A climate change vulnerability assessment of 58 Richtersveld plant species

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Abstract

The Richtersveld is the northernmost region of the Succulent Karoo and is located in the north-western region of South Africa's Northern Cape Province. This region has an incredible arid plant diversity, with both the highest succulent plant diversity and highest rate of endemism in an arid area, globally. It forms part of both a global biodiversity hotspot and a UNESCO world heritage site. However, it is already experiencing significant climate change exposure which is predicted to worsen. Changes in the area's climate are also interacting synergistically with other anthropogenic pressures including mining, poaching and agriculture. The threats to this area, including climate change, are documented but knowledge gaps still remain – especially with regards to plants and climate change vulnerability.

In this study I aimed to find which Richtersveld species are the most vulnerable to climate change while trialling a relatively novel approach in this context. I used a trait-based assessment with correlative species distribution model outputs to assess the sensitivity, adaptive capacity and exposure of 58 plant species occurring within the Richtersveld National Park. This included assessing biological, ecological, environmental and spatial traits of species that contribute to climate change vulnerability.

Traits were scored based on literature, expert opinion and correlative modelling outputs. Trait scores were then combined using both additive and ordinal methods, creating a best-case scenario where unknowns were assumed to have 'low' scores, and a worst-case scenario when these were assumed to be 'high'. These scenarios were applied to both the ordinal and additive scoring methods. For the additive scoring method, there was an additional consideration – trait weighting. It would be inaccurate to assume all traits hold the same importance in determining a species' vulnerability to climate change. Each trait was assigned a weighting based on literature and expert opinion and applied in an additional weighted scoring approach. Therefore, each species had a total of six climate change vulnerability scores: a best-case ordinal, a worst-case ordinal, a best-case unweighted additive, a worst-case unweighted additive, a best-case weighted additive and a worst-case weighted additive score.

Under the worst-case ordinal scoring method, 34 species (59 %), were scored as highly vulnerable to climate change. The most vulnerable species were those that consistently scored high vulnerability scores, across all six scoring methods. This included *Cheilanthes namaquensis* (Not endemic to the region nor the park and Least Concern), *Trachyandra ardimontana* (almost endemic to park and Endangered), *Albuca etesiogaripensis* (almost endemic to park and Data Deficient), *Ruschia glauca* (almost endemic to park and Endangered) and *Schwantesia herrei* (Richtersveld endemic and Least Concern).

I also found a mismatch between species' Red List status and their scores in my climate change vulnerability assessment. This suggests that highly climate change vulnerable species identified in this study currently have a low Red List threat status assigned to them by the responsible conservation organisation. This finding could mean that their status does not accurately reflect their level of conservation risk – especially if climate change is not accounted for. This can cause them to be overlooked in terms of conservation resource provision and decision-making. The IUCN Red List Version 16 Section 12 provides guidelines for assessing climate change vulnerability and its application in determining a species' threat status to climate change. However, its development is relatively recent, and its use is limited, possibly due to the data and technical expertise required. My study provides a possible example of how, even in highly biodiverse region with low data availability, climate change vulnerability assessments may be carried out, and of the value for preventing extinctions. The highest concentration of climate change vulnerable species were found to be in the central western and northern areas of Richtersveld National Park. The spatial representation of these data may aid where within the Park conservation and management can be prioritized.

In conclusion, I trialled an approach that has not previously been applied for Richtersveld plants. The approach produced predictions of climate change vulnerability that could be used for conservation. The approach used in this study helped identify species and areas to which climate change conservation measures could be applied. This approach can be applied to other arid areas and aid in climate-related conservation, including in section 12 of the Red Listing Guidelines (Version 16).

Keywords: Climate change vulnerability, Richtersveld, Plants, Conservation

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Introduction

Background context of climate change

Biodiversity is facing the threat of a sixth mass extinction, due to many anthropogenic factors, including unprecedented rates of climate change (Foden *et al.*, 2018; Shivanna, 2020; Christenhusz and Govaerts, 2024). Other factors are alien invasions, pollution, habitat loss and the overexploitation of ecosystem services – each of which exacerbate the effects of accelerated climate change (Christenhusz and Govaerts, 2024). Climate change has impacted a variety of biological components, across all ecological scales. This includes geographic, behavioural, phenological, genetic and demographic changes, from the cellular to ecosystem level (Foden *et al.*, 2018; Shivanna, 2020).

Studies confirmed that the vertebrate extinction rate over the past century was significantly faster than the background extinction rate (Ceballos *et al.*, 2015; Strona and Bradshaw, 2022). Strona and Bradshaw (2022) stated that by 2100, there will be a global vertebrate diversity reduction of 17.6 % due to climate change. Plants are also under threat. They currently have a higher extinction than speciation rate in the Anthropocene (Gao *et al.*, 2020). More specifically, Gao *et al*. (2022) states the current plant extinction rate is 1000-10 000 times higher than the background extinction rate. Christenhusz and Govaerts (2024) state it is 700 times higher. These rates are expected to rise sharply as climate change progresses (Humphreys *et al.*, 2019; Gao *et al*., 2020; Christenhusz and Govaerts, 2024). While trends and extinction rates have been evaluated and revised, little detail is known about the taxa-specific mechanisms underlying such alarming statistics.

Plants and climate change in South Africa

Plants are globally diverse and of high ecological importance given they are the base for almost all food webs, climate regulation and nutrient cycling among other functions (Adamo *et al.*, 2021; Franklin *et al.*, 2016; Midgley and Thuiller, 2007, Midgley and Thuiller, 2011; Thuiller *et al.*, 2006). However, they are relatively understudied compared to animals (Adamo *et al.*, 2021). A shortage of research on this taxon presents a further problem when considering the uncertain and unpredictable nature of climate change. Climate change is affecting and will continue to affect plant performance, growth, and reproduction as well as other abiotic and biotic ecosystem-and landscape-scale processes (Franklin *et al.*, 2016). While plants are affected by climate change, they are also a key factor in mitigation and adaptation strategies for climate change on a terrestrial, atmospheric and oceanic plane (Franklin *et al.*, 2016). There is the option for plants to shift their range in altitude and latitude to correspond to the changing climate (Franklin *et al.*, 2016; Midgley and Thuiller, 2007, Midgley and Thuiller, 2011; Pagel *et al.*, 2020; Thuiller *et al.*, 2006), or to adapt in situ. These abilities are dependent on many factors including rarity and habitat specialization.

Globally, South Africa is recognised as one of seventeen megadiverse nations and is in the top ten countries for plant diversity due to high levels of plant endemism (Poulsen, 2020). It is also home to three out of the thirty-four major global biodiversity hotspots. One of these is the Succulent Karoo Region (Poulsen, 2020). While biodiversity hotspots are already considered priority areas for conservation (Poulsen, 2020), the need for conservation of the Succulent Karoo is further emphasized by its status as one of only two entirely arid biodiversity hotspots in the world, the other being the Horn of Africa (Critical Ecosystem Partnership Fund, 2012). The Succulent Karoo hotspot is home to 6356 vascular plant species, with 40 % (2440) being endemic (Critical Ecosystem Partnership Fund, 2012). The Richtersveld region is a part of the Succulent Karoo hotspot, found just south of the Orange River and on the border between South Africa and Namibia. This region has 2700 plant species, 560 of which are endemic (SANBI, 2024a). The Richtersveld (**Figure 1**), specifically, is also considered to be of high priority within the biodiversity hotspot as it contains 40% of all global succulent species, 60 % of which are endemic. Since 80% of the plant species of the Richtersveld are succulents, this area is regarded as having the world's highest succulent diversity (SANBI, 2024a; SANBI 2024b). This point endemism is attributed to the highly specialized techniques of the endemic plants to withstand and even prosper in this harsh arid environment and varied geology (Critical Ecosystem Partnership Fund, 2012; Poulsen, 2020; SANBI, 2024a). However, recent studies suggest that these species' specialised adaptations to this harsh region may not all be advantageous under accelerating climate change.

Most succulent species are slow growing and their long generation times prevent timeous evolvability at a rate that matches and minimizes the impact of climate change (Foden and Young, 2016). Specialist species, including endemics, are even more at risk. Their habitat specialization, microhabitat requirements and poor dispersal abilities prevent them from persisting or shifting their range (Franklin *et al.*, 2016; Midgley and Thuiller, 2007, Midgley and Thuiller, 2011; Pagel *et al.*, 2020; Thuiller *et al.*, 2006; Thurman *et al.*, 2020). This makes them particularly vulnerable to climate change (Thurman *et al.*, 2020). This has been documented in the recent 2024 regional Red List of South African plants (SANBI, 2024b).

SANBI's Red List report states that the Northern Cape has seen the largest increase in the number of threatened plant species in South Africa (SANBI, 2024b). Many species have been uplisted, including 85 *Conophytum* species, to vulnerable or higher threat categories (SANBI, 2024b). *Conophytum* species are especially important as they are highly diverse, hold evolutionary significance due to their high levels of adaptation in arid regions and are indicators of environmental well-being (Young and Desmet, 2016). While most of these species were uplisted due to increased poaching threats, others were uplisted due to the combined or individual threat from climate change (SANBI, 2024b). In addition to this, two flagship species, the bastard quiver tree (*Aloe pillansii*) and halfmens (*Pachypodium namaquanum*) have seen a drastic population decline over the last 10 years due to climate change (SANBI, 2024a; SANBI 2024b). Both of these are now regarded as Critically Endangered (SANBI, 2024b). Substantial population declines of some species, and 12 % of the upgraded threat statuses, were due to a long-running drought from 2012-2021 and other pressures arising from climate change (SANBI, 2024b). Such statistics are only expected to worsen when considering future climate projections for the area.

The majority of global climate models project temperature and aridity increases in the west coast of Southern Africa - at a rate plants may not be able to adapt to (Huey *et al.*, 2012; Foden and Young, 2016; Foden *et al.*, 2018; Lalwal *et al.*, 2019; Scholes and Engelbrecht, 2021; Engelbrecht *et al.*, 2024). In fact, Van Wilgen *et al.* (unpublished) (**Appendix 3a** and **b**) showed that, irrespective of model choice to project a climate future, the Richtersveld will undoubtedly become extremely dry and hot. The only difference between these model predictions is the level of aridity and heat change. The Richtersveld is also under threat due to other anthropogenic pressures, which act synergistically with climate change. This other major anthropogenic threats to this region are mining, poaching and agriculture (P. van Wyk, personal comment). An area that is both biologically diverse and under severe threat from climate change demonstrates its need for efficient and effective conservation.

This includes closing knowledge gaps and useful decision-making. One viable method to close the knowledge gaps pertaining to biodiversity loss and climate change in the Richtersveld, is through assessing the climate change vulnerability of a suit of species or functional groups (Willis *et al*., 2015; Foden and Young, 2016; Foden and Young, 2016).

Climate change vulnerability

An entity's vulnerability to climate change is described by the cumulative of both intrinsic and extrinsic factors (Foden and Young, 2016; Foden *et al.*, 2018). The three key dimensions that underlie vulnerability are exposure, sensitivity and adaptive capacity (Foden and Young, 2016; Foden *et al.*, 2018).

In climate change vulnerability assessments, "exposure" is an extrinsic factor that relates to the characteristics, magnitude and rate of climate change and associated environmental factors to which an organism, group or population is subjected (Willis *et al*., 2015; Foden and Young, 2016; Foden *et al.*, 2018). While there is disagreement on whether "exposure" entails the drivers or impacts of climate change, the consensus is that it refers to factors that are beyond the direct control of organisms, systems and humans (Foden and Young, 2016; Foden *et al.*, 2018; Oesterwind *et al.*, 2016). Exposure factors are categorised as either abiotic, biotic or human intervention (Foden and Young, 2016; Foden *et al.*, 2018).

Abiotic exposure factors are the direct and indirect effects of increased greenhouse gas concentrations on the physical environment. These include, ocean acidification, increased temperatures, sea level rise, reduction in glacial ice sheets, altered precipitation and fire frequency amongst others (Foden and Young, 2016; Foden *et al.*, 2018). Biotic exposure factors refer to direct and indirect changes in habitat availability and community composition in response to abiotic pressures and/or increased greenhouse gas concentrations (Foden and Young, 2016; Foden *et al.*, 2018). These include range shifts resulting in enhanced competition and/or predation and even changes in generalist-specialist, predator-prey and plant photosynthetic pathway compositions (Foden and Young, 2016; Foden *et al.*, 2018; Harper *et al.*, 2020). Lastly, societal mitigation and adaptation measures can also impact an organism's level of exposure (Foden and Young, 2016; Foden *et al.*, 2018; Groom *et al.*, 2008; Harper *et al.*, 2020; Winemiller *et al.*, 2016). One example would be natural land conversion for biofuel production to reduce greenhouse gas emissions (Groom *et al.*, 2008). Another would be habitat fragmentation arising from multiple dams being constructed along a water body either to store water or for hydroelectric power (Winemiller *et al.*, 2016).

Different abiotic and biotic exposure scenarios can be projected using different technologies such as general circulation models and species distribution models (Willis *et al*., 2015; Foden and Young, 2016). However, these projections alone do not determine how vulnerable an entity is to climate change (Willis *et al*., 2015; Foden and Young, 2016; Foden *et al.*, 2018). The level to which different exposure pressures affect an entity is dependent on their intrinsic sensitivity and their adaptive capacity.

The level of sensitivity is based on the likelihood, degree and responsiveness of an entity to climate change (Foden and Young, 2016; Foden *et al.*, 2018). This is dependent on beneficial and negative intrinsic attributes, which can either moderate or exacerbate the effects of exposure, respectively (Foden and Young, 2016; Foden *et al.*, 2018). There are differing views on the specific characteristics that make up sensitivity, but there are seven general categories. These are habitat specialization, environmental tolerances and thresholds, dependency on environmental cues, rarity, life history sensitivity and level of threat by other factors (Foden and Young, 2016; Foden *et al.*, 2018). In order to assess these categories, detailed, reliable knowledge bases are required – which is a limitation given that ecological knowledge of many taxa, including endemic plants, is incomplete (Foden and Young, 2016; Foden *et al.*, 2018; Harper *et al.*, 2020). Specifically, plants receive less attention, funding and subsequently research in conservation than animals do, and even then, most botanical research is geared towards colourful, widely distributed flowering plants (Adamo *et al.*, 2021). Similarly, a well-researched knowledge base is required for assessing adaptive capacity.

Adaptive capacity is the likelihood and level to which an entity can adjust to environmental changes in order to lessen possible negative outcomes (Foden and Young, 2016; Foden *et al.*, 2018). This includes taking advantage of emerging opportunities and responding timeously to consequences (Foden and Young, 2016; Foden *et al.*, 2018). While there can be overlap with sensitivity, there are separate categories for assessing adaptive capacity, namely level of phenotypic plasticity, dispersal abilities (and hinderances), genetics and the ability to establish and proliferate– all of which relate to evolvability (Foden and Young, 2016; Foden *et al.*, 2018). Adaptive capacity is regarded as both an intrinsic and extrinsic factor (Beever *et al.*, 2016). The fundamental adaptive capacity is the intrinsic ability to adjust to climate change without compromising genetic variability or range extension and without intensive, human-mediation efforts (Beever *et al.*, 2016; Foden *et al.*, 2018). If human intervention is required, it becomes a realized adaptive capacity (Beever *et al.*, 2016; Foden *et al.*, 2018). An example would be the ability to disperse over wide ranges being limited by habitat fragmentation or a highly modified urban environment (Foden and Young 2016; Beever *et al*. 2016; Foden *et al*. 2018) and therefore, requiring ex-situ conservation and assisted migration efforts to ensure a species survival and prevent genetic depression (Wildt, 2000; Witzenberger and Hochkirch, 2011).

Available assessment approaches

There are three main methods that are either used individually or in combination in order to assess an entity's vulnerability to climate change (Foden and Young, 2016; Foden *et al.*, 2018). These are correlative, mechanistic and/or trait-based assessments – each of which is appropriate depending on data and time availability as well as the scope of interest (Foden *et al.*, 2018; Pacifici *et al.*, 2015). These methods are summarised in **Table 1**. The best vulnerability assessment would be to create an assessment framework and place species into categories based on both correlative and mechanistic models and detailed biological and life history knowledge. However, this is not possible in most cases due to a lack of time and the requirement for extensive, detailed data (Adamo *et al.*, 2021; Harper *et al.*, 2020).

Table 1: Different methods available for climate change vulnerability assessments.

Method	Requires	How it is used	Advantages and Disadvantages
Correlative (climate-matching)	Fine-scale point locality data for taxa of interest[3].	Vulnerability determined by level of overlap between current and projected future distribution patterns[1,2]. Uses statistical models to summarise trends across model predictions[4]. Predictive capacity increased when used in combination with other methods[2,5].	**Advantages**: cheap, fast, occurrence data easily available[4]. **Disadvantages**: prediction at coarse resolution, requires large, accurate occurrence datapoint sets, lack of biological knowledge leads to false assumptions, other factors influence realised niche, results can differ based on model used[2,3,4].

Mechanistic	Fine-scale point locality data and life history information for taxa of interest[3].	Simulations used to predict varying climate change impacts on species and possible responses[1]. Include demographic models, niche-based models and/or species distribution models (SDMs)[1,2,3,5]. Predictive capacity increased when used in combination with other methods[2,5].	**Advantages**: incorporates numerous possible life history impacts of climate change e.g. resource availability, interspecific relations, adaptive capacity, demographic estimates etc., can include human factors such as land use change [1,2,3]. **Disadvantages**: large, detailed datasets required, high cost, time and expertise requirements[1,2,3,4].
Trait-based	Broad-scale distribution data and life history information for taxa of interest[1,3].	Existing knowledge bases used to create taxon-specific framework to rank and score vulnerability. Based on traits contributing to a species sensitivity and adaptive capacity to factors of climate change exposure [1,2,3]. Evaluates where most conservation efforts are required[1,2,3]. Predictive capacity increased when used in combination with other methods[2,5].	**Advantages**: can be used for range-restricted and rare species, time-efficient, cheaper, extensive modelling expertise not required, examine multiple climate change pressures simultaneously, species-specific responses are considered [1,2,3,4]. **Disadvantages**: lack of certainty in trait thresholds, some assessments do not account for trait-importance weighting, no application for cross-assessment comparisons, species-specific knowledge gaps, lack of validation methods[1,2,3,4].

[1]Foden and Young, 2016; [2]Foden *et al.*, 2018; [3]Harper *et al.*, 2020, [4]Pacifici *et al.*, 2015 and [5]Willis *et al.*, 2015

Objectives and aims

The ongoing threat of climate change, the diversity and probable vulnerability of Richtersveld flora, and a general lack of plant research and data, makes this project not only important, but necessary. In this study, I assessed the climate change vulnerability of a randomly selected subset of 58 Richtersveld plant species using a combined trait-based vulnerability assessment (TVA) with correlative species distribution model (SDM) outputs (TVA-Corr approach) (Willis et al., 2015; Foden et al., 2018). This method was applied to plants that occurred within Richtersveld National Park (RNP), in the Northern Cape of South Africa. To assess the vulnerability of flora to climate change within RNP, I undertook three objectives:

1. To identify the most climate change vulnerable species occurring in the Richtersveld National Park (RNP).
2. To trial a TVA-Corr approach for a climate change vulnerability assessment in this context.
3. To explore the value of both the assessment approach and my findings for conservation.

Methods

Study area

The RNP is situated in the northern region of the Northern Cape, South Africa, and shares a border with Namibia (size: 1625 km^2; location: 28°36′0″ S, 17°12′14″ E)

(UNESCO, 2024; SANParks, 2024) (**Figure 1**). The park forms a portion of the Richtersveld Cultural and Botanical Landscape, which is a UNESCO World Heritage Site, due to its biological value, as well as its cultural value to the Nama people (UNESCO, 2024). RNP, together with the |Ai-|Ais/Hot Springs Game Park in Namibia, form the |Ai-|Ais/Richtersveld Transfrontier Park (RTP) (UNESCO, 2024; SANParks, 2024).

The RNP consists of three climatic regions - a warm, temperate winter rainfall region in the west, a subtropical summer rainfall region in the east and a non-seasonal rainfall region in the east interior (SANParks, 2018; van Wyk *et al*., 2024). The amount of annual rainfall is dependent on both climatic region and altitude, given the area's rugged terrain. Hence, the annual rainfall for different locations within the park can range between 0-275mm (SANParks, 2018). The lack of rainfall in this region also causes some species to depend on moisture from fog, especially in the western regions (SANParks, 2018). This fog arises from the Benguela anti-cyclones of the West Coast of Southern Africa (SANParks, 2018). The lifeforms in this area have to be adapted to limited rainfall and rugged terrain, but also the wide temperature range which can bring forth temperature extremes. This includes sub-zero temperatures with snow in winter and heat waves above 50°C in summer (SANParks, 2018). This is the origin of the name “|Ai-|Ais” which translates to “hot, very hot” (SANParks, 2024). The terrain and climate heterogeneity lead to various microhabitats within the Park which may be implicated in the high plant diversity and rate of endemism (van Wyk *et al*., 2024).

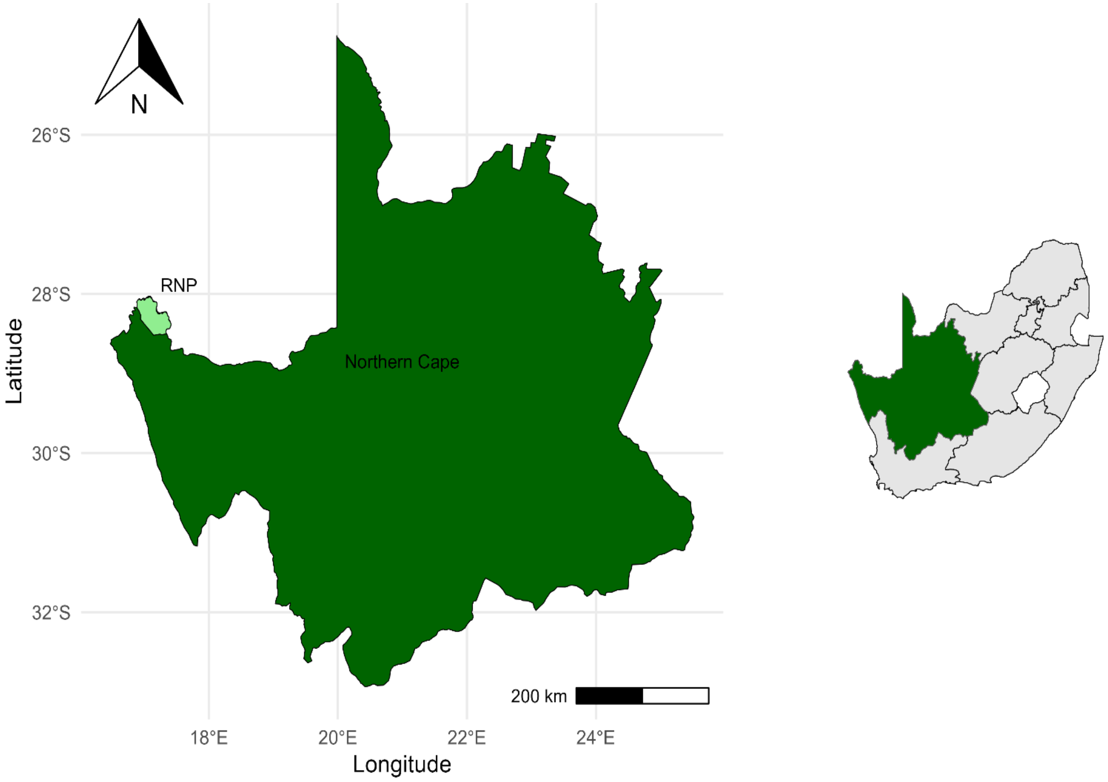

Figure 1: A map showing the location of Richtersveld National Park (RNP - pale green) within the Northern Cape, South Africa.

Species and species occurrence data

SANBI has compiled a list of 900 plant species, randomly sampled from South Africa's entire flora, in order to create a "Red List Index" (SANBI, 2024d). From this list, I selected all 58 Red List Index species occurring within the RNP (n = 58 of the 900 Red List Index plants) (**Appendix 1**). These 58 species were chosen as they had occurrence data that was readily available through SANBI and because they occur in the park.

Occurrence data within southern Africa was obtained for each of the 58 plant species. This included all historical localities of herbarium specimen collections and observations from the iNaturalist citizen science platform. These records were 'cleaned' to remove other ex-situ collections and artificial plantations, and by removing duplicates (the most recent record was kept). From this cleaned list, some species had fewer than ten unique occurrence points. Since a minimum of 10 points are required to run SDMs, more detailed searches for very recent iNaturalist records were made, but fourteen species still had fewer than 10 unique data points. It should be noted that *Bromus pectinatus*, which is an alien, was included in the study as it was assumed to likely have a low vulnerability and therefore provided a valuable test.

Assessment approach

A TVA-Corr approach was used for this project (Willis *et al*., 2015; Foden *et al.*, 2018). This method was selected due to the advantages laid out in **Table 1,** including its use of location and life history data which were available for the target taxa in this area. SDMs are widely used to assess a species' vulnerability to bioclimatic changes but given the rarity and/or small ranges of some of the study species, the heterogeneous landscape of the Richtersveld and the size of RNP, this method was not suitable to use alone (Platts *et al.* 2014; Foden and Young 2016). Hence, I used this component to only assess exposure of the target taxa, while assessing sensitivity and adaptive capacity through trait-based methods. Combining these two methods increased the predictive capacity of the framework (**Table 1**) (Willis *et al*., 2015; Foden *et al.*, 2018). TVA-Corr method has been applied in relatively few studies and is therefore exploratory (Willis *et al.*, 2015). Two papers using this combined approach include Young *et al.* (2012) and Payne *et al.* (2023), which were applied to a North American and southern African arid-zone context, respectively.

I developed an assessment framework which was specific to an arid environment, independent of other anthropogenic factors, and inclusive of all climate change dimensions. The trait groups and the respective climate change dimension under which they fell, were guided by those laid out in Foden and Young (2016) and Foden *et al*. (2018). Extensive literature reviews and meetings with experts helped create a draft list of assessment traits under each trait group. The papers consulted for multiple traits were Agenbag (2006), Franklin *et al.* (2012), Foden *et al.* (2013), Foden and Young (2016), Foden *et al.* (2018), Lee *et al.* (2019) and Kühn *et al.* (2021). **Appendix 2** shows this initial draft framework.

The draft framework was discussed and finalised over multiple meetings with experts to critique and refine it. Due to the lack of extensive knowledge and data on the Richtersveld and its plants, refinement of the trait list included choosing traits that were both applicable and likely to have enough information to actually score. The meetings also included discussing the methods and sources available to assess each trait, the thresholds for scoring and how traits should be weighted during the process of combining trait scores to produce a final vulnerability score for each species.

The scoring thresholds guided the conditions for assigning a species a high or low score for the trait being assessed. The trait weighting was based on how important each trait is estimated to be in determining a species' vulnerability to climate change (Willis *et al*., 2015). This was important as it would be inaccurate to assume all traits contribute equally to a species' climate change vulnerability (Willis *et al*., 2015). Trait weightings were between 1 and 5, with 5 being very important. They were used when combining trait scores into overall vulnerability scores. The scoring thresholds and trait weighting was based on literature and expert consultation – including patterns of mortality observed during and after the region's recent drought. For example, an expert stated perennials had a higher drought mortality in RNP than annuals. Based on this, the scoring threshold for D1: perennial/ annual states that perennials would receive a 'high' score and annuals a 'low' score and the trait weighting for D1 was 1 (**Table 2**).

The final framework included seven trait groups and 19 traits, 14 of which were for sensitivity, three for adaptive capacity and two for exposure (**Table 2**). Raw data were collated for each traits for each species based the guidance in **Table 2**.

Finalized assessment framework

All traits were assessed across the species' entire South African distribution.

Table 2: The final assessment framework that was used to score the climate change vulnerability of the species. Trait weighting refers to how important the trait is estimated to be in determining vulnerability and is based on literature and expert opinion. Sources refer to what was required to assess the trait. (Key: Sensitivity, Adaptive Capacity (in terms of inadaptability), Exposure)

Trait group	Trait	Explanation	Trait measurement	How to score	Trait weighting
A: Specialized habitat and/or microhabitat requirements	A1: Vulnerable microhabitat specialization	Organisms that are adapted to mainly occur in climate-vulnerable microhabitats have a higher sensitivity. If current microhabitat/s are compromised, they have restricted alternative optimal areas to occupy (Foden *et al.*, 2018; Harper *et al.*, 2020; Scheffers *et al.* 2014).	Species occurs mainly or only in **vulnerable** microclimates: • Ephemeral wetlands/ ponds Lowland sandy areas/ flats Highland sandy areas/ flats • Quartz fields Dolomite hills • Specific elevation (100-400 m, 600-900 m, >1300 m) **AND** Is a geological and soil specialist **AND** Species does not occur mainly or only in **buffered** microclimates: • Rock crevices Cliff faces Seepage lines • Riverbed Under rocks • Other shaded microclimates • S to W slopes Elevation: above 400 m, 400-600 m and 900-1300 m • Above 65° inclination	**High:** requires vulnerable habitats AND is a specialist AND does not occur mainly buffered habitats **Low:** all others	5
	A2: Habitat specialization	Species specialised to a small number of habitats are more sensitive to climate change for the same reasons as A1. This has been documented for different taxa in Foden *et al.* (2013), Gardali *et al.* (2012), Harper *et al.* (2020); Payne *et al.* (2023).	Species range includes less than 5 vegetation types.	**High:** < 5 vegetation types **Low:** > 5 vegetation types	5

B: Environmental tolerances or thresholds that are likely to be exceeded by climate change	B1: Narrow precipitation tolerance	Species that experience a low precipitation variability across their range have a smaller tolerance for precipitation changes, making them more sensitive to climate change (Huey *et al.*, 2012; Foden and Young, 2016; Foden *et al.*, 2018; Trull *et al.*, 2018; Lalwal *et al.*, 2019).	Variability in **precipitation** (mean annual precipitation) across the species' historical range, as measured by Average Absolute Deviation (AAD). Historical precipitation data was sourced from the Climate Research Unit (CRU) (University of East Anglia, 2023a).	**High:** lowest 25 % **Low:** all others	3
	B2: Narrow temperature tolerance	Species that experience a low temperature variability across their range have a smaller tolerance for temperature changes, making them more sensitive to climate change (Huey *et al.*, 2012; Foden and Young, 2016; Foden *et al.*, 2018; Trull *et al.*, 2018; Lalwal *et al.*, 2019).	Variability in **temperature** (mean annual temperature) across the species' historical range, as measured by Average Absolute Deviation (AAD). Historical temperature data was sourced from the Climate Research Unit (CRU) (University of East Anglia, 2023b).	**High:** lowest 25 % **Low:** all others	3
	B3: Seasonality	Species that occur in a winter rainfall region and that is reliant on fog, are more sensitive to climate change. This is due to predictions that the west of South Africa (generally a winter rainfall zone) will become drier in the future (Scholes and Engelbrecht, 2021; Engelbrecht *et al.*, 2024). Hence, if a species is restricted to these drying areas, they are more sensitive to climate change.	If species is restricted to winter rainfall zone **AND** species is reliant on fog/ dew.	**High:** species is restricted to winter rainfall zone and does rely on fog **Low:** all others	1
	B4: Root system	Species with shallow roots in an arid area that is projected to become drier are more sensitive to climate change. This is due to increased drought stress. In a worse-case where the plant's thermal threshold is reached, their root growth will begin to decline sooner than deeper rooted plants (Gray and Brady, 2016; Calleja-Cabrera *et al.*, 2020). This can have devastating impacts on a plant's respiratory and photosynthetic functioning (Gray and Brady, 2016; Calleja-Cabrera *et al.*, 2020; Kühn *et al.*, 2021).	If species has shallow roots **AND** species does not have deep roots (<30 cm).	**High:** Shallow roots only **Low:** all others	1

	B5: Photosynthetic mechanism	If a species only has a C3 photosynthetic pathway, it is considered more sensitive to climate change. Such plants experience high levels of water loss due to high stomatal conductance and their inability to close their stomata for long periods of time to avoid excessive water loss (Gray and Brady, 2016; Kühn *et al.*, 2021). This is especially risky in a drying arid area. C3 plants also have a lower thermal optimum for photosynthesis than C4 or Crassulacean Acid Metabolism (CAM) plants, which is a risk in an area that has been projected to get warmer with climate change (Gray and Brady, 2016; Kühn *et al.*, 2021; Scholes and Engelbrecht, 2021; Engelbrecht *et al.*, 2024).	If species uses: •C3 photosynthetic pathway **AND** Species does not use: •CAM •C4 •Switch abilities	**High:** Species uses only C3 photosynthetic pathway **Low:** all others	1
	B6: Drought adaptations	Based on 20 years of monitoring of a wide range of plants in the Richtersveld by one of the experts consulted, other drought adaptations had been observed that were not already included in the above traits (P. van Wyk, personal comment).	Presence of vulnerable traits: • Stem succulent • Large size **AND** Absence of the following resilience traits: • Subterranean/ underground (e.g. stone plants and bulbs) • Bulb with papery covering • Caudiciform • Deep bulb/corm tuber, with hard tunics	**High:** Has vulnerability trait(s) and no resilience traits **Low:** all others	3
	B7: Psammophorous sandstorm adaptation	A species was considered more sensitive to climate change if they did not have psammophorous properties to withstand sandstorms – which have become common in the western Richtersveld plains over the last decade (van Wyk et al., 2024). Such plants are highly adapted to sandy soils and have specialized features that allow them to fix a layer of sand on their surface as a protective layer against wind-blasting (Jürgens, 1996). Some papers also state psammophorous traits may be of relevance to decreasing water and energy loss which again is an advantage under the climate crisis (Jürgens, 1996).	If species is not psammophorous.	**High:** species is not psammophorous **Low:** all others	1

C: Rarity	C1: Species is rare	Smaller populations are known to be more vulnerable to Allee effects, stochastic events, genetic depression and a lowered resilience (Allee and Bowen 1932; Foden *et al*., 2013).SANBI's Red List considered any species with an extent of occurrence (EOO) <500km^2 to be considered rare (SANBI, 2024c), but other papers argue that any vulnerable species would have an EOO <20 000 km^2 (BirdLife International, 2024; Brooks *et al*., 2019, IUCN, 2024; National Geographic Society, 2025).	Species is rare due to being geographically restricted (~EOO<20 000 km^2).	**High:** EOO < 20 000 km^2 **Low:** all others	5
D: Sensitive life history	D1: Perennial/ Annual	While it was initially hypothesised that annuals are more sensitive to climate change due to their shallow roots, observations by experts of survival rates' after the 2014-2022 severe drought indicated higher mortality rates for perennials than annuals.	If species has a perennial life history.	**High:** Perennial **Low:** all others	1
	D2: Seed longevity	With optimum germination settings becoming altered and/or delayed with climate change, seed longevity becomes important. If a species has a longer seed longevity, the seed can survive for longer until optimal germination conditions are provided.	If species has a low seed longevity (< 3 yrs).	**High:** < 3 yrs **Low:** > 3 yrs	3
	D3: Germination seasonality	If a species is restricted to germinating in cooler, winter temperatures, it will be less likely to adjust to germinating in warmer temperatures under climate change.	If species is restricted to germinating in cooler, winter temperatures i.e. less adapted to warmer temperatures.	**High:** Restricted to winter temperatures **Low:** all others	3
	D4: Fragmentation reproduction	It is a form of asexual reproduction in which plants propagate through fragments of stems, roots or even leaves (Gudynaitė-Franckevičienė and Pliūra, 2021). It allows for rapid reproduction, rapid colonization of open areas, resilience to extreme droughts or heatwaves and requires less resources to reproduce - making such species perform better under climate change than species with other forms of reproduction (Gudynaitė-Franckevičienė and Pliūra, 2021). This trait could have been under sensitivity or adaptive capacity but was kept under sensitivity as it is a component of life history.	If species does not adopt fragmentation reproduction.	**High:** Does not use fragmentation reproduction **Low:** uses this strategy	1
E: Dispersal ability	E1: Intrinsic barriers	Species which have short-distance dispersal mechanism/s have limited ability to shift to other areas should their current area, tolerances and requirements for survival be compromised. This	Short distance dispersal mechanisms (dispersal range <1 km): • Ballistic	**High:** Only short distance dispersal mechanism/s and no long-distance dispersal	3

		will limit their ability to adapt to climate change through migration (Foden and Young, 2016; Foden *et al*., 2016).	• Droplet or water • Ant • Endozoochory **AND NOT** Long distance dispersal mechanisms (dispersal range >1km): • Wind • Animal	mechanisms **Low:** all others	
F: Evolvability	F1: Reproductive capacity	Plants with a lower reproductive capacity require special conditions to reproduce and grow and can also have a low genetic variation in their populations (van Daele *et al*., 2023). This limits their ability to reproduce, evolve and adapt to changing environmental conditions. This trait also is indicative of reduced dispersal potential as these plants produce a smaller number of seeds or vegetative propagules (similar to E1) (van Daele *et al*., 2023).	Low reproductive capacity if few reproductive events (< 5 events).	**High:** Number of lifetime reproductive events < 5 **Low:** All others	3
	F2: Generation time	A species with a long generation time has a low adaptive capacity as it prevents the species from adapting at a fast enough pace to match that of climate change (Compagnoni *et al*., 2021). This can mean increased mismatches between environmental conditions and phenological timing, reduced genetic diversity, limited methods of extrinsic adaptations such as migration and/or range expansion and therefore increased exposure to extreme events (Compagnoni *et al*., 2021).	Long generation time if species has a long lifespan (> 20 yrs).	**High:** > 20 yrs **Low:** All others	3
G: Climate change exposure	G1: Range overlap	The larger the overlaps between the current and projected future distribution of species, the less exposed it is to climate change (because predicted distribution change is based on predicted climate envelope shifts). This would limit the need for migration, ecological interactions may remain coupled and there would be reduced genetic depression risk (Duffy and Jacquemyn, 2018; Compagnoni *et al*., 2021; van Daele *et al*., 2023).	If overlap is <70 %.	**High:** <70 % **Low:** all others	3

	G2: Total range change	A species is considered exposed to climate change if their range will reduce in the future. A range reduction can result in steep population declines, a lack of area to migrate to, reduced genetic diversity, disrupted ecological relationships, vulnerability to extreme events and overall, increased population fragmentation decline, Allee effects and risk of extinction (Allee and Bowen 1932; Foden *et al.*, 2013; Franklin *et al.* 2016; Pagel *et al.* 2020; Payne *et al.* 2023).	If range reduces.	**High:** range is reducing **Low:** all others	3

How data were collected for traits requiring GIS methods

All GIS methods were done using R version 4.3.2 (R core team, 2023).

A2: Habitat specialisation: Since all the assessed species occurred in Namibia and/or South Africa, the vegetation types of these two countries were used. For Namibia, the vegetation map shapefile was obtained through Environmental Information Service Namibia: eLibrary (2022). For the South African vegetation type, the 2024 National Vegetation Map of South Africa shapefile (Beta version) was supplied by SANBI and used. The number of vegetation types a species occurred in was estimated by finding the vegetation type at each species occurrence data point and assessing how many individual vegetation types were present across all occurrence data points of the species. This was done separately for each country's vegetation type shapefile and then summed; hence the matching of their resolution was not deemed necessary. The R packages used were "sf" (Pebesma *et al.*, 2024), "terra" (Hijmans *et al.*, 2025) and "dplyr" (Wickham *et al.*, 2023). Scoring was then done accordingly.

B1: Narrow precipitation tolerances: This trait was assessed via the absolute average deviation (AAD) in precipitation across the species range. This was guided by Foden *et al.* (2013) using the following formula:

$$\frac{1}{n}\sum_{i=1}^{n}|X_i - m(X)||$$

X_i = monthly mean precipitation for a cell (i) within a species range

n = total number of X values

$m(X)$ = mean of all X values for species

The data comprised the mean annual precipitation (mm), sourced from the Climate Research Unit (CRU) by the University of East Anglia (TS version 4.08) at a resolution of 55km^2 (University of East Anglia, 2023a). Climate data were originally obtained for the years 1901-2023 but were filtered to only include 1940-1975 and extracted at the points of occurrence for each species. The years 1940-1975 were deemed appropriate for a historical baseline measure as it likely had little influence from climate change. To calculate the tolerance range, monthly precipitation values for each of the required years were extracted. From this a mean precipitation was calculated over the 35-year period and the AAD from this mean over the years was calculated. This was extracted and carried out for each species based on their occurrence data. The data extraction and AAD calculations were all done using the “terra” (Hijmans *et al.*, 2025) and “dplyr” (Wickham *et al.*, 2023) packages on R. Scoring was then done accordingly.

B2: Narrow temperature tolerances: This trait was assessed using the same methodology for B1, except that the variable used was temperature, rather than precipitation. The data comprised the mean annual temperature (°C) between the years 1940 – 1975, sourced from the Climate Research Unit (CRU) by the University of East Anglia (TS version 4.08) at a resolution of 55 km2 (University of East Anglia, 2023b).

C1: Species is rare: This trait was assessed via extent of occurrence (EOO). Coordinates were first extracted at each species’ occurrence point. A convex hull was then created around the species of interest’s coordinate points. The area of the convex hull was used as the measure of EOO and was recorded in km^2. This was done for all species using the “sp” (Pebesma *et al.*, 2025), “sf” (Pebesma *et al.*, 2024) and “dplyr” (Wickham *et al.*, 2023) packages of R.

G1: Range overlap and *G2: Total range change:* To accommodate for the uncertainty in climate change projections, I identified the three most suitable Global Circulation Models (GCMs) representing least, moderate and most extreme possible climate change scenarios. The three chosen GCMs were then used to run my own exposure analyses. To identify these three GCMs, plots of the predicted average changes in temperature, rainfall and/or rainfall seasonality for the Richtersveld, were requested, generated and provided by SANParks for this project (van Wilgen *et al.*, unpublished). This was done for all GCMs available through WorldClim version 2.1 (Fick and Hijmans, 2017).

The plots estimated the projected mean 2050 climate futures for each GCM and how much they differ from the current climate (%) (**Appendix 3a** and **b**). Historical climate was based on 1980-2009 climate data and future climate was based on the 2040-2060 climate projections. While all models projected a very hot and dry climate future, the level of seasonality change, and aridity and temperature increase differed by model (**Appendix 3a** and **b**). The models that were chosen included one for the hottest and driest future, with a short rainy season i.e. most extreme change, one for the warm and wet future with good, consistent rainfall i.e. least extreme change and one in between these extremes (**Appendix 3a** and **b**). These were the HadGEM3-

GC31-LL, MPI-ESM1-2-HR and MIROC6 models respectively. It is important to note that the models did not account for fog or other forms of moisture as no current GCM variables assess this component.

In my analysis, the historical data used the years 1970-2000 (Fick and Hijmans, 2017). Future climate projections and the Coupled Model Intercomparison Project Phase (CMIP6) datasets used the years 2041-2060 (Fick and Hijmans, 2017). The use of 1970-2000 was selected as the historical dataset as that is the oldest set of records that WorldClim version 2.1 has at the time this project was written (Fick and Hijmans, 2017). The resolution of both the future and historical datasets were 10 minutes and both the Shared Socio-economic Pathways (SSP) 246 (Representative Concentration Pathway (RCP) 2.6 – best-case scenario) and the SSP585 (RCP8.5 – worst case scenario) were used for future projections of my exposure analyses (Fick and Hijmans, 2017). The use of two RCPs increases the robustness of this method. The variables that were used for assessing the exposure components were annual mean temperature (Bioclim 1), maximum temperature of the warmest month (Bioclim 5), mean temperature of the warmest quarter (Bioclim 10), mean temperature of the coldest quarter (Bioclim 11), annual precipitation (Bioclim 12) and precipitation seasonality (Bioclim 15).

SDMs were created using these downloaded climate datasets for each model and species' occurrence data. The SDM approach chosen was Bioclim, which is the original "climate-envelope" approach for SDMs and it is a presence-only method (Xie *et al.*, 2023). It is time efficient and easy to understand, making it a good choice for this assessment framework (Xie *et al.*, 2023). Bioclim SDMs may not account for complexities in the way other available models do (Xie *et al.*, 2023), but their use in conjunction with trait-based methods helps bridge this gap. *Pearson et al.* (2007) and Liu *et al.* (2013) recommended using an area suitability threshold of 0.1 when there is a small number of presence-only occurrences available such as in this study. This threshold also removes more extreme environmental outliers and prevents over-prediction, leading to more ecologically sound SDMs (*Pearson et al.*, 2007; Liu *et al.*, 2013).

The resolution of all the downloaded climatic datasets were converted to 1 km^2 using Albers Equal Area projection. The Area Under the Curve (AUC) ranged between 0.5-0.8 as accuracy was limited by the number of occurrence points. The data collected from the SDMs that were subsequently created, were total current area, total future area (RCP2.6 and RCP8.5) and total area of overlap (RCP2.6 and RCP8.5). These were collected for all species for all models. If a species had less than 10 occurrence points, all exposure components were scored as unknown. This is because an SDM made with less than 10 occurrence points would be unreliable. The "bioclim" (Serrano-Notivoli, 2023), "terra" (Hijmans *et al.*, 2025), "raster" (Hijmans, 2025), "sp" (Pebesma *et al*., 2025), "dismo (Hijmans *et al.*, 2024) and the "pROC" (Robin *et al.*, 2011) packages on R were used to create and run SDMs. Once this was done, the calculations for assessing and scoring G1 and G2 could be done.

To calculate G1: range overlap, the formula (total area of overlap / total current area) * 100 was used. To calculate G2: total range change, the formula (total future area-total current area)/total current area * 100 was used. Given that all species had different range sizes, the outcomes were standardized to percentage to better evaluate which species are more exposed. This was done for all species for both the RCP 2.6 (best-case) and 8.5 (worst-case) scenarios for all 3 models. The supplementary information required by the IUCN Red List committee for the use of bioclimatic models is seen in **Appendix 4**.

Scoring methods

Once the raw data were collected for each species and traits scored accordingly, I combined the trait scores to calculate an overall vulnerability score. Harper *et al.* (2020) states that the use of both ordinal and additive scoring methods helps to highlight the most vulnerable species to climate change. This allows a vulnerability assessment approach to be robust. This served as motivation for using both methods in this study. The most vulnerable species were those that had the highest frequency of high vulnerability scores across the different scoring methods.

Ordinal scoring: Used by Foden *et al.* (2013) and Böhm *et al.* (2016), an ordinal approach, involves defining thresholds for a high and low score for each trait. For example, when scoring A2: habitat specialization, the threshold for having a 'high' sensitivity score was occurring in <5 vegetation types while the threshold for having a 'low' sensitivity score was occurring in >5 vegetation types. Once each individual trait was scored as 'high' or 'low', each trait group was assigned a 'high' or 'low' score. This was based on the number of individual traits in that group that scored 'high'. The top fifteen species with the highest number of individual traits that scored 'high' in a trait group, received an overall ‘high’ score for that trait group. For example, trait group B had 7 individual traits to consider. The fifteen species with the highest number of ‘high’ scores out of these 7 traits, scored an overall ‘high’ score for trait group B.

Once all trait groups received their overall ‘high’ and ‘low’ score, each dimension was given a score. The presence of one high-scoring trait group, automatically allowed the respective dimension (sensitivity, adaptive capacity or exposure) to receive an overall ‘high’ score. The final ordinal vulnerability score for a species was dependent on the combination of dimension scores (**Table 3**).

Table 3: How dimension scores were used to give the overall ordinal vulnerability score. (H = High, M= Moderate L = Low)

Sensitivity	Inadaptability*	Exposure	Final	Explanation
H	L	H	**M**	High sensitivity and exposure increase climate change risk, but low inadaptability means a species can lessen this level of risk.
H	H	H	**H**	High sensitivity, inadaptability and exposure means high risk and no way for a species to lessen the level of risk.
L	H	L	**L**	Inadaptability is high but there is no risk as there is low exposure and sensitivity.
H	H	L	**L**	High sensitivity and inadaptability may be concerning, but low exposure means there is low risk.
L	H	H	**M**	Low sensitivity reduces the impact of high exposure, but high inadaptability still allows risk from high exposure.
L	L	L	**L**	All three dimensions are low, meaning the species is not highly vulnerable.
H	L	L	**L**	High sensitivity alone will not make a species vulnerable when other dimensions score low.
L	L	H	**M**	Low sensitivity and inadaptability help reduce risk, but high exposure leads to moderate vulnerability.

*A high inadaptability score = a lack of adaptive capacity. A low inadaptability score = high adaptive capacity. This way of scoring helped avoid confusion when assigning high scores for each dimension - ensuring a high score still meant contributing to a high vulnerability.

Additive scoring: In this scoring method, each trait was scored numerically from 1-3, with 3 being highly vulnerable – as guided by Gardali *et al.* (2012). Once this was done for all traits, the trait scores were then summed up per species to give the overall additive vulnerability score. This was the final unweighted score. This method was then repeated for the weighted scoring – which accounts for how important each trait is estimated to be in contributing to the climate change vulnerability of a species (Willis *et al*., 2015). For the weighted method, each individual, unweighted trait score was multiplied by the relative trait weighting (1 to 5) given in **Table 2**. For example, if a species had <5 vegetation types and received a score of 3 for trait A2: habitat specialization and the trait weighting for A2 is 5, the weighted score for this species for A2 is 3x5, which is 15.

Accounting for unknowns: For some species, there was a lack of data and expert knowledge regarding some traits. These traits were therefore scored as unknown, following Foden *et al.* (2013). To account for this, and subsequently make the method more robust, two scenarios were created for calculating overall vulnerability scores. The best-case scenario was where the unknown traits were given a score of 'low' in ordinal and a score of 1 in the additive scoring method. The worst-case scenario was where the unknown traits were given a score of 'high' in ordinal and a score of 3 in the additive scoring method. This helped give an indication of how vulnerable a species may be to climate change despite uncertainty and having knowledge gaps. Therefore, there were six final vulnerability scores: a best-case ordinal, a worst-case ordinal, a best-case unweighted additive, a worst-case unweighted additive, a best-case weighted additive and a worst-case weighted additive score. The RCP2.6 exposure scores were used when calculating the best-case overall vulnerability scores for both additive and ordinal scoring, and RCP8.5. for the worst-case scores.

Lastly, some traits were described by continuous variables for which there were no obvious species-specific vulnerability thresholds. Notable examples are climate (precipitation and temperature) tolerances (traits B1 and B2 in **Table 2**). For these two traits, species whose values were within the lowest 25 % of all species' AAD values were assigned a 'high' score or a score of 3, for ordinal and additive scoring respectively. Species whose values were within the highest 75 % of all species' AAD values were assigned a 'low' score or a score of 1, for ordinal and additive scoring respectively. For example, if the AAD for temperature for all 58 species ranged between 1 and 5, the species with the lowest 25 % of values in this range received a high score or a score of 3. Species with the highest 75 % of values in this range received a low score or a score of 1.

Exploring conservation implications

Comparing IUCN Red List statuses and TVA-Corr scores: An important component of my study was to assess the relationship between my TVA-Corr assessment ordinal scores, and the Red List status for each species assigned by SANBI. SANBI assigns their threat status using the IUCN 3.1 regional criteria on the National Red List of South African Plants (SANBI, 2010). In order to examine this relationship, a Spearman's rank correlation test was used on ranked statuses (**Table 4**). The Spearman's rank correlation test was chosen for this section as it allowed my ordinal scores to be used without assuming equal intervals between ranks (Field, 2013). I also chose it as it does not assume a normal distribution of data, which is unlikely when dealing with climate change vulnerability scores and IUCN red list statuses (Field, 2013). Lastly, this test accounts for relationships which are not necessarily linear, which a possibility when comparing two sets of data that may already have an ordered ranking (Field, 2013). Many studies undertaking similar objectives have also used this test such as Harper *et al.* (2022) and Pacifici *et al*. (2015). The "stats" package on R was used to conduct this test (R Core Team, 2023). This was done for both the best- and worst-case final ordinal scores.

Table 4: How the ranks for the Spearman's rank correlation test were assigned.

Rank	**Vulnerability score**	**IUCN/ SANBI status**
1	L	Least Concern
2	M	Near Threatened, Rare and Data Deficient*
3	H	Vulnerable, Endangered, Critically Endangered

*Only one study species' Red List status is Data Deficient. It's assignment with rank of 2 is due to 'Data Deficient' being a higher threat status than Least Concern but a lower threat status than the threat status that received a rank of 3, according to SANBI (SANBI, 2024c). This is attributed to the risk of a potential threat being present but unknown due to a lack of data. Least concern species, however, have enough information available for SANBI to conclude there is no or little threat to the species hence its rank of 1. The assignment of a rank of 2 to the Data Deficient species also did not significantly change the spearman's rank if the species removed either, hence it remained.

Identifying the areas of RNP where climate change vulnerable species occur: Heatmaps were created for RNP by representing the 'high' vulnerability scores spatially. This allowed areas with the highest concentration of highly vulnerable species to be located within the park. The species used for this mapping component were only those determined to be highly vulnerable to climate change. For the maps based on ordinal scoring, all species listed with an overall 'high' vulnerability score were used to make the map. For maps based on additive scoring, the top 20 species with the highest total weighted scores were used, as this accounted for the different levels of importance each trait has in contributing to climate change vulnerability. The RNP basemap was acquired from The South African Protected Area Database (SAPAD) website (DFFE, 2024). The species occurrence data for the chosen species were filtered to those occurring only within the boundaries of the RNP. Their occurrence data were standardized to a Universal Transverse Mercator (UTM) of 32 in order to rasterize the data in km^2. A raster was created based on how many of the vulnerable species were present per 40km^2 pixel and this was then used to create a heatmap. This was done for the best- and worst-case ordinal and weighted additive scenarios, giving a total of four maps. The unweighted scenarios were not mapped as the weighted scenarios were deemed more realistic. The packages used to do this in R were "raster" (Hijmans, 2025), "sf" (Pebesma *et al.*, 2024), "ggplot2" (Wickham, 2016) and "viridis" (Garnier *et al*., 2024).

Occurrence data as opposed to the SDMs were used to create the heatmaps as it allowed for areas of confirmed importance as opposed to hypothetical suitability to be highlighted. This allowed for more transparent and conservative conclusions with less uncertainties and assumptions. Volis and Toijbaev (2023) supported this and further emphasized that using occurrence data when mapping species richness maps as opposed to SDMs is suitable for identifying biodiversity hotspots, guiding rapid assessments and for assessing conservation priorities. Graham and Hijmans (2006) supported this choice by stating that SDMs are not always 100% accurate so the use of confirmed points of occurrence prevents accumulating and amplifying the errors of each species' SDM into one map.

Results

Vulnerability dimension summary

Sensitivity: A total of 51 species (88 %) had at least one sensitivity trait that scored 'High' for the ordinal worst-case scenario. This was slightly lower in the best-case scenario (50 species (71 %)). The trait that occurred the most among sensitive species was B7: (a lack of) sandstorm adaptation (57 species (98 %)). The only species found to have psammophorous characteristics was *Euphorbia gummifera*.

The second and third most common sensitive traits were D4: (lack of) fragmentation reproduction (55 species (95 %)) and D1: perennial (48 species (83 %)) (**Table 5**). The trait that occurred the least among sensitive species, was A2: habitat specialization (5 species (9 %)). This was then followed by B5: photosynthetic mechanism and D2: seed longevity (both 10 species(17 %)) (**Table 5**).

Adaptive capacity: A total of 51 species (88 %) had at least one inadaptability trait that scored ‘High’ for the worst-case scenario. This was lower in the best-case scenario (47 species (81 %)). The inadaptability trait that occurred the most among the least adaptable species was F2: long generation time (35 species (60 %)) (**Table 5**). This means these same 35 species have a low chance of evolvability. The remaining two inadaptability traits were present for 14 species (24 %)) (**Table 5**). This means these 14 species have a low chance of evolvability due to a low reproductive capacity and also have intrinsic barriers to their dispersal.

Exposure: Under the worse-case scenario, a total of 46 species (79 %) had at least one exposure trait that scored ‘High’ for one of the models. This was less in the best-case scenario (35 species (60 %)). The trait that occurred the most among exposed species was G2: total range change, more specifically for the MIROC6 model under the best-case scenario (RCP 2.6) (28 species (48 %)) (**Table 5**). This was followed by all other models that were run for this trait (24-27 species (41-47 %)) (**Table 5**). For all models that were run for G1: range overlap, only 2 species (3 %) were highly exposed (**Table 5**).

Availability of data: The availability of data to score each trait varied. In total, across all traits for all species, there were 246 unknown scores (15 %) (**Table 5**). The trait with the highest number of species scored as unknown was B5: photosynthetic mechanism (32 (55 %)) (**Table 5**). This was then followed by G1: range overlap and G2: total range change (both 14 species (24 %)) and B1: narrow precipitation tolerance and B2: narrow temperature tolerance (both 10 species (17 %)) (**Table 5**). Unknown scores for G1, G2, B1 and B2 were due to a lack of occurrence data which prevented climate-related data from being calculated or mapped.

Table 5: The number of species which scored 'High', 'Low', or 'Unknown' for each trait (n = 58) when scoring ordinally. BC refers to best-case scenario (RCP2.6) and WC is worst-case scenario (RCP8.5). This summary is based on the ordinal scoring method. (Key: Sensitivity, Adaptive Capacity, Exposure. The trait with the highest number of species scoring 'High' in that dimension, is in bold and coloured in that dimension's colour).

Trait group	Trait	Total no. species 'High'	Total no. species 'Low'	Total no. species 'Unknown'
A: Specialized habitat and/or microhabitat requirements	A1: Vulnerable microhabitat specialization	10	45	3
	A2: Habitat specialization	5	53	0
B: Environmental tolerances or thresholds that are likely to be exceeded by climate change	B1: Narrow temperature tolerance	13	35	10
	B2: Narrow precipitation tolerance	18	30	10
	B3: Seasonality	38	20	0
	B4: Root system	36	18	4
	B5: Photosynthetic mechanism	10	16	32
	B6: Drought adaptations	14	43	1
	B7: Sandstorm adaptation	**57**	1	0
C: Rarity	C1: Species is rare	21	37	0
D: Sensitive life history	D1: Perennial/ Annual	48	10	0
	D2: Seed longevity	10	46	2
	D3: Germination seasonality	38	15	5
	D4: Fragmentation reproduction	55	3	0
E: Dispersal ability	E1: Intrinsic barriers	14	41	3
F: Evolvability	F1: Reproductive capacity	14	39	5
	F2: Generation time	**35**	20	3
G: Climate change exposure*	G1: Range overlap - BC Model: MPI-ESM1-2	2	42	14
	G1: Range overlap - WC Model: MPI-ESM1-2	2	42	14
	G1: Range overlap - BC Model: HadGEM3-GC31-LL	2	42	14
	G1: Range overlap - WC Model: HadGEM3-GC31-LL	2	42	14
	G1: Range overlap - BC Model: MIROC6	2	42	14
	G1: Range overlap - WC Model: MIROC6	2	42	14

	G2: Total Range Change - BC	Model: MPI-ESM1-2	25	19	14
	G2: Total Range Change - WC	Model: MPI-ESM1-2	24	20	14
	G2: Total Range Change - BC	Model: HadGEM3-GC31-LL	26	18	14
	G2: Total Range Change - WC	Model: HadGEM3-GC31-LL	24	20	14
	G2: Total Range Change - BC	Model: MIROC6	**28**	16	14
	G2: Total Range Change - WC	Model: MIROC6	27	17	14
Total			**602**	**834**	**246**
Total (%)			**35.79**	**49.58**	**14.63**

*HadGEM3-GC31-LL is the model run for the most extreme case of climate change, MPI-ESM1-2-HR for the least extreme change and MIROC6 for moderate climate change. Each was run under best-case scenario (RCP2.6) and WC is worst-case scenario (RCP8.5)

Scoring summary

The final ordinal scores for each species were calculated by seeing the combination of 'high' and 'low' scores for each vulnerability dimension (**Table 3**). The final unweighted additive scores were calculated by summing up the individual trait scores that were between 1 and 3. The final weighted score was calculated by first multiplying the individual trait scores, that were between 1 and 3, by the relevant trait importance weighting. These individual trait scores were then summed. The best-case scenario is where 'unknowns' were assumed to have 'low' scores, and a worst-case scenario when these were assumed to be 'high'. These scenarios were applied to both the ordinal and additive scoring methods. These different scoring approaches are compared across **Table 6**.

Ordinal: For the best-case scenario, 21 species (36 %) were scored as highly vulnerable, while 14 species (24 %) and 23 species (40 %) scored a medium and low vulnerability, respectively (**Table 6**). In contrast, under the worst-case scenario, 34 species (59%) were scored as highly vulnerable (**Table 6**). The number of species scoring medium and low vulnerability were both 12 (~21 %) (**Table 6**).

Additive scoring (unweighted): The total number of points available was 63. Under the best-case scenario, the highest scoring species were *Cheilanthes namaquensis* and *Trachyandra aridimontana*, which each scored 49 points (**Table 6**). The lowest scoring species was *Diclis petiolaris* which scored 27 points (**Table 6**). Under the worst-case scenario, *Trachyandra aridimontana* was the highest scoring species, which scored 61 points (**Table 6**). The lowest scoring species were *Ceropegia articulata*, *Euphorbia gummifera* and *Hermannia eenii*, which each scored 37 points

(**Table 6**).

Additive scoring (weighted): The total number of points available was 189. Under the best-case scenario, the highest scoring species was *Trachyandra aridimontana*, which scored 131 points (**Table 6**). The lowest scoring species was *Diclis petiolaris* which scored 67 points (**Table 6**). Under the worst-case scenario, *Trachyandra aridimontana* was again the highest scoring species, with 167 points (**Table 6**). *Hermannia eenii* was the lowest scoring species with 89 points (**Table 6**).

Table 6: The vulnerability scores for each of the 58 plant species within Richtersveld National Park according to each scoring method under both the best-case (BC) and worst-case (WC). 'Max' refers to the total number of points that were available under the unweighted (UW) and weighted (W) methods. Species are in alphabetical order.

Low score High score

Species	Ordinal BC	Ordinal WC	Additive UW BC (Max: 63)	Additive UW WC (Max: 63)	Additive W BC (Max: 18G)	Additive W WC (Max: 18G)
Adromischus marianiae	H	H	41	42	101	108
Albuca etesiogaripensis	L	H	47	57	117	151
Albuca longipes	H	H	46	44	114	112
Aloe meyeri	L	M	40	53	112	155
Anacampseros albissima	L	H	43	42	107	108
Antizoma miersiana	H	H	42	42	106	106
Asparagus multituberosus	H	H	42	45	104	113
Astridia citrina	L	L	47	45	125	123
Bromus pectinatus	M	H	45	47	111	113
Ceropegia articulata	H	H	41	37	103	95
Ceropegia herrei	L	H	41	54	101	144
Ceropegia perlata	H	H	45	44	113	114
Cheilanthes namaquensis	M	H	49	55	119	141
Codon schenckii	L	H	42	56	108	146
Crassula muscosa	M	M	44	44	114	118
Crassula subacaulis	L	L	37	53	93	141
Crotalaria humilis.	H	H	43	45	111	113
Cucumis rigidus	H	H	41	44	107	116
Cyrtanthus herrei	L	L	45	44	113	110
Diclis petiolaris	L	L	27	45	67	117
Dimorphotheca pinnata	H	L	41	42	99	98
Drosanthemum salicola	M	M	46	44	116	114
Euphorbia gummifera	H	L	40	37	108	103
Euphorbia rhombifolia	H	H	47	46	121	122

Gymnosporia gariepensis	L	H	43	55	109	145
Helichrysum leontonyx	M	M	43	44	103	106
Heliophila cornuta	M	M	44	44	106	106
Hemarthria altissima	M	H	31	48	75	126
Hermannia eenii	H	H	40	37	94	89
Isolepis hemiuncialis	L	H	40	56	102	142
Justicia cuneata	L	L	38	38	92	92
Lapeirousia dolomitica	L	H	41	53	99	135
Lapeirousia littoralis	H	H	45	45	113	113
Lessertia frutescens	M	M	40	46	98	116
Lycium bosciifolium	H	L	43	43	107	107
Manulea robusta	L	H	40	56	102	150
Mesembryanthemum pellitum	M	H	42	46	106	118
Osteospermum karrooicum	L	H	39	51	95	131
Oxalis sonderiana	H	H	42	46	104	116
Ozoroa crassinervia	L	H	42	54	110	146
Parkinsonia africana	M	M	43	44	111	114
Passerina truncata	H	H	41	41	101	101
Pelargonium antidysentericum	H	H	46	47	116	119
Pelargonium echinatum	H	H	47	47	117	117
Peliostomum virgatum	L	M	42	44	104	110
Portulacaria namaquensis	M	L	44	40	110	102
Pseudoschoenus inanis	H	L	39	38	95	92
Ruschia glauca L.Bolus	L	H	46	56	120	154
Schismus schismoides	L	L	39	43	97	101
Schwantesia herrei	L	H	43	57	111	157
Stipagrostis geminifolia	M	M	48	48	124	120
Tapinanthus oleifolius	L	L	39	43	101	109
Tetraena retrofracta	M	M	38	38	94	94
Trachyandra aridimontana	L	H	49	61	131	167
Tylecodon reticulatus	L	H	43	57	113	159
Ursinia nana	H	M	42	44	102	104
Vachellia erioloba	M	M	43	42	109	106
Vahlia capensis	H	H	39	43	95	107
Total "High" scores	***21***	***34***	**N/A**			
Total "Medium" scores	***14***	***12***				
Total "Low" scores	***23***	***12***				

The most vulnerable species

These were determined as species with consistently high vulnerability scores across all six scoring methods. The most vulnerable species was *Cheilanthes namaquensis* (Least Concern), which had a high vulnerability score across all six scoring methods (**Table 7**). This was followed by *Albuca etesiogaripensis* (Data Deficient), *Bromus pectinatus* (Least Concern), *Euphorbia rhombifolia* (Least Concern), *Ruschia glauca* (Endangered), *Schwantesia herrei* (Least Concern), *Trachyandra aridimontana*

(Endangered) and *Tylecodon reticulatus* (Least Concern), which each had high vulnerability scores in five out of the six scoring methods (**Table 7**). Their respective vulnerability scores are seen in **Table 6**. All seven species, under the worst-case scenario, have reducing ranges (G2), long generation times (F2), short roots (B4), lack psammophorous characteristics (B7), germinate in winter (D3) and do not reproduce via fragmentation reproduction (D4) (**Figure 3a-e**). The other traits present in a selection of these seven species is seen in **Figure 3a-e**. Four out of these seven most climate change vulnerable species are Richtersveld endemics, three of which are almost completely endemic to RNP (**Appendix 1**). The least vulnerable species did not score high in any of the scoring methods (**Table 6** and **7**).

Exploring conservation implications

Comparing IUCN Red List statuses and TVA-Corr scores: In the best-case scenario, a moderate negative correlation, that is statistically significant, was found ($r_s = -0.43$, $p<0.05$, $n= 58$). In the worst-case scenario, a weak negative relationship, that is not statistically significant, was found ($r_s = -0.13$, $p= 0.3$, $n= 58$). This means highly climate change vulnerable species identified in this study currently have a low Red List threat status assigned to them by the responsible conservation organisation. Climate change vulnerable species identified in this study that are also impacted by one or more of these anthropogenic factors include *Ceropegia articulata*, *Codon schenckii*, *Laperiosa littoralis*, *Ruschia glauca*, *Stipagrostis geminifolia*, *Trachyandra aridimontana* and *Vachelia erioloba* (**Table 7** and **Appendix 5**). Each of these species received a high climate change vulnerability score in four or more scoring methods.

Identifying the areas of RNP where climate change vulnerable species occur: In the spatial analysis, two pixels in the central western edge as well as some pixels in northern areas of RNP consistently had the highest concentration of climate change vulnerable species, across all scoring approaches (**Figure 4a-d**).

Table 7: The number of times each species scored a high climate change vulnerability, across all six scoring methods (Frequency). Species ordered by descending frequency.

Species	Frequency (Max: 6)	Species	Frequency (Max: 6)
Cheilanthes namaquensis	6	*Anacampseros albissima*	2

Albuca etesiogaripensis	5	*Antizoma miersiana*	2
Bromus pectinatus	5	*Crassula muscosa*	2
Euphorbia rhombifolia	5	*Crassula subacaulis*	2
Ruschia glauca L.Bolus	5	*Cucumis rigidus*	2
Schwantesia herrei	5	*Cyrtanthus herrei*	2
Trachyandra aridimontana	5	*Drosanthemum salicola*	2
Tylecodon reticulatus	5	*Hermannia eenii*	2
Albuca longipes	4	*Lycium bosciifolium*	2
Ceropegia articulata	4	*Oxalis sonderiana*	2
Ceropegia perlata	4	*Parkinsonia africana*	2
Codon schenckii	4	*Passerina truncata*	2
Crotalaria humilis.	4	*Vahlia capensis.*	2
Gymnosporia gariepensis	4	*Dimorphotheca pinnata*	1
Lapeirousia littoralis	4	*Euphorbia gummifera*	1
Pelargonium antidysentericum	4	*Helichrysum leontonyx*	1
Pelargonium echinatum	4	*Heliophila cornuta*	1
Stipagrostis geminifolia	4	*Mesembryanthemum*	1
Aloe meyeri	3	*Portulacaria namaquensis*	1
Asparagus multituberosus	3	*Pseudoschoenus inanis*	1
Astridia citrina	3	*Ursinia nana*	1
Ceropegia herrei	3	*Diclis petiolaris*	0
Hemarthria altissima	3	*Justicia cuneata*	0
Isolepis hemiuncialis	3	*Lessertia frutescens*	0
Lapeirousia dolomitica	3	*Peliostomum virgatum*	0
Manulea robusta	3	*Schismus schismoides*	0
Osteospermum karrooicum	3	*Tapinanthus oleifolius*	0
Ozoroa crassinervia	3	*Tetraena retrofracta*	0
Adromischus marianiae	2	*Vachellia erioloba*	0

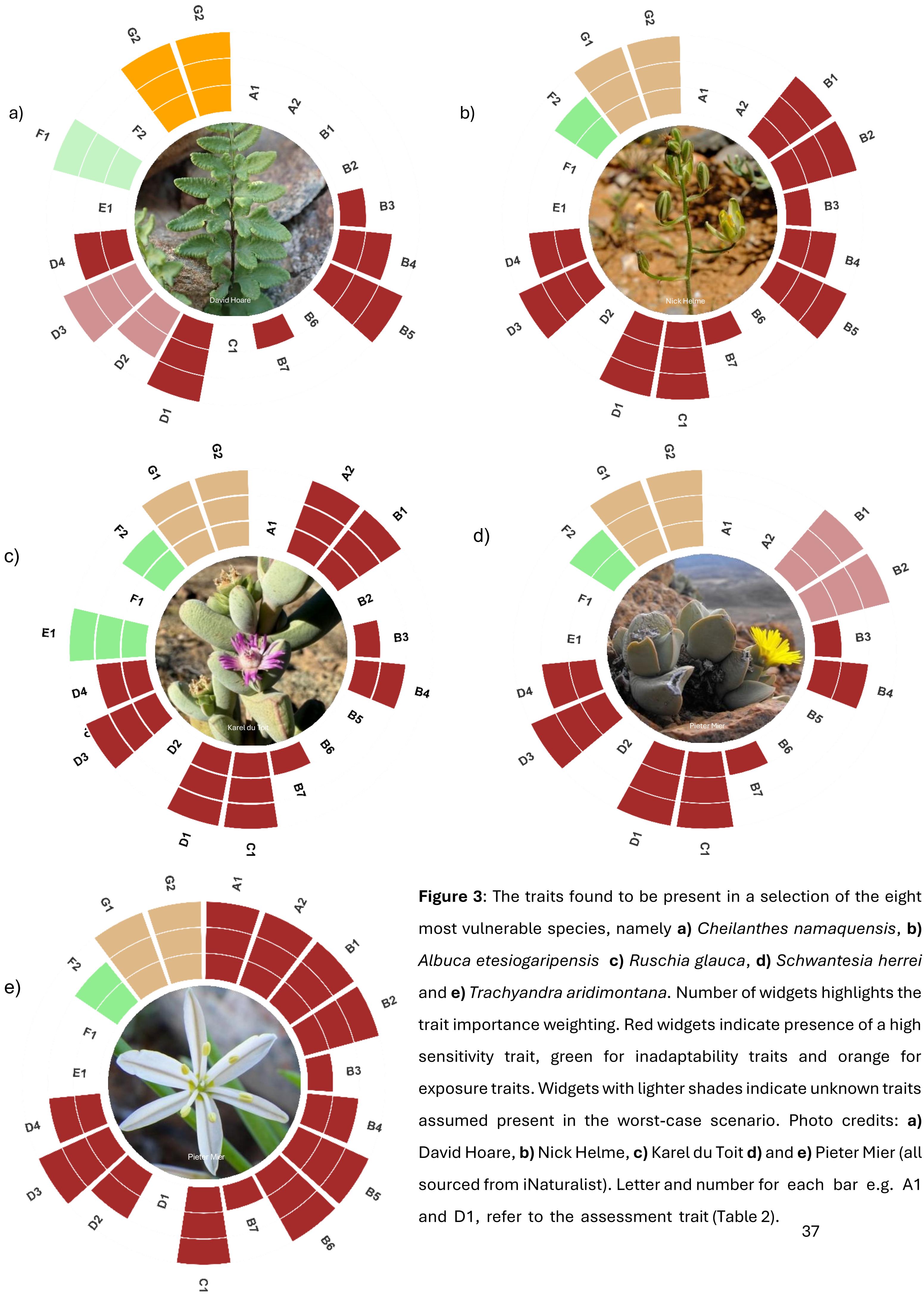

Figure 3: The traits found to be present in a selection of the eight most vulnerable species, namely **a)** *Cheilanthes namaquensis*, **b)** *Albuca etesiogaripensis* **c)** *Ruschia glauca*, **d)** *Schwantesia herrei* and **e)** *Trachyandra aridimontana*. Number of widgets highlights the trait importance weighting. Red widgets indicate presence of a high sensitivity trait, green for inadaptability traits and orange for exposure traits. Widgets with lighter shades indicate unknown traits assumed present in the worst-case scenario. Photo credits: **a)** David Hoare, **b)** Nick Helme, **c)** Karel du Toit **d)** and **e)** Pieter Mier (all sourced from iNaturalist). Letter and number for each bar e.g. A1 and D1, refer to the assessment trait (Table 2).

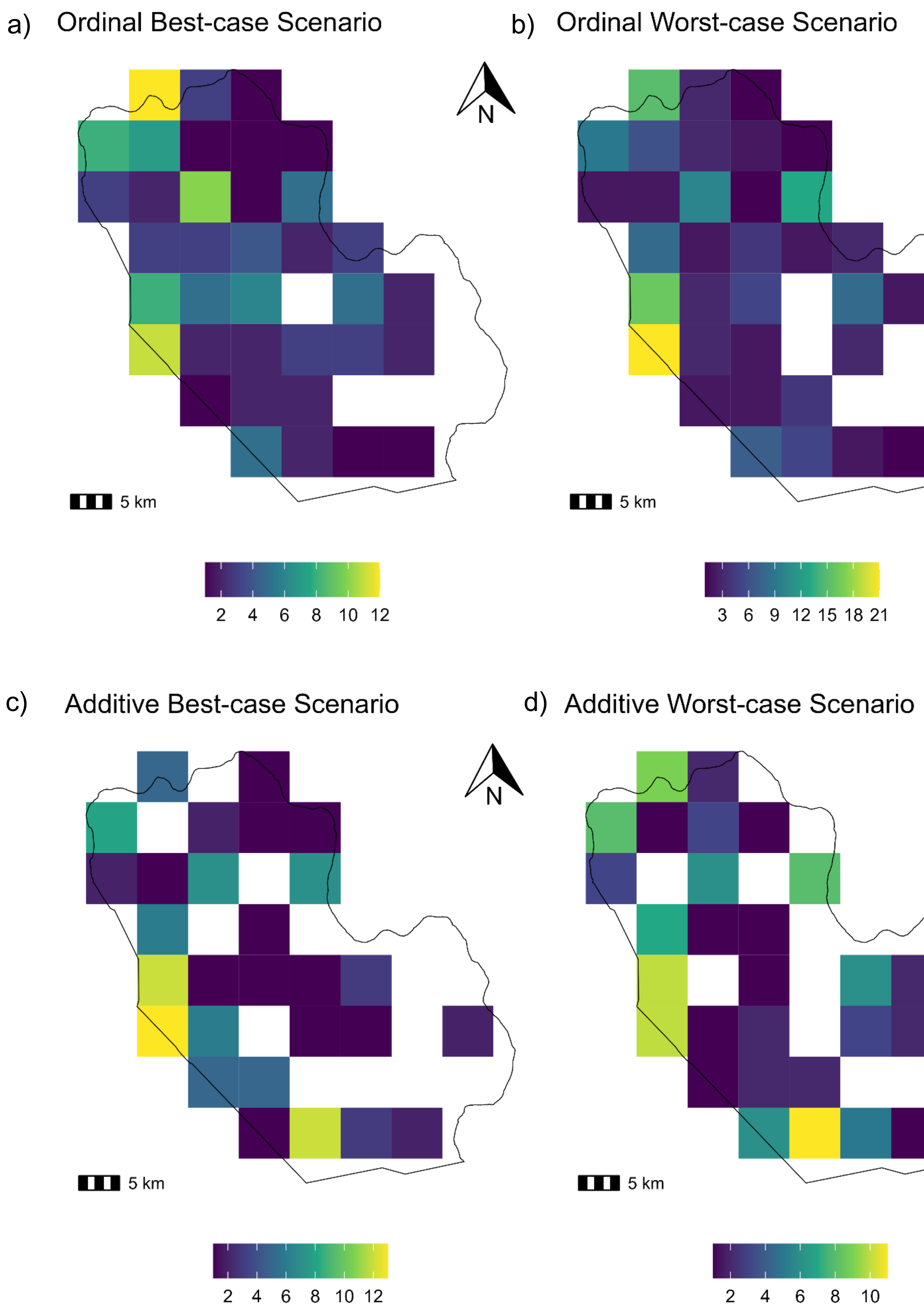

Figure 4: The number of highly climate change vulnerable plant species within Richtersveld National Park under the **a)** ordinal best-case scenario, **b)** ordinal worst-case scenario, **c)** additive best-case scenario and **d)** additive worst-case scenario.

Discussion

Overview

I assessed the climate change vulnerability of a random sample of plants within RNP. This was done using a relatively new and exploratory assessment approach which combined a trait-based vulnerability assessment with correlative species distribution modelling outputs (TVA-Corr approach) (Foden and Young, 2016; Foden *et al*. 2018; Willis *et al*., 2015). This assessment found a high number of these RNP plants to be of a high vulnerability to climate change. Under the best- and worst-case ordinal scoring methods, 21 (36 %) and 34 (59 %) species, respectively, were allocated an overall high climate change vulnerability score. The most vulnerable species were identified as *Cheilanthes namaquensis* (Least Concern), *Albuca etesiogaripensis* (Data Deficient), *Bromus pectinatus* (Least Concern), *Euphorbia rhombifolia*, *Ruschia glauca* (Endangered), *Schwantesia herrei* (Least Concern), *Trachyandra aridimontana* (Endangered) and *Tylecodon reticulatus* (Least Concern)*,* which each scored consistently high vulnerability scores. Despite these species being the most highly vulnerable to climate change, four out of these seven species have a Least Concern Red List threat status. This shows a possible underestimation of their threat status if the threat of climate change is not accounted for. The areas consistently found to have a high concentration of highly vulnerable species were the central western and northern regions of RNP. The identification of the most vulnerable traits, species and their location can aid park management in creating and implementing proactive activities to help prevent future population losses due to climate change. The use of this approach and framework can provide a possible example of how the climate change vulnerability of other arid plants can be assessed.

The strengths and limitations of the study

The strength of the TVA-Corr method lies in the ability to conduct a simultaneous climate change vulnerability assessment of multiple species (Willis *et al*., 2015; Foden and Young, 2016; Foden *et al*. 2018). This would not have been possible using other assessment approaches. The use of multiple scoring methods allowed for a more robust assessment and potentially more reliable conclusions of which species are the most vulnerable to climate change, which traits made them vulnerable and where in the park they are situated. The additive scoring method, specifically, allowed for more nuanced scoring as it allowed traits to be scored between 1 and 3 as opposed to just assigning a ‘high or ‘low’ score. This made the outcomes less uncertain than those for ordinal scoring. This is similar when considering the use of trait weightings in the weighted additive scoring method.

If time and resources were not a limitation, mechanistic methods could be used to give more detailed, and potentially better, species-level outputs by incorporating interacting climate change effects and other morphological and demographic data that was not possible in this assessment (Foden *et al*. 2018). This would, however, require further data collection and refinement, which can take years (Harper *et al*., 2020). Under the fast-paced rate of change and the unpredictable nature of climate change, taking years to reach a single conclusion is not viable (Pacifici *et al*. 2015; Foden *et al*. 2018). Overall, the approach used in this study allowed for extensive and comprehensive assessments within a short space of time (Willis *et al*., 2015; Foden and Young, 2016; Foden *et al*. 2018; Harper *et al*., 2020). The findings of this specific study, provide an effective prioritisation tool to inform conservation interventions.

Trait-based vulnerability assessments are easier in regions of the world and for taxa where there are fewer knowledge gaps. Data and knowledge regarding the Richtersveld is relatively limited and in general, plants have fewer data available than animals (Adamo *et al*., 2021). In my case, this restricted the final traits that were chosen for the assessment. Despite this, there were many species with multiple unknown trait scores. Traits which were excluded and those that had numerous species scoring unknown should be prioritised for research to fill these knowledge gaps. Data were available from literature, but some gaps still persisted. The remaining source of knowledge was limited to only one expert who had extensive knowledge on a majority of the study plants. His availability combined with the limited time of the study meant only 58 species could be assessed. If the study sample was increased, the outcomes of the spearman’s rank correlation test, which was used to compare IUCN Red List statuses and TVA-Corr scores, could have possibly been stronger and more statistically significant, especially for the worst-case scenario (Lakens, 2022). This is due to the wide-known fact that an increase sample allows for increased precision and a larger statistical power Larken (2022).

Another well-known area of uncertainty in trait-based approaches is where vulnerability thresholds should be placed within continuous variables (Foden *et al*., 2013). In my study, narrow temperature and precipitation tolerances were assessed using arbitrary thresholds as in Harper *et al*. (2020) and Foden *et al*. (2013). Harper *et al*. (2020) did find that changing the thresholds (top 75 % and lowest 25 %) by -10 % and +10 % can affect the number of species categorised as highly vulnerable. This could be a possibility in this study, however, time limitations prevented the assessment of these threshold's sensitivity. This should be a point of research in future similar studies.

Another area of research interest is trait weightings and the importance of certain traits. It is clear that all traits will not, biologically, hold the same importance. However, empirical data on the importance of different traits in determining climate change vulnerability is not readily available for many species, including those I studied. Therefore, expert-informed trait-weightings were included in my assessment, following Willis *et al*. (2015). However, these weightings were only estimates. Improving the accuracy of weightings through more research can help ensure that time and resources, which are already limited in conservation, are adequately used to make the most informed decisions (Willis *et al*., 2015). Certain species' scores and positions changed considerably when comparing the additive weighted and unweighted overall vulnerability scores, examples being *Aloe meyeri* and *Bromus pectinatus*. *Bromus pectinatus* is a widespread alien so, its classification as highly vulnerable under a weighted setting further highlights the need for accurate weightings to avoid misleading conclusions. Hence, the traits which significantly shifted species' vulnerability scoring, as well as traits that had the highest number of high scoring species, should be further studied. This can provide a better understanding of the underlying mechanisms and causal pathways through which climate change impacts plants and keep them under consideration during future plant climate change vulnerability assessments.

The emergence of *Cheilanthes namaquensis*, a drought-adapted poikilohydric species, as a highly vulnerable species, highlights the negative implications of omitting important traits, due either through poor data availability or ignorance. Inclusion of traits such as poikilohydry and key aspects of ecophysiology would have improved my assessment. My findings demonstrate the sensitivity of this assessment approach to trait choice and highlights the need for further research and understanding of the system's ecology and plants' ecophysiology.

My study represents an extension on most other TVAs, because I also included an exposure component, based on SDMs. However, most of the AUC values for my exposure models were between 0.5 and 0.8, which is considered poor to moderate model performance (Lobo *et al*., 2008; Guisan *et al*., 2013). This is attributed to the few occurrence points that were available for each species (Lobo *et al*., 2008; Guisan *et al*., 2013). However, Lobo *et al*. (2008) argues that AUC and other evaluation metrics are sometimes misleading and do not always truly reflect model validity, so I included the exposure results in this assessment. Guisan *et al*. (2013) also stated that a limitation of SDMs and exposure analyses are the uncertainties associated with each GCM, a challenge I addressed by using three models under two RCPs for the exposure dimension of the assessment. The lack of specific biological data incorporation in SDMs, also raised by Guisan *et al*. (2013), was addressed by the use of biological data to assess the other two dimensions. However, it would be recommended, for future similar studies, that the use of alternative modelling approaches, particularly those that do well with few occurrence points be considered.

How can these findings aid conservation?

In-situ conservation: The establishment of the park is in-situ conservation, but the findings of this study can aid where within the park climate change conservation management, research and monitoring can be prioritised. The highest concentration of climate change vulnerable species on the central-western edges are likely due to the topographical heterogeneity of the Vandersterberg. This heterogeneity likely allowed a high availability of microhabitats and vegetation types, while also isolating and limiting species' dispersibility – causing habitat specialisation and restriction (Gardali *et al.* 2012; Foden *et al.*, 2013; Scheffers *et al*., 2014; Harper *et al.*, 2020 and Payne *et al.*, 2023). This could have driven the high species diversity and subsequently the high number of climate change vulnerable species in this central western area. The resolution of the maps presented are relatively coarse (~40 km^2) so validation fieldwork should be carried out, such as ground-truthing of species presence/ absence and expert verification. The areas identified with the highest concentration of climate change vulnerable species are also particularly at risk as they are on the edges of the park, meaning edge effects and other threats can also be prominent.

All of the species that were assessed in this study, also have occurrences in areas that are not protected in the region. These unprotected areas need careful monitoring and interventions to decrease other anthropogenic pressures that act in synergy with and exacerbate the effects of climate change (UNESCO, 2023; Yang *et al.*, 2024). According to the Red List assessments available for species that occur in the Richtersveld, the other largest anthropogenic pressures to the region's plants are illegal harvesting, mining and agriculture. The latter two pressures can reduce the range, extent of occurrence and available (micro)habitats for species due to land conversion and soil degradation (UNESCO, 2023; Yang *et al.*, 2024), while Illegal collection causes population decline and a reduction in genetic diversity. This reduces a species' resilience to climate change.

Climate change vulnerable species identified in this study that are also range-restricted and impacted by one or more of these aforementioned anthropogenic factors include *Codon schenckii*, *Laperiosa littoralis*, *Ruschia glauca* and *Trachyandra aridimontana*. These species may be of high priority for ex-situ conservation given the multiple anthropogenic pressures acting upon them. However, this information is also important when considering in-situ conservation. Setting aside areas that are not transformed and remain as connecting corridors, need to be negotiated. This would require either decreasing anthropogenic activities in the Richtersveld or, considering this is a relatively low-income area where people rely on such activities for employment, find ways to decrease the environmental impacts (UNESCO, 2023; Yang *et al.*, 2024). The latter would also apply in the park and surrounding protected areas as SANParks leases them to the local community for grazing (SANParks, 2024).

Ex-situ conservation: Some authors argue that ex-situ conservation efforts should be increasingly considered in light of rapid climate change, as opposed to just being supplementary to in-situ conservation of climate vulnerable species (Pritchard and Harrop, 2010; Fernández *et al.*, 2023). For Richtersveld plants, this is emphasized given the fast pace and magnitude of climate change and the increasing frequency of extreme droughts in the area (Pritchard and Harrop, 2010; Huey *et al.*, 2012; Foden and Young, 2016; Foden *et al.*, 2018; Lalwal *et al.*, 2019, Scholes and Engelbrecht, 2021; Fernández *et al.*, 2023; SANBI, 2024b). Interventions should be catered to the most climate vulnerable species which can be managed in botanic gardens such as |Ai-|Ais/Richtersveld Transfrontier Park and Desert Botanical Garden and Nursery. This can include, scaling up ex situ collections and trialling the effectiveness of assisted migration for species with restricted ranges and with limited dispersal abilities (Pritchard and Harrop, 2010; McDonald-Madden *et al.*, 2011; Havens *et al.*, 2014; Foden and Young, 2016; Foden *et al.*, 2016; Hällfors *et al.*, 2017; Fernández *et al.*, 2023). Ex situ conservation efforts and the targeted collection of seeds and genetically diverse living material from wild populations can also provide the resource base for future reintroductions and/or population augmentation, should this be chosen as a conservation strategy.

The TVA-Corr demonstrated here is an important means to prioritise the species in most urgent need of such ex-situ conservation strategies. Special attention for ex-situ conservation efforts should be on species that are both endemic to the Richtersveld and of high climate change vulnerability. While ex-situ conservation is important in conserving climate change vulnerable species, it is also costly, time consuming and require a lot of research before implementation (Rodríguez-Zúñiga *et al.*, 2022). There is also the risk of genetic erosion and adaptation to artificial conditions (i.e. without natural ecological interactions and processes) (Engels and Ebert, 2021). Introducing species to non-native areas also carries the risk of the species becoming invasive (Pearson *et al.*, 2021). These ecological implications can decrease the chance of successful reintroduction into the wild at a later stage. All of these disadvantages should be accounted when considering ex-situ conservation methods.

Comparison of climate change vulnerability scores and Red Listing: When using both the best- and worst-case scenario scores, each showed a negative correlation with the study species' degree of threat from non-climatic pressures. The best-case correlation was statistically significant and although the worst-case correlation was not statistically significant, it does not mean no relationship exists (Lakens, 2022). These negative relationships in both scenarios show that species with a low Red List threat status are likely to be more vulnerable to climate change. This surprising result may suggest that traits that specifically confer climate change vulnerability may overlap with those that confer resilience to other anthropogenic threats. However, it is not immediately obvious why this would be so, and this possibility requires further research. My findings agree with those for reptiles, birds, and amphibians (Böhm *et al*. 2016; Trull *et al.*, 2018; Harper *et a*l., 2020), which have shown similar mismatches.

Collectively, they suggest that the Red Listing of this and other study taxa underestimates their true threat status if climate change impacts are not accounted for (Foden *et al.*, 2013; Mancini *et al.*, 2024). This omission can lead to poor conservation decisions that leave little to no help for climate change vulnerable species (Foden *et al.*, 2013; Mancini *et al.*, 2024). For example, *Cheilanthes namaquensis* was identified as the most climate change vulnerable species out of all 58 study species as it scored highly in all six methods of scoring, but this threat is not accounted for in its Red List status, which is currently Least Concern. The IUCN Red List Version 16 (IUCN, 2024) does include guidance for assessing climate change vulnerability and its application in determining species' threat statuses (Section 12). However, its development is relatively recent and uptake by users is limited, possibly due to the data and technical expertise required. My study provides an example of how, even in highly biodiverse regions with low data availability, climate change vulnerability assessments may be carried out, and of the value for preventing extinctions.

Conclusions

Plants occurring with RNP, and the Richtersveld at large, are undoubtedly under severe climate change threat. It is therefore of utmost importance that conservation strategies are timeously and accordingly implemented – both in- and ex-situ. These conservation interventions could be prioritised to research, manage and monitor the traits, species and areas within the park that were identified as the most vulnerable to climate change in this study.

An important finding is that species' climate change vulnerability scores did not correspond with their degree of threat from non-climatic threats, as reflected in their Red List assessments. Since the Red List is a globally accepted foundation for conservation prioritisation, this can lead to poor conservation decisions that which leave little to no help for climate vulnerable species. This highlights the possible urgent need for those carrying out Red List assessments to make use of the IUCN's guidance for doing so, as well as for those making use of such assessments to investigate whether climate change has been systematically considered and to accommodate for its possible omission.

This study showcases that an approach that combines a trait-based methods with correlative species distribution model outputs can give comprehensive assessments of climate change vulnerability – even for data limited, relatively understudied and highly exposed taxa and areas such as the Richtersveld. It offers conservation organisations an option that not only provides large sets of data for multiple species, but in a manner that is relatively timeous, cost-effective and that can be undertaken at a national park level. This was also demonstrated in Harper *et al*. (2020) who conducted a climate change vulnerability assessment of indigenous reptiles and amphibians in Table Mountain National Park.

The assessment framework developed in this study can be adapted and used for other arid regions and plants. The framework can be adjusted to include other traits to match the required assessment area's specific current and future contexts. Lastly, the basic framework and methodology can be used to guide both species- and area-based conservation decision-making, thereby lessening the impacts of climate change on the biodiversity.

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Appendices

Appendix 1: The 58 species that were assessed in this study. The table shows the scientific and common name for each species, their IUCN/ SANBI Red List Status, their distribution in Southern Africa and endemism to the Richtersveld and the RNP . (SA = South Africa, Y = Yes, NE = Near Endemic and A= Alien). *Category adjustments were made according to regional assessment procedures.

Scientific Name	Common name/s	Distribution	Richtersveld Endemism	RNP Endemism	IUCN Red List Threat status	SANBI Red List Status
Adromischus marianiae	Namibian resin-tree, Namibiese haarpuisboom and hondehoor	Namibia and SA			Not yet submitted	Least Concern
Albuca etesiogaripensis	taaislymlelie	Namibia and SA	Y	NE	Not yet submitted	Data deficient
Albuca longipes	katballetjies	Namibia and SA			Not yet submitted	Least Concern
Aloe meyeri	Ondersteboaalwyn, Rosyntjiesberg aloe and rosyntjiesberg-aalwyn	Namibia and SA	Y	Y	Not yet submitted	Rare
Anacampseros albissima	Skilpadkos and hoendermis	Namibia and SA			Not yet submitted	Least Concern
Antizoma miersiana	bloubos	Namibia and SA			Not yet submitted	Least Concern
Asparagus multituberosus	tulpies	SA			Not yet submitted	Least Concern
Astridia citrina	Unknown	Namibia and SA	Y	NE	CR	Critically endangered
Bromus pectinatus	Japanese brome or Hawergras	Namibia and SA		A	Not yet submitted	Least Concern
Ceropegia articulata	Guaap	SA			Not yet submitted	Least Concern
Ceropegia herrei	Namaque carion flower and kopseer	Namibia and SA			Not yet submitted	Least Concern
Ceropegia perlata	Brain plant, oumapram, perdepiel and hondebal	Namibia and SA			Not yet submitted	Least Concern
Cheilanthes namaquensis	Namaqua lip fern	Namibia and SA			Not yet submitted	Least Concern
Codon schenckii	Yellow nectarcup	Namibia and SA			Not yet submitted	Least Concern
Crassula muscosa	Watch-chain, Toy-cypress, African Grass, Clubmoss Crassula, Rattail Crassula, Princess Pine, Lizard's tail, Zipper plant, Moss plant, Moss succulent, koorsbossie, skoenveterbossie	Namibia and SA			Not yet submitted	Least Concern
Crassula subacaulis	skeweplakkie	Namibia and SA	Y	NE	Not yet submitted	Vulnerable
Crotalaria humilis.	Sandklawer and klapklappie	SA			Not yet submitted	Least Concern

Cucumis rigidus	Unknown	Namibia and SA			Not yet submitted	Least Concern
Cyrtanthus herrei	Juniperbushman, Richtersveld kranslelie and Richtersveld cyrtanthus	Namibia and SA	Y	NE	Not yet submitted	Near threatened
Diclis petiolaris	Vlei snapddragon	Botswana, Namibia and SA			Not yet submitted	Least Concern
Dimorphotheca pinnata	Witmagriet	Namibia and SA			Not yet submitted	Least Concern
Drosanthemum salicola	kleindoubossie	SA			Not yet submitted	Least Concern
Euphorbia gummifera	Gum milk bush, Southern Namib euphorbia, Gomnoors, Gommelkbos and Stinkmelkbos.	Namibia and SA			Not yet submitted	Least Concern
Euphorbia rhombifolia	Bloumelkbos, Kirriemoer, Moerwortel, Moerworteltjie, Sikkiri, Sikkiriwortel, Skaapmelkbos, Soetmelkbos, Springbokmelkbos	Namibia and SA			Not yet submitted	Least Concern
Gymnosporia gariepensis	Orange river spikethron	Namibia and SA			Not yet submitted	Least Concern
Helichrysum leontonyx	Motsuoane-oa-metsi and Toane-ea-metsi	Namibia and SA			Not yet submitted	Least Concern
Heliophila cornuta	sporrie	Namibia and SA			Not yet submitted	Least Concern
Hemarthria altissima	Limpo grass, Halt rass, Batavian quick grass, Swamp couch gras, Red swamp grass, Red vleigrass, Snake grass, Red quick	Botswana, Namibia, SA, Zimbabwe, Mozambique, Zambia, Malawi, Eswatini and Lesotho			Not yet submitted	Least Concern
Hermannia eenii	Doll's roses, Poprosie, Moederkappie	Botswana, Namibia and SA			Not yet submitted	Least Concern
Isolepis hemiuncialis	Unknown	Namibia and SA			Not yet submitted	Least Concern
Justicia cuneata	Ribbokbos	Namibia and SA			Not yet submitted	Least Concern
Lapeirousia dolomitica	Unknown	Namibia and SA			Not yet submitted	Least Concern
Lapeirousia littoralis	Unknown	Botswana, Namibia and SA			Not yet submitted	Least Concern
Lessertia frutescens	Balloon pea, Cancer bush, Jantjie-bêrend, kankerbossie and Sutherlandia	Botswana, Namibia, SA and Lesotho			Not yet submitted	Least Concern
Lycium bosciifolium	Limpopo honey-thorn and karriedooring	Botswana, Namibia and SA			Not yet submitted	Least Concern
Manulea robusta	Unknown	Namibia and SA	Y		Not yet submitted	Vulnerable
Mesembryanthemum pellitum	soutslaai	Namibia and SA			Not yet submitted	Least concern

Osteospermum karrooicum	African daisy, South African daisy, Cape daisy, blue-eyed daisy, and Cape marigold	Namibia and SA			Not yet submitted	Least Concern
Oxalis sonderiana	Unknown	SA			Not yet submitted	Least Concern
Ozoroa crassinervia	Namibian resin-tree, Namibiese haarpuisboom and Slangvelboom	Namibia and SA			Not yet submitted	Least Concern
Parkinsonia africana	Green-hair tree, wild green-hair tree, and green-hair thorn	Namibia and SA			Not yet submitted	Least Concern
Passerina truncata	Unknown	SA			Not yet submitted	Least Concern
Pelargonium antidysentericum	Namiewortel, Rabas, Rooistorm, Rooistormwortel and T'kami	Namibia and SA			Not yet submitted	Least Concern
Pelargonium echinatum	Cactus geranium, Pweetheart geranium, and Prickly-stemmed pelargonium	SA			Not yet submitted	Least Concern
Peliostomum virgatum	Twiggy Veld Violet, Groot Karooviooltjie and Blue Trumpet	Namibia and SA			Not yet submitted	Least Concern
Portulacaria namaquensis	Namaqua porkbush, Hotnotsriem, Wolftoon, Namakwariem, Namaqualand ceraria and Namakwaspekboom	Namibia and SA			Not yet submitted	Least Concern
Pseudoschoenus inanis	Hardematjiesgoed	Namibia and SA			Not yet submitted	Least Concern
Ruschia glauca L.Bolus	Beesvygie	SA	Y	NE	Not yet submitted	Endangered
Schismus schismoides	Haasgras	Namibia and SA			Not yet submitted	Least Concern
Schwantesia herrei	kristalvygie	Namibia and SA	Y		Not yet submitted	Least Concern
Stipagrostis geminifolia	Fyn twa and Kortbeenboesmangras	Namibia and SA			Not yet submitted	Near Threatened*
Tapinanthus oleifolius	Bird-lime, Lighted Candles, Lighted Matches, Mistletoe, kooitjie nam-nam and Voelent	Botswana, Namibia, SA and Eswatini			Not yet submitted	Least Concern
Tetraena retrofracta	Hondepisbos, Jakkalsbos and Vaalkareedoring	Namibia and SA			Not yet submitted	Least Concern
Trachyandra aridimontana	Unknown	SA	Y	NE	Not yet submitted	Endangered
Tylecodon reticulatus	Thorny butterbush, Sifkop, sifkopkandelaar and oukoe	Namibia and SA			Not yet submitted	Least Concern

Ursinia nana	Small ursinia, Yellow margaret, Kleinbergmargriet and Geelmagriet	Botswana, Namibia, SA and Lesotho			Not yet submitted	Least Concern
Vachellia erioloba	camel thorn and kameeldooring	Botswana, Namibia and SA			Not yet submitted	Least Concern
Vahlia capensis	Unknown	Botswana, Namibia, SA , Lesotho and Angola			Not yet submitted	Least Concern

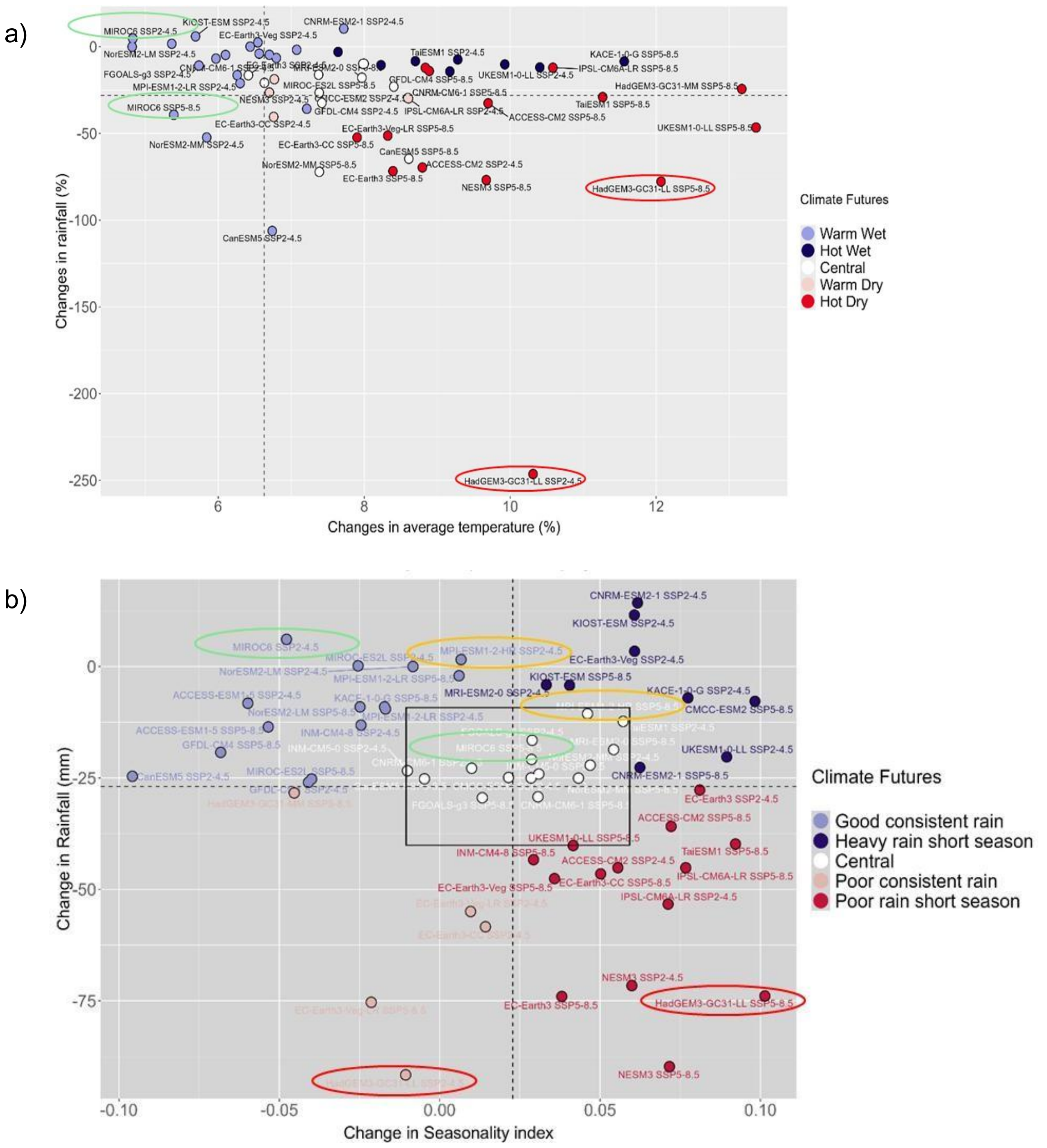
Appendix 2: A table showing the intial draft framework for assessing the climate change vulnerability of Richtersveld plants. (Key: Sensitivity, Adaptive Capacity (in terms of inadaptability), Exposure)

Trait group	Trait	Assumption	Notes
A: Specialized habitat and/or microhabitat requirements	A1: Vulnerable microhabitat specialization	Species occurring in vulnerable microclimates are more likely to be affected by climate change. This includes occurring in ephemeral wetlands/ ponds, lowland sandy areas/ flats, quartz fields (also flats), dolomite hills.	Combined into one trait. Added in another trait for final framework called specialized habitat which is based in the number of vegetation types (Table 2)
	A2: Buffered microhabitat specialization	Species occurring in buffered microhabitats are likely less vulnerable to climate change. This includes species occurring in rock crevices, cliff faces, underground/ subterranean (e.g. stone plants and bulbs), seepage lines, riverbed and under rocks. NB! Where high shade	
	A3: High elevation specialist	Species restricted to high elevations are more susceptible to climate change as their niche may move up at a faster rate than the species can.	
B: Environmental tolerances or thresholds that are likely to be exceeded by climate change	B1: Narrow precipitation tolerance	Species with narrow precipitation ranges are most sensitive to climate change. This includes changes in morning fog and dew availability. Winter rainfall areas more vulnerable than summer rainfall areas as predicted to become drier.	Split into two traits: B1 – narrow precipitation tolerance and B3 – seasonality which is based on rainfall seasonality and seasonal dew/ fog dependency
	B2: Narrow temperature tolerance	Species with narrow temperature tolerance ranges are more sensitive to climate change	Kept as is
	B3: Narrow drought tolerance	Species with mechanisms to withstand droughts and desiccation are a less sensitive to climate change. While most Richtersveld plants have these mechanisms, they may differ in tolerance levels – some may be closer to their thresholds than others. Consider: Seed germination temperature, leaf properties, Psammophorous properties (withstand sandstorms), photosynthetic pathways	Split these mechanisms into separate traits to assess (Table 2)
C: Dependence on environmental triggers that	C1: High Rain-drought/ drought-rain pattern dependency	Some species require periods of drought followed by a period of wet weather or vice versa in order to produce seeds and/or germinate and/or flower. Climate change can	Grouped with other traits such as germination seasonality, sensitive life

are likely to be disrupted by climate change		affect the timing, length and intensity of these events.	history, seed longevity, generation time (Table 2)
	C2: Dependency on temperature	Some species rely on certain temperatures and/or temperature fluctuations in order to produce seeds and/or germinate and/or flower. Climate change can affect the timing, period length and intensity of these temperatures.	
D: Dependence on interspecific interactions that are likely to be disrupted by climate change	D1: Species is parasitic/ epiphytic and relies on other species in order to derive its nutrients or to perform other functions	Some species rely on specific host, parasites, pollinators, dispersers and other life forms to complete their life cycles and processes. Climate change can affect their availability, movement (including migrations), environmental cues and even their ability to perform the function. As a result, climate change can affect these different interactions. Species with less alternative species for a similar interaction/s are more sensitive.	No species have high pollination or seed dispersal specificity. Limited knowledge on other interspecific interactions.
	D2: Species depends on other species for pollination		
	D3: Species depends upon only one or a few other species for seed dispersal		
	D4: Species has highly specialized mycorrhizal associations		
	D5: Species is experiencing increased negative interactions	Climate change is altering the range of many species and causing them to shift and/or expand their distribution. This can cause other species to increase and/or decrease and cause more negative interactions with the study species via Predation, competition (including bush encroachment and alien invasives), parasitism, disease etc.	
E: Rarity	E1: Species is rare	Species that are rare means that their population/s are limited in range and number of individuals. This makes them susceptible to stochastic events which are becoming more common with climate change such as diseases, prolonged, intense droughts, flash floods etc. If a species is in minimum one out of the following four rarity categories, it is considered vulnerable:) geographically restricted (~EOO<500km^2) b) Sparsely distributed) Few individuals (~<10,000 individuals) d) Habitat restricted	Some of the species are already sparsely distributed, have few individuals and have a restricted habitat. Hence only EOO was retained. However, the threshold was changed to 20 000 km^2. While rarity is if the species' EOO is <500 km^2, most papers say a species is vulnerable to climate change if their EOO is less than 20 000 km^2.
F: Sensitive life history	F1: Life cycle strategy	Annual vs perennial: Annual species that face conditions that are incorrect in one year will be more sensitive than	Pieter found that perennials are actually

		perennials. This exposure to unfavourable conditions will be more frequent with climate change.	currently doing worse than annuals.
	F2: Seed production	Species with small seed production are more vulnerable to stochastic events, which are becoming more common with climate change. This is especially true for annuals.	
	F3: Growth form	Species with growth forms that are equipped to function under very water- and heat-stressed conditions will be less vulnerable to climate change than those that are less so. This includes whether the plants is herbaceous, woody, leaf succulent, stem succulent, geophyte etc.	Grouped as a part of drought adaptation.
G: Phenotypic plasticity	G1: Ability of a phenotype to enable climate change adaptation	Epigenetic processes that alter gene expression can result in genotypic and phenotypic expression. This can enable adaptation to altered climate conditions. A species with low phenotypic plasticity would be more dependent on the other adaptive capacity measures below.	Taken out as little to no information.
H: Dispersal ability	H1: Extrinsic barriers	If a species dispersal is hindered by physical barriers, the smaller the range is where the species can occur. This has genetic consequences, makes the species susceptible to stochastic events and prevents movement along with and at the rate of climate change. This is evident on: a) Island b) Mountain-top c) Transformed land (habitat fragmentation) d) Other suspected barriers	Taken out as: a) Richtersveld is not an island b) Mountain-top occupation is accounted for in being an elevation specialist (Group A of traits) c) We wanted assessment to not include other anthropogenic factors d) No other barriers we could think of as well as not enough information
	H2: Intrinsic barriers	If a species has a naturally low dispersal ability (distance), it makes them more susceptible to climate change for the same reasons as H1. This is if the dispersal mechanism is: a) Ballistic b) Splash c) Drop d) Ant e) Endozoochory	Kept as is and added some others of what short and long dispersal distance mechanisms (Table 2) is.
	H3: Proliferation	Species that mature later in their life cycle and/or produce small numbers of propagules have a lowered dispersal ability. This is especially true for species that have a sexual reproductive strategy.	This was grouped with other traits such as reproductive events, fragmentation reproduction and reproductive capacity (Table 2)
	I1: Reproductive capacity	If a species has few reproductive events (e.g. perennial or annual) and/or small seed production, they are	

I: Evolvability		less likely to develop helpful novel traits, less likely to do so at a rate that matches with climate change and less likely to increase their genetic pool. This makes them less likely to withstand stochastic events, leaves them vulnerable to genetic consequences and overall, less likely to adapt and keep up with the rate of climate change.	Kept in – just simplified to using number of seed events in lifetime as a proxy.
	I2: Generation time	Species that have a longer lifespan and take long to reach a maturation age, reproduce less frequently and it therefore takes longer for genetic adaptation and natural selection to take place. This is not beneficial given the rate of climate change.	Kept in – used life span as a proxy
	I3: Genetic diversity	If a species had a low genetic diversity, it has a lower micro-evolutionary potential and therefore less resilient to climate change. This is true for smaller, isolated populations.	Not enough direct information, only can be derived from above two traits.
J: Other "winner" traits	J1: Colonising potential	Species is a pioneer with rapid growth, early maturation and a persistent seedbank. This includes colonising potential drier areas of Fynbos at the Succulent Karoo-Fynbos boundary. This can include invasive potential.	Deemed not as important as other traits.
	J2: Human use	If artificial dispersal is currently being done by humans e.g. for medicine, food, ornamental use etc., a species' barrier to dispersal and sensitivity to climate change may be reduced/ overcome. Must be careful of potential, disadvantageous invasive nature, however.	Removed as wanted assessment to be independent of other anthropogenic factors.
	J3: Carbon storage	Has carbon storage organs, mutualisms for carbon capture etc. can also be beneficial for species under increased greenhouse gas conditions. This is true for many succulents, but some may have a higher threshold than others, making them have a higher adaptive capacity	Deemed not as important for actual climate change vulnerability.
Exposure added in only to final framework.			



Appendix 3: This figure was produced by N. van Wilgen from SANParks and is reproduced here with her permission, in order to illustrate the nature of the exposure models I used. The addition of the circles highlight the models I chose for my own further exposure analysis in this thesis – red for model with most extreme change, orange for the model with a moderate change and green for least extreme change. The scatterplots show the changes in mean climate from historical to 2050 as **a)** changes in average temperature vs precipitation (%) and **b)** change in seasonality index vs change in rainfall (mm) under the RCP 2.6 and 8.5 projections.

Appendix 4: The supplementary information for bioclimate models as required by the IUCN Red List committee under Section 12 (IUCN, 2024).

Category	Required information	Details
Species data (response variable)	a. type	Presence-only
	b. species occurrence data	**i) Source and ii) Record types:** SANBI's Red List Index for species names, herbarium specimen collections and research-grade observations from the iNaturalist citizen science platform, for occurrence data. Both supplied by SANBI. **iii) Geographic extent**: Africa **iv) Temporal extent**: All historical records **Bias reduction**: Duplicates removed, with only most recent record retained, research-grade observations only and filtered to Geographic extent.) **Sample size**: varied depending on which of the 58 species. Overall, ~10 000 occurrence records. Species occurrence record number ranged from <10 to ~400.
	c. Background (pseudo)absence data	N/A
Environmental (predictor) variables	a. Climatic variables	Bioclim variables used: annual mean temperature (Bioclim 1), maximum temperature of the warmest month (Bioclim 5), mean temperature of the warmest quarter (Bioclim 10),), mean temperature of the coldest quarter (Bioclim 11), annual precipitation (Bioclim 12) and precipitation seasonality (Bioclim 15). Species are highly adapted, and their biology is heavily coupled to this harsh arid environment. With climate projections showing a very hot and dry future for the Richtersveld and a change of rainfall seasonality, these variables were deemed the most applicable.
	b. Climate scenarios	RCP 2.6 (SSP246) and RCP8.6(SSP585). Since worst- and best-case scenarios were created for this study, the use of these two RCPs and SSPs were used respectively. Using more than one RCP and SSP also helped increase the robustness of the vulnerability assessment method.
	c. Climate models	Van Wilden et al. (Unpublished) supplied plots showcasing the mean climate futures for the Richtersveld under all available Global Circulation models. Three models were chosen - one for the worst, best and moderate possible change. Based on this, the final three models that were selected for further SDM and exposure analysis were the HadGEM3-GC31-LL, MPI-ESM1-2-HR and MIROC6 models respectively. This helped avoid bias and helped with the robustness of my assessment.
	D. Time points	Historical: 1970-2009 Future: 2040-2060
	Non-climatic variables	Threshold used was 0.1. This threshold helps reduce the impact of outliers, preventing overprediction, and creates more ecologically sound SDMs. This increases the reliability of the results and robustness of the assessment.
Model building and evaluation	a. Modelling approaches	Bioclim modelling was used which is a basic climate envelope approach based on presence-only data (Xie *et al.*, 2023).
	b. Model complexity	A low threshold decreased the chance of over-prediction. While Bioclim and other presence-only SDMs can overlook complexities, its use in conjunction with trait-based methods helps bridge this gap.
	c. Model evaluation	Area under the curve was used.
	d. Uncertainties	N/A

	e. Exclusions	Data cleaning allowed only reliable occurrence and subsequently climatic variables to be used. Using a 0.1 threshold helped exclude climatic outliers to prevent skewing the predictions.
Results	a. Calculation of Red List parameters	The SDMs were used to calculate range overlap and total range change between the current and future distributions. This was used as a measure of exposure to assess the vulnerability of the study species to climate change.
	b. Model results	All AUC values for all models ranged between 0.5 and 0.8. Due to some species being restricted, accuracy was limited by the number of occurrence points.

Appendix 5: Other anthropogenic pressures acting on the 58 study species.

Species	Mining	Agriculture	Poaching
Adromischus marianiae	N	N	N
Albuca etesiogaripensis	N	N	N
Albuca longipes	N	N	N
Aloe meyeri	N	N	N
Anacampseros albissima	Y	Y	N
Antizoma miersiana	N	N	N
Asparagus multituberosus	N	N	N
Astridia citrina	Y	Y	N
Bromus pectinatus	N	N	N
Ceropegia articulata	N	Y	N
Ceropegia herrei	N	N	N
Ceropegia perlata	N	N	N
Cheilanthes namaquensis	N	N	N
Codon schenckii	N	Y	N
Crassula muscosa	N	N	N
Crassula subacaulis	N	N	N
Crotalaria humilis.	N	N	N
Cucumis rigidus	N	N	N
Cyrtanthus herrei	N	N	N
Diclis petiolaris	N	N	N
Dimorphotheca pinnata	N	N	N
Drosanthemum salicola	N	N	N
Euphorbia gummifera	N	N	N
Euphorbia rhombifolia	N	N	N
Gymnosporia gariepensis	N	N	N
Helichrysum leontonyx	N	N	N
Heliophila cornuta	N	N	N
Hemarthria altissima	U	U	U
Hermannia eenii	N	Y	N
Isolepis hemiuncialis	N	Y	N
Justicia cuneata	N	N	N

Lapeirousia dolomitica	N	N	N
Lapeirousia littoralis	N	Y	N
Lessertia frutescens	N	N	N
Lycium bosciifolium	N	N	N
Manulea robusta	N	N	N
Mesembryanthemum pellitum	N	N	N
Osteospermum karrooicum	N	N	N
Oxalis sonderiana	N	N	N
Ozoroa crassinervia	N	N	N
Parkinsonia africana	N	N	N
Passerina truncata	N	N	N
Pelargonium antidysentericum	N	N	N
Pelargonium echinatum	N	N	N
Peliostomum virgatum	N	N	N
Portulacaria namaquensis	Y	Y	Y
Pseudoschoenus inanis	N	Y	N
Ruschia glauca L.Bolus	Y	Y	N
Schismus schismoides	N	N	N
Schwantesia herrei	N	N	N
Stipagrostis geminifolia	N	Y	N
Tapinanthus oleifolius	N	N	N
Tetraena retrofracta	N	N	N
Trachyandra aridimontana	N	Y	N
Tylecodon reticulatus	N	N	N
Ursinia nana	N	N	N
Vachellia erioloba	N	Y	N
Vahlia capensis.	N	N	N