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Comparing IUCN and probabilistic assessments of threat: do IUCN red list criteria conflate rarity and threat?

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Abstract. Estimates of threat form an intrinsic element of World Conservation Union (IUCN) Red List criteria, and in the assignment of species to defined threat categories. However, assignment under the IUCN criteria is demanding in terms of the amount of information that is required. For many species adequate data are lacking. Further, many of the terms and parameters used under IUCN criteria are subjective and open to varying interpretations. During the last decade a number of probabilistic statistical models have been developed which use historical sighting data, such as herbarium and museum collections, to generate objective, quantitative inference of threat and extinction without the requirement for extensive formal survey procedures and where little or no other data exists. In this study these statistical models were applied to herbarium data for the genus *Guzmania* (Bromeliaceae) from Ecuador. The results suggest that, for species for which collection records are adequate, these methods can be of use in strengthening IUCN Red List assessment procedure. Further, these methods present a unique means of prioritising threat when few biological data are available.

Introduction

The absolute magnitude of contemporary extinction is uncertain, primarily because, for the majority of taxa, observations are insufficient to directly conclude that extinction has occurred (Diamond 1987). However, it is a widely held view that we are currently entering a major extinction event – one of potentially far greater magnitude than the last significant wave of extinction of the Cretaceous-Tertiary boundary. Recent extinction rates have been estimated which are far in excess of those of the geological past (Pimm 1998). Indeed, calculations of projected extinction rates in relation to background rates estimated from the fossil record, suggest impending extinction at least four orders of magnitude greater than in the geological past (May et al. 1996).

Roberts and Kitchener (in press) provide a number of recent examples of supposed ‘extinction’ and subsequent rediscovery, which serve to illustrate the difficulties in achieving effective survey and monitoring of endangered species, and establishment of extinction events. This is especially so for taxa of difficult habitats, such as rainforests. False alarms of extinction pose difficulties to conservation effort because they have the potential to undermine both effective remedial conservation action, and public confidence in conservation science.

In an ideal scenario, a conservation biologist would have perfect knowledge of the extinction risk for a given species, and know the best means to protect it. In reality, they have to find practical methods of assessing extinction risk (Mace and Hudson 1999). Estimates of extinction and threat are therefore of primary concern to conservation biologists, with threat usually expressed as a combination of the magnitude of the impending decline within a given time-frame and the probability that a decline of that magnitude will occur (Burgman et al. 1999). This assessment should be a scientific process, which ideally should be completely objective (Mace and Lande 1991).

Estimates of threat form an intrinsic element of World Conservation Union (IUCN) Red List criteria in the production of Red Lists and Red Data Books, and in the assignment of species to a ranked threat category (Hilton-Taylor 2000). Under the current classification process, a range of quantitative criteria must be fulfilled for listing under each of these categories. Meeting any one of those criteria qualifies a species for listing at that level of threat. There are five quantitative criteria, (A–E), used to determine threat status, as follows:

A. Declining population, past, present and/or projected.
B. Geographic range size, and fragmentation, decline or fluctuations.
C. Small population size and fragmentation, decline or fluctuations.
D. Very small population size or very restricted distribution.
E. Quantitative analysis of extinction risk (IUCN 2001).

The five criteria are based on biological indicators of populations that may be threatened with extinction, and were developed specifically with the objective of creating criteria suitable for universal application across a broad range of organisms with diverse life histories. However, application of these criteria each requires reference to high-quality data, although in the absence of such data IUCN policy states that assessment should still be undertaken, and that estimation, inference or projection are acceptable (IUCN 2001). IUCN Red List guidelines, (IUCN 2003), recognise that data used to evaluate taxa against IUCN criteria are often obtained under considerable uncertainty. This uncertainty may be in the form of lack of information or data uncertainty, the latter being broadly categorised as either semantic (vagueness of terms), natural variation or measurement error (Akçakaya et al. 2000). In this respect, Willis et al. (2003) reviewed some of the practical difficulties associated with the application of IUCN criteria in the assessment of threat. Most of these issues relate to subjectivity in interpretation and in implementation of many of the terms and parameters employed under IUCN criteria. Terms such as 'location' (criteria B and D), are scale-dependant and subjective, and require assessors to be clear about the specific threats existing at a given location. Similarly, 'fragmentation' (criteria B and C), is a parameter open to variable interpretation, since the severity of fragmentation will vary widely between taxonomic groups. 'Area of occupancy' (AOO), is a widely used parameter (criteria A, B and D), and IUCN guidelines specify that grid size, used to measure AOO, be appropriate to the species concerned. However, assignment of grid size is problematic and fraught with subjectivity. Willis et al. (2003) demonstrated how, in applying different grid sizes to species of *Plectranthus*, threat category could be assigned as Critically Endangered (CR), Endangered (EN), Vulnerable (VU), Near Threatened (NT) or Least Concern (LC).

Sparse knowledge of species numbers and distributions, both in time and space, severely restricts any ability to inform conservation planners (Graham et al. 2004). In such circumstances, the determination of conservation status may become a subjective matter, with little clear evidence to guide opinion. However, in order to set conservation priorities legislators require, in each case, some statement of status, however weak the information available (Mace and Lande 1991). In reality, for the majority of species, most of the available data is in the form of collections held in museums and herbaria (Burgman et al. 1995). These natural history and herbarium collections do provide a unique, and potentially invaluable, resource for conservation assessment. In the order of 2.5 billion specimens are estimated to be held globally; each with an associated collection record documenting the time when, and place where, the specimen was collected. The potential to harness this resource to aid conservation planning has been vastly strengthened with the advent of web-accessible databases, and the subsequent availability of computerised biological collections via the internet. This resource continues to grow as computerisation of biological collections proceeds worldwide (Suarez and Tsutsui 2004).

Detection is a function of density, distribution, habitat structure and visibility, and hence rare or cryptic species are at risk of being overlooked during any survey (Reed 1996). McArdle (1990) demonstrated that, for rare species, statistical certainty of extinction can be almost impossible to derive from fieldwork. However, recently a number of probabilistic statistical models have been presented (Solow 1993a, b; McCarthy 1998; Solow and Roberts 2003; McInerny et al. in press) which use historical sighting data, of the type held within museum and herbarium collections, to generate quantitative inferences of threat where little alternative information is available. As such they may prove a valuable tool in the assessment process when data is limited.

Rarity and endemism represent two factors which have particular significance in the consideration of risk of extinction and decline. Indeed, species most prone to extinction currently are often considered to be those that are naturally rare (Pimm 1998). Past extinctions have been primarily concentrated within relatively small endemic-rich areas, and it is these regions that hold the key to current threat (Pimm et al. 1995). It has been estimated that species endemic to a single country represent 46–62% of world flora (Pitman and Jørgensen 2002). Further, they observed that the number of plant species endemic to a country represents a reasonable surrogate for the number of globally threatened plant species in that country.

However, rarity does not itself necessarily represent threat i.e. not all rare species are threatened. This is especially so for many plant species which, provided habitat remains intact, may exist successfully as rare species in small populations and at few locations. We studied herbarium data of the genus *Guzmania* (Bromeliaceae) from the montane cloud forests of Ecuador, a habitat under great pressure from habitat destruction (Valencia et al. 2000). The primary questions which this study set out to address, were,

Can statistical indices derived from sighting data be used to generate inference of threat?

Is there a dichotomy between rarity and threat, and can this be differentiated, either by IUCN criteria, or by the application of statistical indices?

Materials and methods

Data

'Libro Rojo de Las Plantas Endemicas del Ecuador' (Valencia et al. 2000), lists all known vascular plants endemic to Ecuador. Almost all have been assessed and have been ascribed a threat category under current IUCN criteria (Valencia et al. 2000; IUCN 2001). Data from Valencia et al. (2000) were used to list all endemic species of *Guzmania* (Bromeliaceae). Collection data were extracted from the Tropicos database based at Missouri Botanical Garden (http://mobot.mobot.org/W3T/Search/vast.html, data assessed May 2004). For each species with ≥3 sightings, the year of collection of each specimen was recorded. Specimens derived from plants flowering in cultivation were excluded, but in cases where the date of collection of the original material could be firmly established, this original date was substituted. Finally, application of the statistical models requires that collections be made independently of each other; therefore multiple sightings within each time unit were recorded as a single sighting.

Statistical models

Recently, a number of probabilistic statistical models have been presented (Solow 1993a, b; McCarthy 1998; Solow and Roberts 2003; Solow 2005; McInerny et al. in press) to infer extinction from a sighting record, such as that found in biological collections, and have been review by Burgman et al. (2000) and more recently by Solow (2005). McCarthy (1998) used such probabilistic models to infer decline i.e. the lower the *p*-value the greater the decline.

The data were arranged as a binary series within the period, T, at ordered times, $t_1 < t_2 < \cdots < t_n$ with multiple sightings recorded as a single sighting for any single time unit, as the methods assume collections are independent of one another (McCarthy 1998). Sustained collecting of *Guzmania* began in 1956, therefore only specimens collected after this date were considered. For each species, the start date, t_0, was taken as the date when the first specimen was collected, therefore n reduces by 1. An end-date for observation of 2003 was used.

Collection effort is not a uniform process, so instead of using time as a measure of the period between sightings, an index of collection effort for each year (e_i) is used. Collection effort can be calculated as the proportion of the total species observed in each time unit (McCarthy pers. comm. 2002), assuming all species have an equal chance of being observed at any time in the locality. If collection effort does not vary over the period (0 to T), then the equation reduces to the Solow equation, $p = (t_n/T)^n$, (McCarthy 1998).

The following five probabilistic models were used to infer species decline (McCarthy 1998),

1. Solow (Solow 1993a)
2. Partial Solow (McCarthy 1998)
3. Solow/Roberts (Solow and Roberts 2003)
4. Partial Solow/Roberts (modified Solow and Roberts 2003 using e_i)
5. Sighting Rate (McInerny et al. in press)

Recording method

Spearman's rank correlation tests for positive correlations between the calculated p-values (Table 1) and the ranked IUCN Red List categories (EX = 1, CR = 2, EN = 3, VU = 4, NT and LC = 5) were performed. This naturally leads to a one-sided test. The performance of each model was evaluated in terms of its relationship to IUCN rank order.

Rarity vs. threat

Under current IUCN criteria, the threat category assigned to a taxon should reflect assessment of extinction risk under prevailing circumstances (IUCN 2001, 2003). As described earlier, five quantitative criteria, (A–E), are used to determine threat status, and a taxon may be assessed against as many criteria as available data permits. Hence multiple criteria may apply. Criterion D relates solely to populations that are small or restricted either in terms of population size, area of occupancy or number of locations.

Under the assumption that, for the genus in this study, rarity may not itself represent threat, then a higher correlation between ranked p-values and ranked IUCN threat assessment would be expected after removal of those species whose threat status is based solely on rarity. This is because indices generated by the statistical models infer species decline (McCarthy 1998), not rarity. It was therefore necessary to identify the elements of threat assigned to each species under IUCN assessment. The vast majority of species have elements of

Table 1. Probability values generated by the different statistical models; (1) Solow (Solow 1993a), (2) Partial Solow (McCarthy 1998), (3) Solow/Roberts (Solow and Roberts 2003), (4) Partial Solow/Roberts (modified Solow and Roberts 2003 using e_i) and (5) Sighting Rate (McInerny et al. in press).

Species	IUCN Category	Statistical Models				
		1	2	3	4	5
G. aequatorialis	VU *	0.620	0.314	0.300	0.392	0.587
G. alborosea	VU	0.528	0.769	0.400	0.741	0.461
G. andreettae	VU	0.125	0.285	0.286	0.438	0.010
G. asplundii	LC	0.711	1.000	0.500	1.000	0.682
G. atrocastanea	VU*	0.266	0.444	0.286	0.438	0.132
G. bergii	VU*	0.479	0.671	0.6	0.759	0.366
G. condorensis	EN	0.564	1.000	0.500	1.000	0.479
G. dalstroemii	VU	0.735	1.000	0.500	1.000	0.694
G. ecuadorensis	EN	0.174	0.234	0.222	0.273	0.028
G. foetida	NT	0.700	1.000	0.500	1.000	0.664
G. fosteriana	NT	0.655	0.778	0.571	0.854	0.621
G. fuquae	EN	0.128	0.177	0.250	0.290	0.010
G. fusispica	VU	0.619	0.742	0.400	0.741	0.579
G. harlingii	VU	0.709	0.897	0.250	0.632	0.67
G. hirtzii	VU*	0.291	0.649	0.500	0.811	0.171
G. hollinensis	VU	0.393	1.000	0.333	1.000	0.250
G. jaramilloi	NT	0.485	0.612	0.250	0.632	0.422
G. kentii	VU*	0.346	0.391	0.222	0.273	0.210
G. madisonii	VU	0.553	1.0	0.333	1.0	0.48
G. pseudospectabilis	VU	0.35	0.759	0.4	0.741	0.216
G. remyi	LC	0.294	1.0	0.333	1.0	0.125
G. roseiflora	EN	0.499	0.401	0.25	0.383	0.432
G. rubrolutea	EN	0.499	0.401	0.333	0.439	0.432
G. septata	NT	0.724	0.787	0.5	0.811	0.702
G. teuscheri	NT	0.772	0.826	0.4	0.741	0.756
G. xanthobractea	NT	0.143	0.305	0.167	0.27	0.031
G. zakii	VU*	0.16	0.207	0.308	0.371	0.03

Asterisks classified under criterion D (VUD1/VUD2).

both rarity and decline inherent in their specified threat category. Only those species within categories VUD1 or VUD2 were threatened solely on the basis of rarity. Once these species were removed ranking and correlation values were generated for the revised data sets.

Results

Of the 41 endemic species of *Guzmania* only one, *G. barbei*, was described as Data Deficient and thus unassigned to any IUCN threat category. Taxonomic and identification difficulties were cited as the probable reason for lack of data for this species (Valencia et al. 2000). The useable data set comprised 27 species, (66% of the total), with at least three sighting records. Of these, 19

(70%) were classified as threatened; the p-values generated by the five equations are shown in Table 1. Within the Vulnerable category, six species (22%) were classified as Vulnerable (VUD1 or VUD2).

Although the correlation results are not significant in the traditional sense ($p < 0.05$) (Table 2), a number of models produce correlations close to significant ($p < 0.1$) and therefore warrant further investigation. A significant rank correlation ($p < 0.1$) between the p-values generated by both the Partial Solow (2) (McCarthy 1998) and Partial Solow/Roberts equations (4) (modified Solow and Roberts 2003 using e_i) and the IUCN classifications was shown ($r_s = 0.361$ and 0.351, respectively), but was not significant when collection effort was not included (equations 1, 3 and 5). However, improvement in the absolute values of the correlation coefficients was evident for each of the five equations, when those species classified as VUD1 or VUD2 where removed. However, the increase was only minor for equations (1)–(4) and countered by the higher critical values imposed as a result of the drop in sample size from 27 to 21 species. Correlation between the IUCN Red List categories and the sighting rate equation (5), became significant ($r_s = 0.364$) (Table 2).

Discussion and conclusions

Results suggest that biological collections such as those found in herbaria may be used to infer threat and thus aid conservation prioritisation, although collection effort does have to be taken into consideration. However, increased correlation between the probabilities generated by the different statistical models and IUCN categories when rare (but not necessarily declining) species were excluded from the analyses suggests that IUCN criteria do not successfully distinguish between rarity and threat. Difficulties relating to interpretation of data under the IUCN red listing assessment process may have an even greater effect. In particular, the mass grouping of species, and hence lack of resolution, within the 'Vulnerable' category reduced the ability to interpret the

Table 2. Spearman's rank correlation between IUCN categories and indices generated by each model for *Guzmania* collections from 1956 to 2003; (1) Solow (Solow 1993a), (2) Partial Solow (McCarthy 1998), (3) Solow/Roberts (Solow and Roberts 2003), (4) Partial Solow/Roberts (modified Solow and Roberts 2003 using e_i) and (5) Sighting Rate (McInerny et al. in press).

	Statistical models				
	1	2	3	4	5
Total ($n = 27$)	0.276	0.361*	0.272	0.351*	0.296
Excluding VUD1/VUD2 ($n = 21$)	0.326	0.372*	0.323	0.378*	0.364*

Asterisks indicate significant correlation $p < 0.1$.

degree of correlation between IUCN classification and indices of threat generated by the models.

In this case, epiphytic species can exist as rarities plants, provided their habitat remains intact, as small and stable populations. Dodson and Gentry (1991) observed that local endemism is a common phenomenon within western Ecuador, and that habitats occupied by an endemic taxon may be no more than 0.5–10 km^2. However, these results suggest that perhaps anticipated future threat, in the form of potential habitat loss, may have been incorporated into IUCN threat classification i.e. a generalised statement of threat to a particular habitat type without any knowledge of whether the species is actually threatened at its precise locality.

The IUCN Red List assessment process, although recognised and relied upon worldwide as the primary basis for setting conservation priorities, suffers a number of significant theoretical and practical difficulties (Willis et al. 2003). An inherent difficulty within the IUCN classification process relates to the sharp boundaries which divide each category. In reality no clear line separates threatened and non-threatened species, rather they form a continuum. When defined discrete categories, such as ‘Endangered’ or ‘Vulnerable’, are used as a means to determine threat status then species which may have very similar attributes may be treated very differently depending on which side of the category divide they fall (Regan et al. 2000). IUCN Red List guidelines (2003) recognise that it is rare for detailed, relevant data to be available across the entire range of a taxon. Although the Red List criteria have been designed to allow for inclusion of inference and projection, this is often of little benefit for species that are not well known and where the scarcity of data may generate unreliable estimates of a species’ status (Todd and Burgman 1998). This lack of information may result in inaccurate classification of threat and, especially in the case of rare or cryptic species, in assignment of threat where none may exist. However, specimen-based collections in herbaria and museums contain data relating to the distribution of known taxa in both space and time, and represent the most comprehensive and reliable source of knowledge for the majority of described taxa (Ponder et al. 2001), but are still a much underused data source.

The conclusions drawn from this study as to the performance of the statistical models are that, given adequate collection data, these models could be used to infer threat and decline. However, results can vary widely and the power of the models is dependent on the accuracy and fullness of the data for each of the species under consideration. Further, the performance of the models improves with increased number of sighting records. Hence the data sets most likely to be excluded are those relating to the species that are most rare, and also those that may be most threatened – however these are the very species that are most likely to be of interest and concern.

It has been shown, in both this and previous studies, that the different models each generate differing results (McCarthy 1998; Burgman et al. 2000). As Burgman et al. (2000) pointed out, none of them provides a consistently better or worse measure of decline or extinction than others. Rather, each is sensitive to differing elements of deviation from a wholly random process. Used appropriately, each can have a contribution to make to the assessment process, and the utilisation of complimentary tests should enhance the overall ability to detect decline. The objective of these models is to flag unusual patterns of sighting activity, which may otherwise be overlooked, and to find explanations for them. These methods are not intended to replace existing IUCN Red List assessment procedures but rather to strengthen them and give a greater understanding of how threat and rarity affect the classification of taxa. This is especially relevant for the vast majority of plant species for which data is sparse and is, for most part, held within herbarium and museum collections.

Advances in the accessibility to such databases via the Internet make these data potentially of even greater importance for conservation biologists. Greater global awareness of the potential uses for these data would serve to help improve the quality of collection records and in turn increase their value to conservationists, politicians and indeed all users of threatened species lists (Graham et al. 2004; Suarez and Tsutsui 2004). Further, research is now being directed toward the development of methods to quantify and include uncertainty to ensure that IUCN categories are less prone to misclassification resulting poor data (Colyvan et al. 1999). It may be more appropriate for the criteria to be revised giving one assessment based on threat and another on rarity, with a final assessment based on both as happens using the current system.

References

Akçakaya H.R., Ferson S., Burgman M.A., Keith D.A., Mace G.M. and Todd C.R. 2000. Making consistent IUCN classifications under uncertainty. Conserv. Biol. 14: 1001–1013.

Burgman M.A., Grimson R.C. and Ferson S. 1995. Inferring threat from scientific collections. Conserv. Biol. 9: 923–928.

Burgman M.A., Keith D.A., Rohlf F.J. and Todd C.R. 1999. Probabilistic classification rules for setting conservation priorities. Biol. Conserv. 89: 227–231.

Burgman M.A., Maslin B.R., Andrewartha D., Keatley M.R., Boek C. and McCarthy M. 2000. Inferring threat from scientific collections: power tests and an application to western Australian Acacia species. In: Ferson S. and Burgman M.A. (eds), Quantitative Methods for Conservation Biology. Springer-Verlag, NY.

Colyvan M., Burgman M.A., Todd C.R., Akçakaya H.R. and Boek C. 1999. The treatment of uncertainty and the structure of the IUCN threatened species categories. Biol. Conserv. 89: 245–249.

Diamond J.M. 1987. Extant unless proven extinct? Or, extinct unless proven extant? Conserv. Biol. 1: 77–79.

Dodson C.H. and Gentry A.H. 1991. Biological extinction in western Ecuador. Ann. Missouri Bot. Gard. 78: 273–295.

Graham C.H., Ferrier S., Huettman F., Moritz C. and Peterson A.T. 2004. New developments in museum-based informatics and applications in biodiversity analysis. Trend. Ecol. Evol. 19: 497–503.

Hilton-Taylor C. 2000. Toward the 2000 IUCN red list of threatened species. Species 33: 21–29.

IUCN. 2001. IUCN Red List Categories and Criteria. Version 3.1. IUCN Species Survival Commission, Gland, Switzerland and Cambridge, UK.

IUCN. 2003. Guidelines for Using the IUCN Red List Categories and Criteria. IUCN Species Survival Commission, Gland, Switzerland and Cambridge, UK.

Mace G.M. and Hudson E.J. 1999. Attitudes towards sustainability and extinction. Conserv. Biol. 13: 242–246.

Mace G.M. and Lande R. 1991. Assessing extinction threats: towards a re-evaluation of IUCN threatened species categories. Conserv. Biol. 5: 148–157.

May R.M., Lawton J.H. and Stork N.E. 1996. Assessing extinction rates. In: Lawton J.H. and May R.M. (eds), Extinction Rates. Oxford University Press, Oxford.

McArdle B.H. 1990. When are rare species not there. Oikos 57: 276–277.

McCarthy M.A. 1998. Identifying declining and threatened species with museum data. Biol. Conserv. 83: 9–17.

McInerny G.J., Roberts D.L., Davy A.J. and Cribb P.J. in press. Significance of sighting rate in inferring extinction and threat. conserv. biol.

Pimm S.L. 1998. Extinction. In: Sutherland W.J. (ed.), Conservation Science and Action. Oxford, Blackwell Science Ltd.

Pimm S.L., Russell G.J., Gittleman J.L. and Brooks T.M. 1995. The future of biodiversity. Science 269: 347–350.

Pitman N.C.A. and Jørgensen P.M. 2002. Estimating the size of the world's threatened flora. Science 298: 989–989.

Ponder W.F., Carter G.A., Flemons P. and Chapman R.R. 2001. Evaluation of museum collection data for use in biodiversity assessment. Conserv. Biol. 15: 648–657.

Reed J.M. 1996. Using statistical probability to increase confidence of inferring species extinction. Conserv. Biol. 10: 1283–1285.

Regan H.M., Colyvan M. and Burgman M.A. 2000. A proposal for fuzzy International Union for the Conservation of Nature (IUCN) categories and criteria. Biol. Conserv. 92: 101–108.

Roberts D.L. and Kitchener A.C. in press. Inferring extinction from biological records: Were we too quick to write off Miss Waldnon's Red Colobus Monkey. (*Piliocolobus badins Waldronae*) Biol. Conserv.

Solow A.R. 2005. Inferring extinction from sighting data. Ecology 74: 962–964.

Solow A.R. 1993b. Inferring extinction in a declining population. J. Math. Biol. 32: 79–82.

Solow A.R. 2005. Inferring extinction from a sighting record. Math. Biosci. 195: 47–55.

Solow A.R. and Roberts D.L. 2003. A nonparametric test for extinction based on a sighting record. Ecology 84: 1329–1332.

Suarez A.V. and Tsutsui N.D. 2004. The value of museum collections for research and society. Bioscience 54: 66–74.

Todd C.R. and Burgman M.A. 1998. Assessment of threat and conservation priorities under realistic levels of uncertainty and reliability. Conserv. Biol. 12: 966–974.

Valencia R., Pitman N., León-Yánez S. and Jørgensen P.M. (eds) 2000. Libro Rojo de las Plantas Endemicas del Ecuador 2000. Herbario QCA, Pontificia Universidad Catolica del Ecuador, Quito.

Willis F., Moat J. and Paton A. 2003. Defining a role for herbarium data in red list assessments: a case study of Plectranthus from eastern and southern tropical Africa. Biodivers. Conserv. 12: 1537–1552.