughout the sensitivity analysis. For the five different scenarios only two sites failed to continue to score highly. This would suggest that for this data set, the PI metric is quite robust in identifying sites that perform well by its measure of added conservation benefit ∑dPImin.

The effect of the scale at which AOO was measured had a major impact on species coverage and therefore conservation priorities. The significance of spatial scale in conservation decision making is documented, but its impact in regional level planning is not (see Larsen & Rahbek 2003 and Hulbert and Jetz 2007 for studies on how scale affects coarser scale conservation planning). Of the sensitivity tests carried out in this study it is noteworthy that changing the scale at which AOO was measured had the biggest impact on outcomes, what goals were met in terms of species protection (PImin)and what sites were deemed valuable (table 4-5). Obviously not all metrics rely directly on assessment of AOO to derive benefit assessments but the scale at which species distribution data is collected and presented will have an impact on outcomes (see Hulbert and Jetz 2007 , Rondini et al 2006 and Hartley & Kunin 2003). The scale at which input data is measured or presented should be suitable for the type of decisions being made.

5.1 Sensitivity Analyses

5.1.1 Analyses of biases in the data set

We found that although the FNAI database is extensive and represents one of the best natural area inventories available there were inevitably biases in the dataset. The information presented in results (section 4.1) illustrates the taxonomic and threat ranking based biases present in the FNAI database. The over-representation of birds and herpatofauna (Table 4-2) likely reflects both their 'charisma' as a group as well as their relative detectability. By way of contrast, plants despite making up by far the most species (119 out of 181) are under-represented in terms of number of occurrences. Many plants are in the higher threat categories (G1-G3) so their low EO numbers may represent real rarity. It is at the lower threat levels that they are proportionally underrepresented. One could speculate that this reflects a lack of 'charisma' amongst the less threatened members of this group. It may also be true that more wide ranging plants are less detectable and therefore less represented (McIntyre et al 1992). On the other hand in certain areas like the Lake Wales Ridge rare endemic plants have received a lot of focus (Muller et al 1988). Much further work on species traits would provide useful information with regards to intrinsic and extrinsic factors that may influence representation in the database.

One of the disadvantages of using Grank as assessed up to present by NatureServe is its qualitative component (see section 3.3.1). This means that one should be cautious in drawing conclusions in comparisons between species on the basis of Grank alone. A general trend of under- and over-representation displayed in Figure 4-1 likely represents the targeted nature in tracking the higher threat categories (G1 and G2) contrasted with a more opportunistic approach to the less threatened (G3-5).

The biased nature of species based data is well documented (Pressey 2004, Cowling et al 2004). Identifying some of the biases present in the FNAI data base and using these in the strategic deletions was done to reflect what might happen in a data poor environment. Much data collection tends to focus on rarer species and taxa such as plants and invertebrates do tend to be underrepresented.

5.1.2 The impact of unbiased random deletions

The main pattern noted in the unbiased deletions is one of increasing variation with the increasing proportion of data removed. This is illustrated very well for changes in site ∑dPI particularly Withlacoochee State Forest Macrosite (Figure 4-9) with data points spreading out as the percentage deletion increases. A similar pattern of increased variability is seen for species protection (PImin) and sites whose value comes from representing these species are more sensitive to absence of data. The studies by Freitag and Van Jaarsveld (1998) and Grand et al (2007) found an increase in the variability of selection process outcomes in response to depletion of data sets. The study by Grand et al (2007) was using a much bigger set of planning units and ran many repeat iterations which meant that variation in site selection would be amplified. In this study however, we were looking at a smaller suite of real sites which meant that less variability in selection process outcomes may be expected – there are less possible combinations (many sites contributed nothing). However a small set of sites are much more sensitive to removal of data than others, those sites with a small number of high value occurrences. This has significant implications for conservation planners as sites that may be important in terms of protecting rare species with only a few occurrences may be missed when assessed in data poor situations. Conservation plans with goals that involve increasing representation of rare species alone are likely to be very sensitive to this effect. A planning process for which the rarer species are most likely to be missed is a concern. Of course data is not missing from inventories or databases in a random manner although patterns of increasing variability in outputs as less and less data are available is true regardless of the nature of data loss.

The exaggeration of the taxonomic bias in the database through data depletion based on taxonomic group had the most profound impact of the two biased deletion scenarios explored. For some sites, containing a number of valuable plant occurrences this affected their overall performance (Figure 4-16). As taxonomic biases are well established within species inventories (Gaston & Rodrigues 2003) this means that planning tools focussing on species occurrences will potentially miss valuable sites.

The patterns seen as a result of the Grank biasing were little different from the effect of random deletion of the same proportion of data. This means that the site performance indicator was very resilient to this process with the same sites generally performing well. For this data set, this suggests a good representation of threatened species in the high performing sites.

5.2 Limitations and Future Work

A number of problems were encountered or identified during the study:

The main problem encountered related to the limitations of ArcGIS in not allowing processing of the spatial data whilst retaining the boundary integrity of small sites. Given the significance attached to measuring site performance for the TNC portfolio, site integrity was crucial and no 'work-round' within the software was found. Communication with ESRI confirmed the limitations of the package for this task. This meant that directly measuring AOO across a range of scales as intended for the sensitivity analysis was not possible. It was still possible using the methods described to assess the impact of scale on the PI metric.

For reason of computational time only a small number of iterations (n=40) was available for a given % deletion within the sensitivity analysis. This minimised the probabilistic effects of the random component of the deletions that may skew results but a higher number would allow more confident predictions to be made. The study by Grand et al (2007) ran 1000 sets with 10,000 permutation sets, although it should be noted utilising the pre-existing software tool in MARXAN. It is easily possible for this study to be extended for more iterations and generate more predictive power accordingly. A comparison of the robustness of different planning tools to data quality would provide a very useful review of the utility of conservation planning tools under real world data constraints. Such a review could include the most commonly used tools Marxan (Ball & Possingham 2000, Game and Grantham 2008) and Zonation (Moilanen & Kujala 2006).

Following the study by Nicholson et al (2007) we used 1980 as a cut off for most recent observation. In all likelihood, given the pace of development in the region this will have included extirpated occurrences. The NatureServe guidelines recommend that any occurrence last observed over 20 years ago be designated as historical (H). A more conservative cut off date would be useful for up to date planning (Meier & Dikow 2004).

There is much scope for further work following on from this study. There is a plethora of information within the FNAI database which could inform further investigation of biases in the dataset. Investigation of species with regard to life history and other intrinsic factors would be informative, and could add an extra level of understanding with regards to how species are represented within the database. As it stands the study lacks any component relating to persistence of biodiversity, by incorporating the viability records that exist for each EO this could be partly rectified. Following Nicholson et al (2007) demonstrating the utility of this method for assessing conservation progress in the Florida scenario and the use of the sensitivity analysis in replicating data poor scenarios it would be fascinating to use a less well endowed data set from another region. It would be informative to have information of how the occurrence data was collected for this study to allow comparison of survey method and its impact on outputs.

5.3 Recommendations

This study is potentially unique in applying a sensitivity analysis to a real world conservation planning scenario at a regional scale. A number of significant findings have implications for further work and conservation action on the ground as well as data collection and survey effort. The analyses of biases within the data set, although identifying well recognized patterns of data bias (Pressey et al 2004) does not seem to be a commonly performed part of planning processes,

‘..a feature common to all implementations is the acceptance of biological data at face value...’ Moilanen et al (2006)

but is a vital aspect of understanding how the available information will affect outcomes. The over – representation of some groups within species datasets, particular those that are of low conservation priority may mean that reserve networks are missing valuable sites. The greater sensitivity of some sites to taxonomic bias in this study is of note with regards to this. Particular attention needs to be focused on the data not included within databases. The data depletion process identified sites performing well in the current situation that are highly sensitive to a poor data situation. Typically this was found to be due to them having only a few valuable occurrences. This has implications for how best to target survey efforts. Little value is gained for conservation planning by repeat surveys in sites already well represented with occurrences, efforts to identify outlying populations or narrowly distributed species of conservation concern may be more significant, although such surveys may be useful for other purposes, such as monitoring or demographic studies. The example of *Gymnopogon chapmanianus* in section 4.4.3 illustrates the importance of gaining as good as possible as estimation of species range. That said, it is to be acknowledged that often the most expensive component of the planning process is data acquisition and as Cowling et al (2004) state, ‘data do not save species, they merely allow us to measure them’. In addition the scope for unbiased surveys in many developing nations is not there (Lombard et al 2003). This study is an example of a sensitivity analysis of a single conservation metric but there is much scope for extending and expanding work both within this data and application elsewhere. The effect of spatial bias in terms of survey effort and extent, for example proximity to roads is well documented (Freitag et al 1998, Brooks et al 2001). The preliminary analysis of biases did investigate this and found there was indeed a bias towards occurrences along roads but analysis of impact was beyond the scope of this study. Further work on what is typically a major bias would be informative for a sensitivity analysis with a view to advising future survey effort (Grand et al 2007 and Freitag and van Jaarsveld 1998).

A conclusion from this study is the limitations of using a metric such as the PI as the sole instrument for conservation decision making. If the overall goal is to ensure persistence of biodiversity many other factors need to be considered; including landscape structure such as patch size and connectivity (Margules & Pressey 2000), dynamic processes such as impact of climate change (Hannah et al 2007) and maximising evolutionary potential (Forest et al 2007). Real world factors such as acquisition and ongoing management cost (Naidoo et al 2006), feasibility, nearby land use changes and opportunity (Knight et al 2007) to name a few, are also critical in determining where conservation action can and should go ahead. Identifying goals and objectives have to be the first part of any planning process in the structured process decision theory framework (see Nicholson & Possingham 2006, Westphal & Possingham 2003 and McBride et al 2007) that is necessary for integrating such different and competing factors for rigorous and sound decision making (see Nicholson & Possingham 2006, Westphal & Possingham and McBride 2007).

This study has demonstrated that the biases within data have an impact on the outputs of a conservation planning tool. It has also demonstrated the application of sensitivity testing as a method of exploring the uncertainties that exist within input data for a real conservation planning scenario. All data is biased to some extent, creating uncertainty in the inputs to decision making mechanisms. It is crucial to acknowledge, study and communicate this aspect of data uncertainty (Rae et al 2007). The potential significance of this is acknowledged in the literature but the study of its impact on decision making and the implications of this are few. Any planning process can and should use sensitivity testing to better understand how it performs as a decision making tool and ensure that 'it is robust enough to aid, rather than hinder the decision making process' (Crosetto & Tarantola 2001).

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