Medicinal Plant Distribution and Supply: Conservation Issues and Implications

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Abstract

Medicinal plants form a vital component of the healthcare system in many developing nations, with up to 90% of the population using at least some material from them. In Africa alone, millions of people in the rural areas rely on medicinal plant species for medical care. To utilize and conserve these species, it is important to understand their distribution and supply. However, their are still limited studies on the distribution and supply of medicinal plant species in terms of groups of species that grow together, and those used against various diseases, especially the common diseases like malaria and stomach ache. Accurate assessment of the distribution and supply of groups of medicinal plant species that grow together, and those used against various diseases, especially those used against common diseases could be crucial to enhancing their potential, improving the fight against common diseases and prioritizing conservation areas. So far, the distribution and supply of medicinal plants has been assessed, but only rarely in terms of groups of species that grow together, and those used against various diseases, especially the common diseases. This thesis aims to investigate the distribution and supply of medicinal plants in terms of groups of medicinal plant species that grow together, and those used against various diseases, especially the common diseases, bring forward recommendations regarding their conservation, as well as evaluate their implications for conservation. Towards this end, 3 research papers were developed to evaluate different aspects of medicinal plants distribution and supply.

The first paper compared the supply of medicinal service by wild plants among MPA in a dryland in Kenya. This study showed that the patterns of medicinal plant co-occurrence among the MPA were driven by variations in grazing pressure, drought, slope and sand content in the soils. It also revealed the difference in medicinal service supply redundancy of medicinal plant species used against different diseases in the MPA. The study further evidenced that the forest MPA had the highest supply diversity with the plant species used to treat 67 illnesses, while the savanna MPA had the highest supply redundancy, and should therefore be given the highest conservation priority. Besides, key species responsible for the supply security in each assemblage were identified. The second paper focused on predicting the impact of climate change on anti-malarial plants in a high burden malaria area, and on the future overlap between malaria vector species suitable habitat and anti-malarial plant species richness. The study revealed that the effects of climate change will be detrimental, since most areas will witness huge losses in anti-malarial species suitable habitat while only a few gained or remained stable. The distributional overlap between low anti-malarial plant species richness areas and the suitable habitat for malaria vectors was predicted to increase in future, thereby increasing the vulnerability of the population to malaria. These findings have implications for the anti-malarial plant species conservation and malaria control strategies.

Collectively, the first and second papers also assessed the current and future threat levels of the medicinal plants and anti-malarial species respectively, and identified species of high conservation priority. The third paper used a combination of satellite remote sensing data and an ensemble one class classifier algorithm to map the richness of medicinal plant species and those species used to treat common diseases: stomach ache, diarrhoea and wounds. This paper further assessed the effectiveness of ensemble suitability SDM (Suit-SDM) and ensemble binary SDM (Bin-SDM) in mapping species richness of medicinal plant species and those species used to treat common diseases. The results showed a strong spatial congruence in the distribution patterns of all medicinal plant species and those used to treat stomach ache, whereas the distributional patterns of species used against wounds and diarrhoea were different from majority of the medicinal plant species. Based on these distributional patterns, the study identified the overlapping high richness areas of medicinal plants and those used against stomach ache, as well as of species used against wounds and diarrhoea as priority conservation areas. Examination of the prediction accuracy of the two modelling approaches revealed that Suit-SDM best predicted medicinal plant species richness. In light of this finding, conservation ecologists should adopt the Suit-SDM in predicting the richness of medicinal plant species as well as other species of conservation concern.

This thesis applied two approaches to investigate medicinal plants distribution and supply. The first approach used a combination of the classification and ordination techniques, as well as the N+1 redundancy concept to compare the supply of medicinal service by wild plants among MPA. As demonstrated, this approach enables one to understand the drivers of medicinal plants co-occurrences, and differences in medicinal supply diversity and supply redundancy among MPA. Here, we identified the redundancy levels of plant species used against different diseases, pin pointed the redundancy levels of species used against common diseases and identified the MPA which had the highest redundancy, and therefore that which requires the highest conservation priority. The second approach entailed mapping the richness of medicinal plant species and those species used against common diseases. This approach provides richness maps that can provide a scientific basis for decision making in regard to identifying priority conservation areas. This thesis further makes suggestions and recommendations to improve further research on medicinal plants distribution and supply.

Investigating the distribution of medicinal plants also requires some understanding of the impact of site history on the co-occurrence of the medicinal plant species, but site history is not easy to reconstruct. Future research could use Landsat time series since they cover a long time period. Time series of each band and vegetation related indices such as NDVI can be analyzed for differences at medicinal plant species presence and absence sites, to establish the impact of site history on medicinal plants occurrences. Further assessment on the impact of fire history on medicinal plants co-occurrences should not only focus on the recent fire history but could instead be conducted using both ground observation and MODIS burned product. Future research should also integrate mapping of medicinal plants with conservation gap analysis aimed at understanding both the *ex-situ* and *in-situ* conservation gap analysis of medicinal plant species. Lastly, this thesis should encourage conservation ecologists to assess the distribution and supply of medicinal plants in terms of groups of species that grow together, and those used against different diseases, especially the common diseases.

Zusammenfassung

Medizinpflanzen sind ein wesentlicher Teil des Gesundheitssystems vieler Entwicklungsländer, in denen bis zu 90% der Bevölkerung wenigstens irgendein Material davon nutzt. Allein in Afrika hängen Millionen von Menschen in den ländlichen Regionen von medizinischen Pflanzenarten für medizinische Versorgung ab. Um diese Arten zu nutzen und zu erhalten ist es wichtig, ihre räumliche Verteilung und Häufigkeit zu verstehen. Jedoch gibt es derzeit nur eine limitierte Anzahl an Studien zur Verteilung und Häufigkeit von Medizinpflanzen, insbesondere Arten, die zusammenwachsen, und die gegen verschiedene Erkrankungen genutzt werden, darunter verbreitete Erkrankungen wie zum Beispiel Malaria und Bauchschmerzen. Deswegen könnte eine genaue Einschätzung der Verteilung und Häufigkeit medizinischer Pflanzen, die zusammenwachsen, und die gegen typische Erkrankungen genutzt werden, entscheidend sein zur Erweiterung ihre Potenzials, Verbesserung der Bekämpfung typischer Erkrankungen und Priorisierung von Schutzgebieten. Die Verteilung und Häufigkeit medizinischer Pflanzen wurde zwar bereits eingeschätzt, allerdings nur selten bezogen auf Artengruppen, die zusammenwachsen, und die gegen (insbesondere typische) Erkrankungen genutzt werden. Diese Thesis zielt darauf ab, die Verteilung und Häufigkeit von Gruppen medizinischer Pflanzen, insbesondere deren, die zusammenwachsen, und die gegen typische Erkrankungen eingesetzt werden, zu untersuchen, Bewusstsein über Angelegenheiten zu ihrem Schutz zu schaffen und Empfehlungen zu ihrem Managment und Schutz voranzubringen. Basierend auf diesen Zielen wurden drei wissenschaftliche Veröffentlichungen entwickelt, um verschiedene Aspekte der Verteilung und Häufigkeit medizinischer Pflanzen zu evaluieren.

Die erste Veröffentlichung verglich die Häufigkeit die Häufgkeit medizinischer Dienstleistungen von Wildpflanzen in Verbünden medizinischer Pflanzen (engl. Medicinal Plant Assemblages, MPA) in einem Trockengebiet in Kenia. Diese Studie zeigte, dass die Muster des gemeinsamen Auftretens der MPA von unterschiedlichem Beweidungsdruck, Trockenheit, Gefälle und Sandanteil im Boden getrieben wurden. Sie enthüllte auSSerdem den Unterschied in der Häufigkeit medizinischer Dienstleistungen. Es zeigte auch die Unterschiede in der Redundanz der Versorgung mit Heilpflanzen, die gegen verschiedene Krankheiten im MPA verwendet werden. Die Studie belegte weiterhin, dass die Wald-MPA die höchste Häufigkeitsdiversität mit Arten, die gegen 67 Erkrankungen genutzt werden, hatte, während die Savannen-MPA die höchste Häufigkeitsredundanz aufwies und dewegen die höchste Schutzpriorität haben sollte. Darüber hinaus wurden die Hauptarten identifiziert, die für die Sicherstellung der Versorgung in jeder Gemeinschaft verantwortlich sind. Die Zweite Veröffentlichung konzentrierte sich auf die Vorhersage der Auswirkung des Klimawandels auf Anti-Malaria-Pflanzen in einer von Malaria stark getroffenen Region, sowie der zukünftigen Überschneidung von geeignetem Habitat für Malaria-

Vektorarten und Häufigkeit von Anti-Malaria-Arten. Die Studie hat ergeben, dass die Auswirkungen des Klimawandels nachteilig sein werden, da die meisten Gebiete erhebliche Verluste an geeignetem Lebensraum für antimalarische Arten verzeichnen werden, während nur wenige Gewinne erzielen oder stabil bleiben werden. Eine Zunahme der Überschneidung der räumlichen Verteilung zwischen Gebieten geringer Häufigkeit von Anti-Malaria-Arten und geeignetem Habitat von Malaria-Vektorarten wurde für die Zukunft vorhergesagt, wodurch die Anfälligkeit der Bevölkerung für Malaria steigt. Diese Befunde haben Implikationen für den Schutz von Anti-Malaria-Arten und Malaria-Kontrollstrategien. Insgesamt haben das erste und zweite Paper auSSerdem das jetzige und zukünftige Gefährdungsniveau der medizinischen Pflanzenarten bewertet und Arten mit hoher Schutzpriorität identifiziert. Die dritte Veröffentlichung nutzte eine Kombination aus Satelliten-Fernerkundungsdaten und einem Ensemble Ein-Klassen-Klassifizierer-Algorithmus, um die Häufigkeit medizinischer Pflanzen und Arten, die gegen typische Gebrechen wie Bauchschmerz, Durchfall und Wunden zu kartieren. Diese Veröffentlichung bewertete weiter die Effektivität eines ensemble suitability SDM (Suit-SDM) und eines ensemble binary SDM (Bin-SDM) in Bezug auf die Kartierung der Arthäufigkeit medizinischer Pflanzenarten und solcher, die gegen typische Erkrankungen genutzt werden. Die Ergebnisse zeigten eine klare räumliche Übereinstimmung in den Verteilungsmustern aller medizinischer Pflanzenarten und solcher, die gegen Bauchschmerz genutzt werden, wohingegen die Verteilungsmuster der Arten, die gegen Wunden und Durchfall genutzt werden, sich von der Mehrheit der medizinischen Pflanzenarten unterschieden. Basierend auf diesen Verteilungsmustern identifizierte die Studie die sich überschneidenden Gebiete hoher Häufigkeit medizinischer Pflanzen und solcher, die gegen Bauchschmerz genutzt werden, und der Arten, die gegen Wunden und Durchfall genutzt werden als prioritäte Schutzgebiete. Die Untersuchung der Vorhersagegenauigkeit der zwei Modelle enthüllte, dass Suit-SDM am besten die Häufigkeit medizinischer Pflanzenarten vorhersagte. Angesichts dieses Ergebnisses sollten Ökologen im Umweltschutz das Suit-SDM übernehmen, um die Häufigkeit medizinischer Pflanzenarten und anderer Arten mit Bedenken bezüglich ihrer Gefährdung übernehmen.

Diese Thesis wendete zwei Herangehensweisen an, um die Verteilung und Häufigkeit medizinischer Pflanzen zu untersuchen. Die erste Herangehensweise nutzte eine Kombination der Klassifizierungs- und der Ordinationstechnik und das N+1-Redundanz-Konzept um das Angebot medizinischer Dienstleistungen von Wildpflanzen in MPA zu vergleichen. Wie gezeigt wurde, ermöglicht diese Herangehensweise das Verständnis der Treiber der Ko-Existenz medizinischer Pflanzen und der Unterschiede der medizinischen Angebotshäufigkeit und Angebotsredundanz unter den MPA. Hier identifizierten wir die Redundanzniveaus von Pflanzenarten, die gegen verschiedene Krankheiten genutzt werden, zeigten die Redundanzniveaus von Arten, die gegen typische Erkrankungen genutzt werden auf, und identifizierten die MPA, die dringliche SchutzmaSSnahmen erfordern. Die zweite Herangehensweise schloss die Kartierung der Diversität medizinischer Pflanzen und solcher, die gegen typische Erkrankungen genutzt werden, ein. Diese Herangehensweise stellte Diversitätskarten zur Verfügung, die eine wissenschaftliche Basis für Entscheidungsprozesse bezogen auf die Identifikation prioritäter Schutzgebiete zur Verfügung stellen. Diese Thesis gibt weiterhin Vorschläge und Empfehlungen zur Verbesserung weiterer Forschung über die Verteilung und das Angebot medizinischer Pflanzen.

Die Untersuchung der Verteilung medizinischer Pflanzen erfordert auch ein Verständnis der Auswirkungen der Standortgeschichte über die Ko-Existenz der medizinischen Pflanzen, aber diese Standortgeschichte ist nicht leicht zu rekonstruieren. Zukünftige Forschung könnte Landsat-Zeitserien nutzen, da sie eine lange Zeitspanne abdecken. Zeitserien jedes Bandes und vegetationsbezogene Indizes wie NDVI könnten auf Unterschiede von Vorkommens- und Abwesenheitsstandorte medizinischer Pflanzen analysiert werden, um die Auswirkung der Standortgeschichte auf Vorkommen medizinischer Pflanzen herzustellen. Weitere Untersuchung der Auswirkung der Feuergeschichte auf die Ko-Existenz medizinischer Pflanzen sollte sich nicht nur auf die jüngste Feuergeschichte fokussieren, sondern könnte stattdessen unter Nutzung von Bodenbeobachtungen und des MODIS-Feuer-Produktes durchgeführt werden. Zukünftige Forschung sollte auch die Kartierung medizinischer Pflanzen mit conservation gap analysis integrieren mit dem Ziel, ex-situ und in-situ conservation gap analysis medizinischer Pflanzen zu integrieren. SchlieSSlich soll diese Thesis Umweltschutz-Ökologen ermutigen, die Verteilung und das Angebot medizinischer Pflanzen im Sinne von Artengruppen, die gegen verschiedene und sogar typische Erkrankungen genutzt werden, zu untersuchen.

Contents

1. Introduction

1.1. Research Motivation

In this dissertation we investigate the *medicinal plants distribution and supply* in the context of groups of medicinal plant species that grow together, and those species used against various diseases, especially the common diseases. There are a number of stakeholders who could benefit from such knowledge: Among them, locals who depend on medicinal plants, conservation ecologists, traditional herbalists, medical practitioners, medical planners, pharmaceutical companies and governmental agencies concerned with environmental conservation.

Most individuals, from the aforementioned stakeholders, who make collection trips to gather medicinal plant species from the wild do so somewhat without any knowledge on their occurrence sites. As a result, they spend a lot of energy, resources and time in search of these species, and at times even return from the wild without anything in their hand. This may result to death of the patient, in situations where these medicinal plant species are urgently needed for treatment, as is the case in most remote areas in Africa. As demonstrated by Akerele et al. (1991) human health in a critical component, of which assurance on the availability of medicinal plant species is needed when the species are sought from the wild.

The continued use of medicinal plants by many people in based on the assumption that the species will be available on a continuous basis. However, no concerted efforts have been made to ensure this, in the face of threats and increasing demand for medicinal plants. In fact, in societies where medicinal plant species are commonly used, the species are mainly gathered from the wild using destructive methods like debarking and uprooting, which pose a threat to the survival of the species (Tugume and Nyakoojo, 2019). The medicinal plants industry though well established, still lacks an organized and systematic structure which can provide direction and guidance to the many stakeholders in the industry (Hamilton, 2004; Kokwaro, 2009). The utilization and conservation of medicinal plants is based on certain principles which should be in place and adhered to. The formulation and adherence to the principles in medicinal plants utilization and conservation are imminent, so as to tap into the full potential of these plants.

For the purpose of enhancing the utilization and conservation of medicinal plants, studies on the distribution and supply of medicinal plants have been conducted. The few existing studies have mainly focused on investigating the distribution and supply of all medicinal plants utilized in the respective study areas (Kaky and Gilbert, 2016; Cahyaningsih et al., 2021; Silva et al., 2022). The majority of studies on medicinal plants distribution and supply so far, hardly focus on groups of plant species that grow together, and those used against different diseases, especially the diseases that are common in their respective study areas. We argue that this poses a challenge to the fight against common diseases, and undermines the utilization and conservation of medicinal plant species and vegetation formations that are of medicinal value. Considering that one of the Sustainable Development Goals (SDGs) (WHO, 2015) stresses the need to eradicate common diseases like malaria, it is crucial to at least understand the supply and distribution patterns of plants used against such diseases, as this will help in the attainment of the SDGs.

1.2. Conservation ecology

1.2.1. Definitions

Conservation ecology is a field of ecology that deals with management and preservation of biodiversity or natural resources (Pimm et al., 1995; Meine et al., 2006). While plant and animal resources have been used since time immemorial (Dharani and Yenesew, 2010), the field of conservation ecology emerged during the 20th century following increased demand for biological resources, especially after World War II (Meine, 2010). However, it is not until the 1970s that biodiversity conservation became an important aspect, and the contemporary field of conservation ecology was shaped (Meine, 2010). The field further developed because the proposals of the 1993 Convention on Biological Diversity questioned the policies and legislations regarding the management and conservation of natural resources (Junninen and Komonen, 2011). Although the underlying principles of conservation ecology are old (Meine et al., 2006), the field currently stands out due to its emphasis on appreciation of biodiversity's intrinsic worth, modelling, quantitative theory and integration of non-biological disciplines (Groom et al., 2006). Conservation ecologists warn that, in the next 30 years, approximately 35% of all species may be driven into extinction (Singh, 2002). Conservation ecology mainly involves investigation of different types of biodiversity losses, understanding the factors responsible for the losses, developing techniques to prevent or counteract the losses, and, when feasible, restoration of the biodiversity.

The frequently used term biodiversity has three main levels: genetic, species and ecosystem diversity (Verma, 2017). Ecosystem diversity refers to the collective presence of all species and abiotic factors that are distinct to a given region (Alsterberg et al., 2017). It entails both the non-biological and biological drivers of variability. Species diversity is the variety of species found within a given region (Alsterberg et al., 2017), while genetic diversity refers to the variation in genes across individuals of the same species, which facilitates the ability to respond to natural selection and adaptation to the environment (Verma, 2017). Our main focus in this dissertation was on species diversity, specifically, medicinal plant species. In this dissertation, I will use the term medicinal plant following Sofowora (1993) as

> "any plant that contains either in some or all of its parts substances that can be used as starting raw material in the manufacture of conventional drugs or even for disease prevention and treatment."

This definition makes it possible to differentiate between plants that have been scientifically proven to have therapeutic properties and those that are considered medicinal but haven't undergone comprehensive scientific research. Many plants have been utilized for their medicinal value over the years. While some plants have shown potential effectiveness, there might not be enough scientific evidence, to fully verify their efficacy. Nonetheless, these plants can still be considered medicinal due to their historical use in traditional medicine.

1.2.2. Medicinal plants

According to the World Health Organization, approximately 80% of the global population relies primarily on medicinal plant species for their daily healthcare needs (Cao and Kingston, 2009). These species also provide an important source of raw material for the pharmaceutical industry, and more often than not is the manufacture of conventional drugs inspired by their effectiveness in the traditional healthcare system (Gakuya et al., 2013). The significance of medicinal plants in healthcare is gaining recognition within the health sector. This is evident by the discussions on the role of medicinal plants in contributing to the attainment of health-related SDGs (UN, 2015), as well as efforts to establish a European harmonized criteria for assessing traditional medicinal plants products (Steinhoff, 2005) and the classification of medicinal plants as an important component of the primary healthcare by WHO (WHO, 2013). Other than their contribution to the healthcare system, medicinal plants also contribute to the economic empowerment of the individuals involved in their sales, especially in rural areas (Ticktin et al., 2002).

The International Union for Conservation of Nature estimates that there are approximately 70,000 plant species utilized globally for medicinal purposes (IUCN, 2008). The African continent is endowed with a great variety of plant species (Kokwaro, 2009). It is estimated that there exists between 42,000 to 45,000 plant species in Africa, and out of this; around 5,000 are believed to be of medicinal value (Mahomoodally, 2013; Van Wyk, 2015). This is not surprising since the continent is geographically positioned within the subtropical and tropical climate, and it is widely known that plants species accumulate chemical metabolites by way of evolution, as a natural means of withstanding a hostile environmental condition (Manach et al., 2004).

In Kenya, for example, there are as many as 1,100 medicinal plant species, from a rich flora of around 11,000 plant species which are distributed across the country (Kokwaro, 2009). Due to its location along the equator, the country enjoys an unfair share of solar radiation, suggesting that Kenya's medicinal plants are more likely to posses a lot of chemical metabolites (Kokwaro, 2009). It is estimated that over 80% of the population in Kenya still uses medicinal plants as their primary healthcare (Kipkore et al., 2014). For instance, in Kenya, an estimated US $40 million worth of medicinal plant resources are consumed each year (Kokwaro, 2009). Worryingly, in the recent past, Kenya has been ranked among the countries with the highest risk of future medicinal plants extinction (Dharani and Yenesew, 2010). Unfortunately, this statistic came at a time when the country was up scaling efforts on the use of medicinal plants and its potential integration into the national healthcare system (Dharani and Yenesew, 2010). Considering that a large majority of Kenya's population depend on these plants, their loss will negatively affect the national healthcare system (Dharani and Yenesew, 2010). This warrants immediate conservation of the plants.

1.3. Medicinal Plants Distribution and Supply

Medicinal plants distribution is not uniform across the world (Rafieian-Kopaei, 2012). For instance, China (11,123) and India (7,401) have the highest numbers of medicinal plant species, followed closely by Colombia and South Africa (Chen et al., 2016). The specific vegetation type responsible for the supply of medicinal plants is not often extensively examined, and the findings of the few existing studies tend to vary across cultures and regions. Studies conducted in South America (Albuquerque and Oliveira, 2007), Asia (Song et al., 2022) and Africa (Kitula, 2007) indicate that many medicinal plants are found in conserved forests. According to Rajasekharan and Wani (2020), 70% of the worlds medicinal plants are found in tropical regions, especially in the forests and savannas. The other 30% is distributed in the alpine and temperate areas, especially in the higher altitudes. Other studies reported that most medicinal plants are found in dry and deciduous vegetation in comparison to the temperate vegetation (Chen et al., 2016). This variation in medicinal plants distribution is also evident on a local scale (Dharani and Yenesew, 2010). Such distributional variations are due to preferences of various medicinal plant species, or even families to specific environmental conditions (Dharani and Yenesew, 2010).

Supply of medicinal plants is affected by different competing resource uses- among them, utilization of the plants as building material and fuel, extraction of pharmaceuticals components, timber logging and over-harvesting for commercial use (Hamilton, 2004). This has led to increased demand for the plants, which may be accompanied by the depletion of the most effective and favored medicinal plant species. Even now, the supply of some most effective medicinal plant species cannot be guaranteed, and it is predicted that this situation will only worsen in the future (Srivastava et al., 1996). Kenya's situation sheds some light to the extent of this problem. Particularly, species whose supply is most affected are those with restricted distribution and specific habitat requirements. Considering that most medicinal plants grow in the wild, concerns have been raised over the continued supply of medicinal plant resources (Dharani and Yenesew, 2010).

It is believed that human impacts and environmental conditions play a substantial role in shaping the distribution and supply of medicinal plants by altering their spatiotemporal patterns (Moustafa and Klopatek, 1995). The impact of these factors is particularly pronounced in arid areas (Hamilton, 2004). This supports the argument that sound management of medicinal plant species begins with a comprehensive understanding of the ecological interactions between species and their environment (Kaky and Gilbert, 2016; Tshabalala et al., 2022). The identification of the ecological conditions responsible for the distribution and supply of medicinal plant species could prove pivotal in identifying suitable areas for collection trips (Rana et al., 2017) and help to design meaningful conservation plans (van Andel et al., 2015).

1.4. Conservation Issues and Implications

Concerns over a possible "medicinal plants" crisis have been raised by many scholars, based on evidence from different research (Akerele et al., 1991; Kaky and Gilbert, 2016; Tshabalala et al., 2022). This has been largely blamed on the increased utilization of medicinal plants. Due to this increase, coupled with the accelerated loss of the plants, it has become apparent that the exploitation of these plants must be accompanied with meaningful conservation strategies (Hamann, 1991). It is important that any conservation strategy should prioritize the conservation of wild medicinal plants that are at risk of extinction (Srivastava et al., 1996). Consequently, urgent identification of at-risk wild medicinal plant species, protection, conservation planning and timely delivery of conservation intervention calls for more concerted efforts and actions. The calls by FAO (2009) and SCBD (2010) for increased efforts to conserve medicinal plants, especially those of great importance to the low income countries only serve to stress the need to conserve this crucial bio-resource. Such calls have been echoed due to the belief that the conservation of medicinal plant species is also a means of conserving other species, ecosystem and biodiversity within the same habitat (Hamilton, 2004; Tshabalala et al., 2022). In fact Qian et al. (2020), asserted that medicinal plant species may be used as flagship species to monitor and conserve biodiversity, as well as raising public awareness regarding conservation strategies. Therefore, medicinal plants conservation strategies should be formulated with care because the beneficiaries of medicinal plants conservation are not limited to the plants alone (Qian et al., 2020). This is especially true in remote areas with high biological and cultural diversity, where medicinal plants hold significant importance for the locals (Hamilton, 2004). Additionally, medicinal plants conservation strategies need to balance two important factors: ensuring the survival of the species and maintaining a sustained supply of the plant materials (Rasool et al., 2020). This is important in order to meet the healthcare need of the people who rely on them (Sheldon et al., 1997).

The conservation of medicinal plants has been extensively studied (Akerele et al., 1991; Uprety et al., 2012; Kaky and Gilbert, 2016). Many studies on medicinal plants primarily focused on assessing the impacts of gathering and establishment of sustainable harvesting thresholds (Akerele et al., 1991; van Andel and Havinga, 2008). Other studies focused on identifying the at-risk species and suggesting appropriate conservation strategies. Some attempted to identify the priority conservation species based on their local importance and characteristics (Albuquerque and Oliveira, 2007; Rajasekharan and Wani, 2020). Few studies investigate the conservation of medicinal plants from the perspective of groups of medicinal plant species that grow together, and groups of species used against various diseases, especially the common diseases. Several recommendations have been put forward regarding the conservation of medicinal plants, including establishment of systems for medicinal species monitoring, keeping of species inventory, as well as the importance of coordinated *in-situ* (on site) and *ex-situ* (off site) conservation strategies (Rajasekharan and Wani, 2020). Wild nurseries and protected areas are typical examples of areas intended to conserve medicinal plants in their natural habitats, whereas seed banks and botanical gardens play a crucial role in *ex-situ* conservation (Coley et al., 2003). In a situation where medicinal plants have limited supplies, the sustainable use of medicinal plants resources is considered a viable option (Chen et al., 2016).

Some developed nations like the United States have heavily invested in the conservation of medicinal plants (Srivastava et al., 1996). Such efforts are needed in developing countries, at least for some important medicinal plant species. But since limited resources are available for the conservation of medicinal plant species in developing nations (Hamann, 1991), identification of priority conservation species and areas could be a crucial step towards utilization of the limited resources (Aguilar-Støen and Moe, 2007). In Kenya, medicinal plant species conservation combine both *in-situ* and *ex-situ* strategies (Kokwaro, 2009). But still, information regarding the priority conservation species, vegetation formations and areas, conservation status of the species and appropriate conservation strategies are limited. This is the case, especially for plants species used against common diseases. Information on medicinal plant species distribution and supply patterns could be crucial to identifying the priority areas for conservation actions, formulation of appropriate conservation strategies and enhancing the potential of the species (Aguilar-Støen and Moe, 2007).

1.5. N + 1 Redundancy Concept

The N + 1 redundancy concept originated from Information Technology (Albuquerque and Oliveira, 2007). This concept is perceived as a type of resilience, which guarantees uninterrupted operation of system in case of component failure. In an N + 1 redundancy system, "N" represents the minimum number of independent operational components needed for a system to work. In this equation, the "1" denotes the number of additional components which perform the same function as N, and therefore act as a separate backup to ensure that the system continues operating even in the event that the main operating component "N" fails to operate. In the absence of this concept, a single failure of a modular power supply could cause a complete shutdown of the entire power system. For instance, if a system needs 10 power supply modules to operate, the N+1 system will have 11 power modules. In this way, the power system will continue operating with the help of the additional module in the event that one module ceases to operate. In Fig. 1.1 the airplane is fitted with two engines (left and right engines), such that in case of failure of the left engine then the right engine takes over and begins operating to avoid a complete shutdown of the plane power system. The N + 1 has so far been applied in studies on information and technology. Important to say, is that, this concept could be also applied to understand the medicinal service supply security. While, a brief and general explanation of this concept is given in the introduction section so as to clarify its meaning because it will be repeatedly mentioned in the introduction section, detained description of this concept and its application to our study species is found in section (2.2.4.2).

Figure 1.1.: Airplane diagram illustrating the N+1 redundancy concept

1.6. Classification and Ordination techniques

Classification and ordination techniques can be useful tools in the analysis of plant communities, and have proved valuable in vegetation data interpretation (Grabherr et al., 2003). Classification is the act of putting sites into related groups (Greig-Smith, 2010), in such a way that sites with similar species are grouped together (Grabherr et al., 2003). Two main forms of classification are applied by ecologists: hierarchical classification and cluster analysis. Hierarchical classification involves nesting of groups within other groups, while cluster analysis divides a given number of quadrates into groups on the basis of high internal similarity of the species or samples utilized (Greig-Smith, 2010).

Ordination refers to the techniques used to summarize a complex datasets so that the inherent patterns of the data are easily visually inspected (Pielou, 1984). Consequently, ordination can be helpful in understanding the structure of a complicated data set (i.e. medicinal plant species data set in our case). By applying different mathematical calculations, the technique helps to identify patterns and similarities among sites and species. It arranges sites and species, on a two dimensional graph, in such a way that sites and species most dissimilar from one another will be located far apart, while sites and species most similar to each other will be close (Tavili and Jafari, 2009). In this way, the distances between the sites and species represents their ecological distances (Legendre and Legendre, 1998). Two main methods can be used in ordination: unconstrained and constrained ordination. The first approach, seeks to identify major variations, and then relate those variations to environmental variations (Gauch, 1982; Palmer, 1993). The second approach seeks to identify only what can be explained by the variables of interest (Gauch, 1982).

In light of the discussion above, it is evident that the two techniques are not conflicting, but rather complement each other. Consequently, both techniques can be reasonably employed to examine multivariate samples (Peet, 1980). Classification and ordination approaches have been widely used in various ecological studies (Zhang et al., 2005; Yibing et al., 2004; Tatian et al., 2010; Haq et al., 2017). Classification and ordination studies on medicinal plants examined endangered medicinal plant *Glycyrrhiza uralensis* communities, spatio-temparal effects on classification of medicinal plants communities and habitat characterization of medicinal plants (Ahmad et al., 2009; Khalifehzadeh and Ghazani, 2014; Song et al., 2022). One study in Pakistan demonstrated that soil nutrients and soil moisture are major determinants of medicinal plants distribution (Ahmad et al., 2009). In Sri Lanka, Russell-Smith et al. (2006) showed that medicinal plant conservation areas and species occur under different habitat conditions. So far, there have been few attempts to apply the two techniques to examine the supply of medicinal plants used against various diseases, based on groups of medicinal plant species that grow together (also known as medicinal plant assemblages). Therefore, it is important to apply these techniques to assess the patterns of medicinal plant species co-occurrences and the differences in medicinal service supply among medicinal plant assemblages, as this will contribute to the formulation of meaningful conservation strategies. In this section, we provide detailed explanation of both the classification and ordination techniques because they have not been described in details in the ensuing chapters. Also, the two techniques are frequently mentioned in the introduction section and it would be better to understand what they entail, but further description of classification and ordination techniques is done in section (2.2.4.1)

1.7. Species Distribution Models

1.7.1. Background

The application of Species Distribution Models (SDMs) to predict the distribution of plants and animals has been on the rise over the past two decades (Guisan and Thuiller, 2005; Franklin and Miller, 2009; Kaky et al., 2020). Currently, different names which denote different meanings have been formulated for SDM (for instance: bioclimatic models, (ecological or environmental) niche models, spatial models, resource selection functions, habitat distribution models, climate envelope models and range maps (Elith and Leathwick, 2009). The growing demand for information on species' distribution has led to advancement in techniques required for such simulations like Geographic Information System (GIS), Global Position System (GPS), Remote Sensing (RS), as well as new statistical and machine learning algorithms (Guisan and Thuiller, 2005; Franklin and Miller, 2009).

Two approaches can be used to estimate species' distribution (Kearney, 2006). The first approach involves the use of a mechanistic model, which incorporates information on species tolerances to environmental conditions, like minimum temperature within which a species can survive (Kearney, 2006). This approach requires detailed data regarding the species' physiological response to environmental factors, which is unavailable in most cases (Mitchell, 2005). The second and the most common approach currently used to predict the geographical distribution of a species involves identifying and describing an appropriate environment of the species, and then estimating the distribution of these appropriate environments within the environmental space (Kearney, 2006; Pearson et al., 2007; Elith and Leathwick, 2009). Put simply, a model is fitted, for instance, for a plant species that grows well in dry sand soils; thereafter we identify habitats with low rainfall and sand soils to simulate the distribution of the species. The is approach operates on the principle of correlating presences, and sometimes absence, data of a species with various environmental variables to generate a predictive map of the species (Pearson et al., 2006). This approach is based on the assumption that the distribution of a species is a strong indicator of its ecological requirements (Pearson and Dawson, 2003). However, the degree of a model to fully describe the range of environmental conditions in which a species can be found (fundamental niche), largely depends on its capacity to capture ecological conditions which define the species' distributional range or limits (Hutchinson, 1957; Pearson et al., 2006). Actually, additional factors which may not have been included in the modelling (i.e. geographic barriers and biotic interactions) indicate that the species rarely occupies the entire area with suitable habitat (Araújo and Pearson, 2005). Consequently, the outputs of SDM should be carefully interpreted (Soberón and Peterson, 2005). The results of a SDM can be interpreted as habitat suitability, probability of species occurrence, and species richness if individual models are summed up (Yi et al., 2016).

Basically, SDM using the aforesaid second approach require information on occurrence points of biodiversity and the environmental variables which will be used in modelling. Such information is nowadays freely available. For instance on climate (i.e. CHELSA and Worldclim), remote sensing products (i.e. Corpenicus) and data on species occurrences (i.e. GBIF). The models relate biodiversity information at given sites to the environmental conditions present at the sites. Various statistical algorithms can be used for this purpose. After estimating the relationship between the biodiversity and the environment, prediction can be made in time and space by applying the model to the available environmental data layers (Fig 1.2).

In the introduction section, we provide a detailed explanation on how models generally operate because these aspects are not provided in the other chapters. The general steps of building a model are given in Fig. 1.4. However, detailed steps on how each modelling step was conducted, for each algorithm used in this thesis is given in sections 3.2.4 and 4.3.

1.7.2. Concept and Theory

To conceptualize the operation behind a SDM, it is important to consider the occurrence of a species within an environmental space, which is defined by a set of environmental variables to which the species respond (Pearson et al., 2007). The concept of SDM can be explained by visualizing the distribution of species within an environmental and geographical space (see Fig. 1.3 Pearson et al., 2007). Fundamental to understanding of the SDM is the niche theory (Soberón, 2007). According to Soberón (2007), four main elements determine the occurrence of a species at any location: biotic factors (i.e. negative interaction between species, for instance, competitors and parasites or positive interaction between species, for instance, seed dispersers and pollinators); abiotic factors (i.e. substrate conditions or environmental variables like topography, sunlight, soil pH, rainfall); adaptation of the species to new environmental

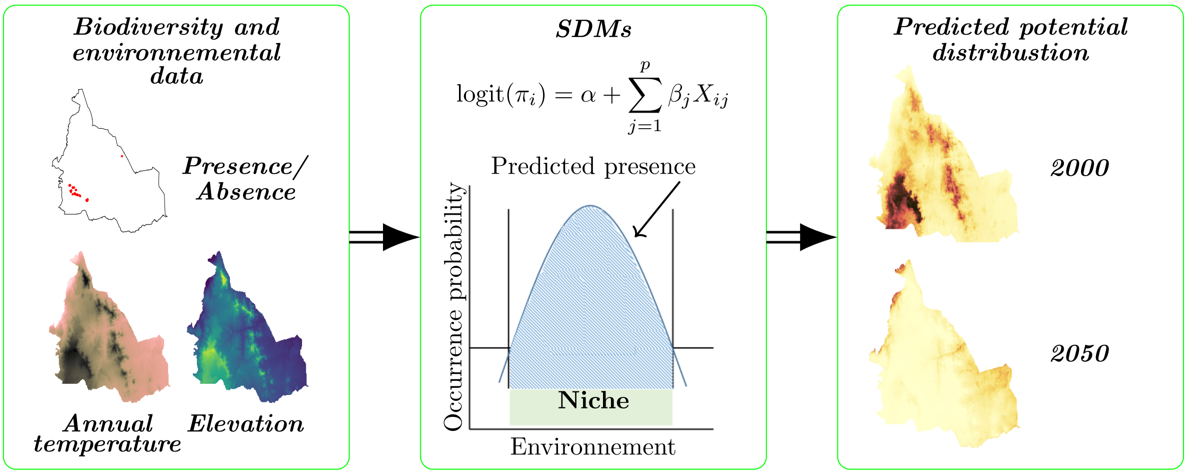


Figure 1.2.: Schematic representation showing the basic concept of SDM. 1) Collection of the biodiversity and environmental information within the geographic space 2) Application of a statistical model, for instance Generalized Linear Model, to analyze and correlate relationship between the species and the environmental variables. 3) Mapping of the relationship between the species and the environment into the geographic space. This mapping process can be extrapolated for a different time period i.e future. From Zurell (2020)

conditions based on their evolutionary ability; and lastly dispersal capacity (Fig. 1.3). All these aforesaid factors strongly interact together to determine the geographic distribution of a species (Soberón, 2007). The commonly known BAM diagram depicts interaction between all these factors. For example in Fig. 1.3 the circle A represents the abiotic conditions required by a species. Circle B represents the biotic interactions, while the intersection between the two circles is the realized niche. Circle M indicates the parts which can be accessed by the species through movement. The intersection between M, A and B represent the actual distribution of the species (Soberón, 2007).

The positioning of SDMs within the niche theory is currently clear. However, a lot of debate has been ongoing regarding whether the estimated relationship between the species and the environment (Fig. 1.3) approximates the realized niche (shown by green part in Fig. 1.3), the occupied niche (the intersection of M, B, A as seen in Fig. 1.3) or the fundamental niche (area A of Fig. 1.3). Soberón and Peterson (2005) believe that SDM generally capture the fundamental niche, and do not take into account the environmental conditions which describe biotic interactions and dispersal limitations. Some exceptions are made to this rule, especially, when interactions between abiotic and biotic factors take place, since in this case the SDM prediction is closer to the realized niche (Soberón and Peterson, 2005). A different opinion is propagated, that in instances where the variables used as predictors are not direct drivers of the species distribution, then the predictions will be closer to the realized niche than the fundamental niche (Hutchinson, 1957). However, some scholars (Guisan and Thuiller, 2005; Araújo and Pearson, 2005) argue that these models represent the realized niche although they solely rely on abiotic factors as predictors, since the information regarding the occurrence records used in model fitting contains actual (realized) distribution. This debate surrounding the SDMs is reflected in the many names used in

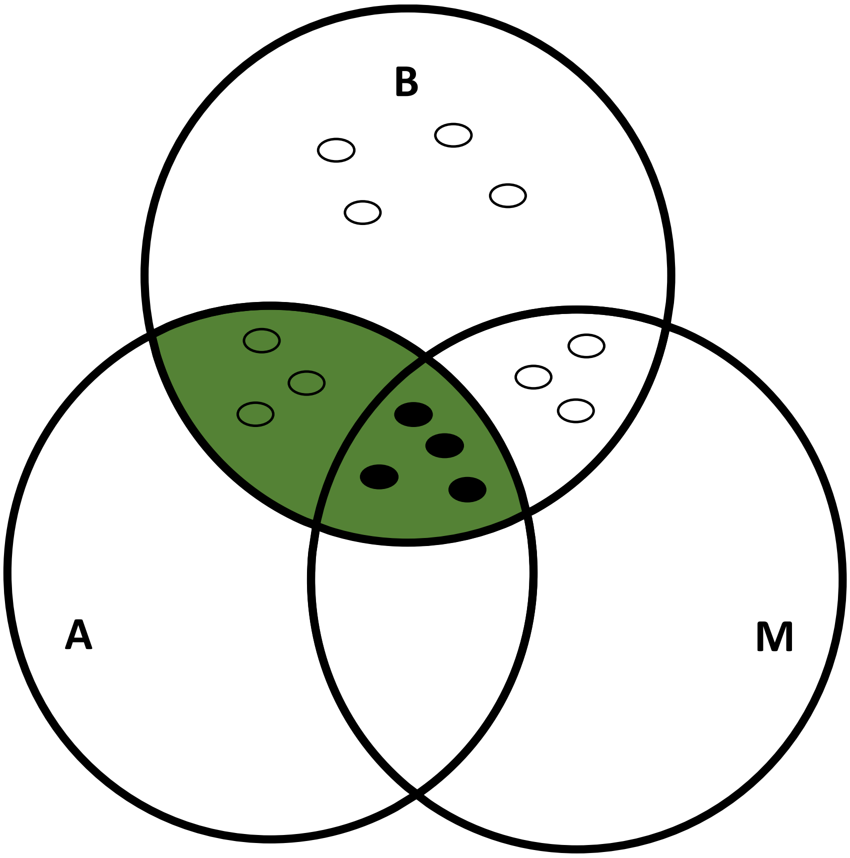


Figure 1.3.: The BAM diagram, according to Soberón (2007) depicts the factors that limit species distribution. A species can only thrive in the areas where both the biotic interactions (B) and abiotic environmental conditions (A) allow for its population growth. The intersection between A and B represents the species potential distribution or realized niche (shown in green colour). The species movement capability determines the geographic area which will be accessible to it within a given time frame. The intersection of B, A and M (shown by the filled black circles) represents the actual occupied area by the species. The sink population which have negative population growth are represented by open circles.

reference to them. Important to note is that the fitted species-environment relationship is influenced by many factors, which eventually determine the aspects of the niche that will be represented in the SDM. Therefore, a careful interpretation of the underlying assumptions of a model are vital for its application.

1.8. Remote sensing

1.8.1. Basics

In this section, we cover the basics of remote sensing because this has not been covered in the other chapters. Also, since this thesis my be of interest to a community that is not well-versed with knowledge on remote sensing, it is important to cover these basics from the onset in the introduction.

Remote sensing refers to methods of gathering information regarding an object without coming into contact with it. In this work, remote sensing refers to the study of the characteristics of the earth's surface from above (Fig. 1.5). The methods typically rely on recording the intensity of electromagnetic radiation, and this provides information about density radiation energy in watts per square meter. Such measurements cover a single or multiple segments of the electromagnetic spectrum. For instance, a color photograph depicts the reflectance in the blue, red and green segment of the visible region of the electromagnetic spectrum (400-700nm). Other than the visible region of the electromagnetic spectrum, remote sensing has the capability of covering many regions of the electromagnetic spectrum, among them short-wave infrared, thermal infrared and near infrared.

Remote sensing systems can be divided into two groups: passive and active systems. Passive remote sensing systems record the solar radiation reflected by the earth's surface. In many instances, the resulting output takes the form of an image that consists of different layers which represent information gathered from the various segments of the electromagnetic spectrum. These segments together make up a spectral band, which can have different band widths, depending on the wavelength length range it covers. Pixels of a given size, which defines the spatial resolution of the image, normally represents each layer. The spatial resolution of images may vary greatly based on distance to the object in question and the instrument.

On the other hand, active remote sensing systems measure the reflected radiation energy which was beforehand emitted on the study object. Examples of this include LiDAR and Radar instruments. Measurements of active remote sensing instruments normally cover a single wavelength. The acquisition of remote sensing data could be conducted from various platforms including, satellites, airborne for instance Unmanned Aerial Vehicles and aircrafts, or ground-based platforms. Satellite platforms normally cover large spatial extents, compared to airborne platforms (Jones and Vaughan, 2010). For this thesis, Sentinel-2 remote sensing satellite data and other remote sensing satellite data will be used. Both data sets will be described in details in section (4.2.3)

1.8.2. Remote sensing of medicinal plants

Remote sensing technology has gained significance as a valuable method for gathering information on medicinal plants (Guo et al., 2021). The use of this technology has addressed the limitations of the conventional or traditional methods such as use of climatic variables (Ferrier, 2002). Previous remote sensing studies on medicinal plants so far primarily focused on mapping medicinal plant species (Malahlela

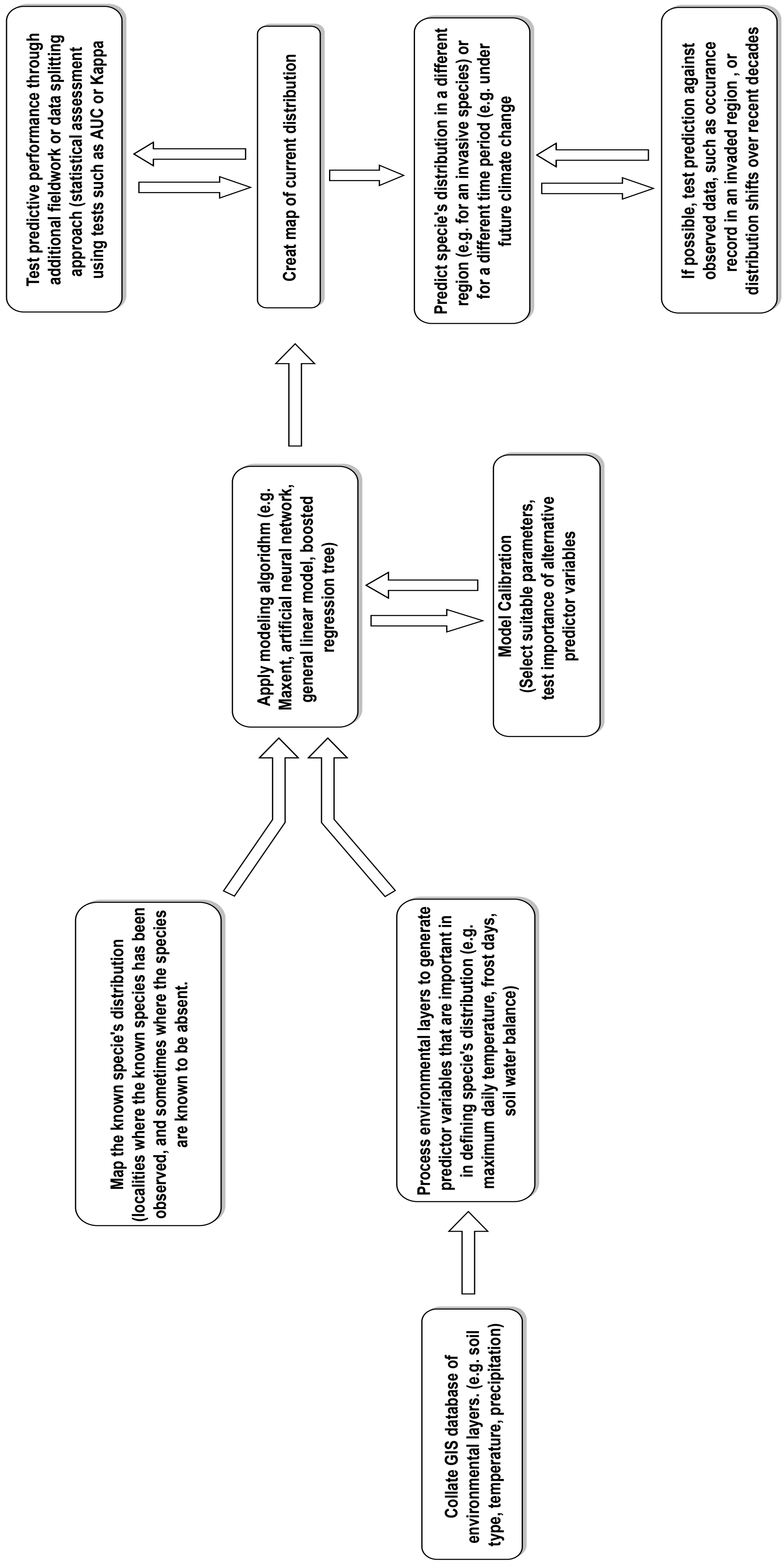


Figure 1.4.: Flow chart showing the critical steps for fitting and validating a SDM, according to Pearson et al. (2007)

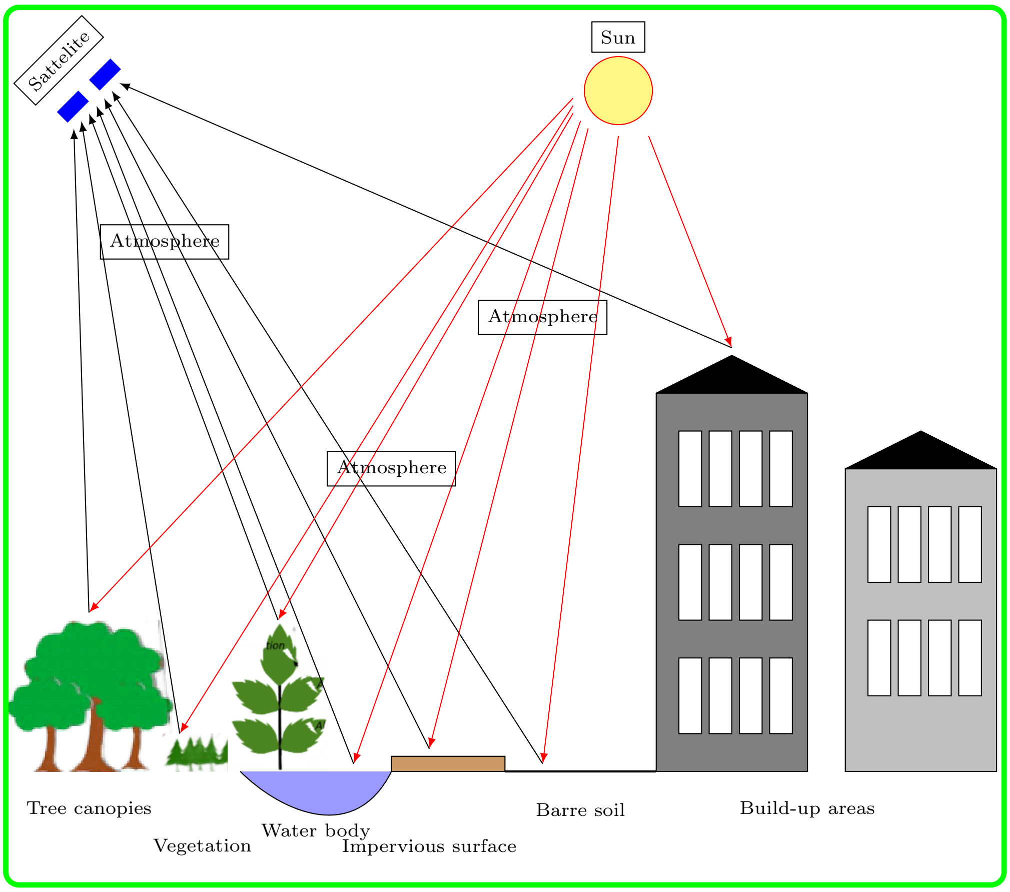


Figure 1.5.: Schematic diagram illustrating remote sensing technique of gathering information

et al., 2019; Ding et al., 2023) and predicting their biomass yields (Tshabalala et al., 2021). This has been proved to work well for individual medicinal plant species like *Lippia Javanica* in an inaccessible area in South Africa (Malahlela et al., 2019), *Lamiophlomis rotata* in a high elevation area in China (Ding et al., 2023) and for *Moringa oleifera* in South Africa (Tshabalala et al., 2021).

In the recent past, distribution maps have been derived using a combination of field inventories and remote sensing data (Piiroinen et al., 2018; Yang et al., 2022), or just field inventories (Cahyaningsih et al., 2021; Kaky and Gilbert, 2016). Distribution maps that are at least partly based on field inventories are likely to be more accurate, and hence valuable for conservation planning, compared to maps solely based on remote sensing data (Ferrier, 2002). However, remote sensing studies that use of a combination of various remotely sensed data and field inventories to map medicinal plants is rather limited. Malahlela et al. (2019), for instance, used only Sentinel-2 satellite and topographic data to map the distribution of an anti-malaria plant species, *Lippia Javanica*, in a malaria endemic region in South Africa. Kishor and Amit (2018) used hyperspectral remote sensing data to map the distribution of cultivated medicinal plant species, *Picrorhiza kurrooa*, *Saussurea costus* and *Valeriana jatamansi*, in the Indian Himalayan region. Ding et al. (2023) used UAV to identify and map *Lamiophlomis rotata* in high elevations of Tibetan Mongolia. One main task at this point is to showcase that remote sensing data, combined with field inventories and ensemble modelling approach can be useful in generating accurate maps for conservation planning.

1.9. Research Needs

The distribution and supply of medicinal plants has been a subject of interest for several research papers, including individual species case studies (Ray et al., 2011; Yang et al., 2013; Malahlela et al., 2019), many species case studies (Gaikwad et al., 2011; Rokaya et al., 2012; Kaky and Gilbert, 2016; Cahyaningsih et al., 2021), and many review papers (Beyene et al., 2016; Dar et al., 2017; Balogun and Ashafa, 2019). Notwithstanding, there is still a growing demand for more research, since crucial ecological information for medicinal plants that grow together, and those considered important in the fight against common diseases is still limited, and the distributional response of medicinal plant species also vary in different areas (Kaky and Gilbert, 2016). Besides, most medicinal plant species continue to decline, implying that they are not effectively conserved probably because of limited knowledge on their distribution and supply. Whereas the distribution and supply of medicinal plants are basically well investigated, focus on groups of medicinal plant species that grow together, and species groups used against different diseases, especially the common diseases, as well as the conservation issues about them has received somewhat little attention (but see Khakurel et al., 2022). At this point, classification and ordination techniques (Grabherr et al., 2003), the N+1 redundancy concept (Albuquerque and Oliveira, 2007), as well as Species Distribution Models (SDM) can provide valuable insights on the distribution and supply patterns of medicinal plant species (Kaky and Gilbert, 2017). However, to date, only a few studies have use these techniques to assess the distribution and supply of groups of medicinal plant species in terms of species that grow together, and those used against various diseases, especially the common diseases. To the best of my knowledge, no other study has investigated the distribution and supply of medicinal plant species in terms of groups of medicinal plant species that grow together, and those used against various diseases, especially the common diseases, and brought forward recommendations regarding their conservation.

Most research on medicinal plants distribution and supply focus on all medicinal plants across a study region, with limited information on groups of plant species that grow together, or those used against various diseases, especially those diseases which frequently affect the locals. Kaky and Gilbert (2016) found that Egypt's medicinal plants are mostly found in the north east and south west, which are characterized by high elevation. Cahyaningsih et al. (2021) evidenced that medicinal plant species in Indonesia are mostly concentrated in the Sumatra, Sulawesi and Java islands. Li et al. (2015) observed that the distribution patterns of native medicinal plant species are concordant to those of vascular plants in northwest China. Grouping of medicinal plant species according to assemblages and the diseases they treat is particularly relevant to ensure that appropriate management strategies are separately given to each group. In addition, focus on common diseases which affect locals in an area may be of greater impact. We argue that plants species used to treat common diseases hold greater significance than other medicinal plant species due to their therapeutic value to the locals (Akerele et al., 1991). Ordination and classification techniques, the N+1 redundancy concept, and SDMs can deliver information of the distribution and supply patterns of medicinal plant species in terms of groups of species that grow together, and those species used against different diseases, especially the common diseases.

1.10. Thesis structure and research questions

The aim of this thesis was to assess the distribution and supply of medicinal plant species, in terms of groups of species that grow together, and those used against various diseases, especially the common diseases, bring forward recommendations regarding their conservation, as well as evaluate their implications for conservation. For this reason, this thesis adopts different applications of distribution and supply that hold premise to enhance our understanding of medicinal plants availability, and are beneficial for conservation of the plants. The first paper was based on the premise that conservation strategies geared towards conserving both the medicinal plant species and assemblages are likely to yield more promising results that those that only focus on individual medicinal plant species. The paper focuses on evaluating the supply of medicinal service by wild plants among medicinal plant assemblages (MPA). Specifically, this paper compares medicinal service supply by wild plants among different MPA. The paper reveals the patterns of medicinal plant co-occurrences and identifies the drivers of these patterns. Besides, the first paper shows the level of supply redundancy for groups of species used against each disease in the different MPA. Whereas the first paper focused on all medicinal plants in Samburu, the second paper focused on anti-malarial plants and malaria vectors, since malaria is the most common and deadliest disease in the area. The second paper predicts the impact of climate change on the availability of anti-malarial plants. This paper also predicts the current and future overlap between anti-malarial plant species richness and malaria vector species suitable habitat, which is critical to understanding malaria vulnerability. Therefore, this paper addresses the fact that the current approaches of estimating malaria vulnerability by mapping only malaria vectors distribution have limited practical utility. Accordingly, the paper makes recommendations regarding the adoption of anti-malarial plants conservation and malarial control measures, currently and in the future. Finally, the third paper evolved from the second paper, since other than malaria, the locals in the study area are known to be affected by other common diseases like stomach ache. This paper therefore uses remote sensing data together with an ensemble one class classification methodological approach to map medicinal plant species, as well as species used against common diseases: diarrhoea, stomach ache and wounds. It also tested the effectiveness of ensemble binary SDM (Bin-SDM) and ensemble suitability SDM (Suit-SDM) in predicting medicinal plant species richness. Accordingly, based on the aforesaid research papers, the present thesis seeks to answer the following research questions:

1. How do medicinal plant assemblages differ in terms of medicinal service supply by wild medicinal plants?
2. Does climate change impact on the availability of anti-malarial plants?
3. Can remote sensing data combined with an ensemble one class classification workflow be used to map medicinal plant species?

1.11. List of papers

The aforementioned research gaps were addressed in three papers. Paper 1 and paper 2 are already published in international peer reviewed international journals. Paper 3 has been submitted.

1. **Gafna D.J.**, Obando, J.A., Reichelt M., Schmidtlein, S., Dolos K. (2021). Medicinal service supply by wild plants in Samburu, Kenya: Comparisons among medicinal plant assemblages. *Global Ecology and Conservation*

2. **Gafna D.J.**, Obando, J.A., Kalwij J.M., Dolos K., Schmidtlein, S. (2023). Climate Change Impacts on the Availability of Anti-malarial Plants in Kenya. *Climate Change Ecology*

3. **Gafna D.J.**, Obando, J.A., Dolos K., Schmidtlein, S., Fassnacht, F. E (2023). Remote sensing based mapping of medicinal plants using an ensemble one class classification algorithm in Samburu dryland, Kenya. *International Journal of Applied Earth Observation and Geoinformation*. Submitted

1.12. Summary of the authors contribution

All research papers were prepared in collaboration with the co-authors. I originally drafted the manuscripts and subsequent revision was conducted by the co-authors. Apart from drafting the manuscripts, I was involved in designing of the study and field work. I conducted the data analysis, triggered by the suggestions of the co-authors. Finally, the findings were interpreted and discussed with the co-authors.

2. Medicinal service supply by wild plants in Samburu, Kenya: Comparisons among medicinal plant assemblages

Dikko Jeff Gafna, Joy A. Obando, Martin Reichelt, Sebastian Schmidtlein, Klara Dolos

Abstract

Supply of medicinal plants from African landscapes is crucial because of their widespread use. Rapid climate change and land use change are potential threats to this resource but knowledge about the ecological needs of many of these plants is still rather limited. More knowledge about potential threats to medicinal plants supply and options to prevent future losses are desirable. Therefore, the objectives of the study were to examine (1) the effects of environmental drivers on the occurrence of medicinal plant species, (2) how different vegetation formations contribute to the provision of plants used for the treatment of diseases and (3) how these contributions are secured by redundancy. The analysis was based on a sample of 130 sampling plots in Samburu County, Kenya. We identified patterns in medicinal plants co-occurrences using classification and ordination analyses and analyzed these pattern in terms of environmental drivers, service diversity and service security. The pattern in medicinal plants co-occurrences reflected the distribution of broad formations (bushed grassland, forest, wooded grassland, savanna) driven by differences in grazing pressure, drought, slope and fraction of sand in soils. Each of the formations brought with it its own characteristic endowment with medicinal plants. The formations differed in the diversity and security of medicinal services provided. All resulted as fulfilling unique services with diseases treated by plants occurring exclusively in one or another formation. Forests featured the highest diversity of medicinal services, with medicinal plants used against 67 diseases. The supply security in forests, resulting from redundancy in supply provision, was moderate. In contrast to this, savanna grasslands featured plants with uses against 49 diseases, some of them were treated exclusively by plants from savanna grasslands. This formation also showed the highest redundancy. Wooded grasslands showed very little redundancy and is likely to be adversely affected by climate change. We suggest that urgent and highest conservation priority should go towards the savanna grassland that had the highest supply redundancy for traditional medicine.

2.1. Introduction

Apart from maintenance of the ecosystem, medicinal plants form a key element of the local medical systems (Dharani and Yenesew, 2010). In many developing countries, they form a major component of the primary health care systems and are used in the treatment of many illnesses, whereas in the developed countries, they provide a broad reservoir upon which potential conventional drugs can be developed (Ngari et al., 2010). According to the World Health Organization, medicinal plants are among the safest ways of ensuring worldwide access to health care (WHO, 2013). Their significance is highlighted by their incorporation into WHO's strategy for attaining the Millennium Development Goals (MDGs), which include improving maternal health, combating HIV/AIDs and other diseases and reducing child mortality (WHO, 2014). A key factor of reaching these ambitious goals is a sound understanding of the supply of medicinal plants, especially in rural areas.

The contribution of spontaneously growing medicinal plants to the health care system especially in rural areas cannot be emphasized enough. For the millions of people in Africa, medicinal plants are the primary, occasionally the solitary source of medical care that is close to their home (Chalo et al., 2016). The frequent use of medicinal plants in the continent is also attributed to the fact that they are cheap and culturally accepted in many communities (Ngari et al., 2010). In Kenya alone, 80% of the population uses medicinal plants from the wild for their primary health care. This makes sense in light of the figures released by the Ministry of Health in Kenya in 2016. These showed that the budgetary allocation for conventional drugs catered to a mere 30% of the population (GOK, 2016). The 70% without access to conventional treatments was thus left to depend on traditional treatments based on medicinal plants. Since it seems highly unlikely that medicinal plants might be replaced with pharmaceutical equivalents, at least in the next few decades, the conservation of medicinal plants is of great interest to Kenya's society (Dharani and Yenesew, 2010).

In Kenya, some 1200 plants have scientifically confirmed medicinal value. Apart from their medicinal value, the plants are also a source of income to traditional healers, food (*Rhus natalensis*), appetizers (*Carissa edulis*) and disinfectants (*Acacia tortilis*) (Gakuya et al., 2020). However, decline in medicinal plant resources due to overexploitation, unsustainable harvesting and land use has threatened to take with it medicine that is crucial for treating the country's illnesses (Kamau et al., 2016). Whereas this threat has existed for decades, unprecedented loss of medicinal plants in the country (Wambugu et al., 2011), just like in India (Sharma and Kala, 2018) or Mozambique (Ribeiro et al., 2010) has led to huge decline in medicinal service supply. Conservation of medicinal plants remains key to improvement of medicinal service supply. Additionally, medicinal plants conservation can also provide a base for the conservation of natural habitats (Gafna et al., 2017). Therefore, there is an urgent need to conserve medicinal plants as a means towards improvement of livelihoods and local healthcare in the country (Gakuya et al., 2020). Consequently, a number of recommendations have been made regarding medicinal plants conservation. These include strengthening of customary conservation laws, establishment of species monitoring systems in combination with coordinated *in situ* and *ex situ* conservation efforts (Nanyingi et al., 2008). Despite these efforts, decrease in medicinal service supply continues (Njoroge, 2012), perhaps because growth conditions deteriorate or scientific insights are not incorporated in the formulation of local conservation programs. Thus, knowledge about the environmental conditions that secure medicinal service supply of ecosystems is crucial for conservation planning.

Climate change affects these environmental conditions. It may either contract, expand or shift the geographical range of medicinal plants (Kotir, 2011). The report by IPCC (2014) indicates that East Africa will experience increase in temperature by 15% and 8% decreased rainfall by 2050. Growing human population combined with the rural-dependent lifestyle puts pressure on the already vulnerable vegetation formations, highlighting the need for adoption of climate change strategies in the management of medicinal supply. However, the effects of climate change on medicinal supply of spontaneous vegetation is still unclear.

Despite calls to evaluate the medicinal services provided by spontaneous vegetation (Albuquerque et al., 2005), research on that topic is scarce. So far, most studies have exposed the potential of forest types to supply medicinal plants (Shanley and Luz, 2003; Eliá and Mariniová, 2017). Little effort has been made to extend this to other formations and in particular to undertake detailed quantitative analyses on the impact of environmental conditions on medicinal service supply with regards to individual diseases. We argue that this limits the utilization of the traditional medical system. Medicinal plants management strategies need to be formulated based on the determinants of medicinal plants supply patterns. Such patterns in medicinal plants supply have been found to be determined by abiotic factors, including elevation, climate (Rokaya et al., 2012), land use such as logging and nomadic grazing (Albuquerque et al., 2005) and edaphic factors (Dharani and Yenesew, 2010). These factors generally determine medicinal plants supply by influencing their richness and abundance. Additionally, cultural factors such as knowledge on medicinal plants use also plays a critical role (Gafna et al., 2017). As shown by Chalo et al. (2016), plants are only used for medicinal purposes if they are culturally acceptable to a community.

The current paper aims at answering the following questions: (1) What are the effects of environmental drivers on the occurrence of medicinal plant species in Samburu, Kenya?, (2) how do different vegetation formations contribute to the treatment of diseases through medicinal plants and (3) how are these contributions secured by redundancy of services.

2.2. Material and methods

2.2.1. Study area

Samburu County is situated in the arid and semi-arid biogeographic part of northern Kenya and approximately 400 km from Nairobi, the capital city of Kenya (Fig. 2.1). It encompasses an area of 21,328 km^2 and has a population density of 11 persons per square kilometer (KNBS, 2019). The county has a rugged terrain with different soil types based on topography, geology and climate. The main soil types are deep brown soils, sandy soils and loamy soils. The area receives a mean annual rainfall of 500-600 mm, characterized by a bi-modal pattern of distribution with the short rains occurring from July to September and the long rains falling from March to May (KMD, 2019). The dry season spans from December to February. River Ewaso Nyiro is the only permanent river in the area. During the wet season, natural water ponds, artificial ponds, laggas and seasonal rivers are filled with water (Omwenga et al., 2014). Annual mean temperature was 29°C in the time periods from 2010 to 2016. The elevation of the area ranges from 340 to 2780 m a.s.l with great topographic relief on the central region (Nanyingi et al., 2008). The Global Land Cover Characterization depicts evergreen broadleaved forests, closed and open shrub lands, savanna and grasslands as the vegetation forms in the area (USGS, 2019). The area is dominated by the Samburu community which practice nomadic pastoralism as the main economic activity (Gafna et al., 2017).

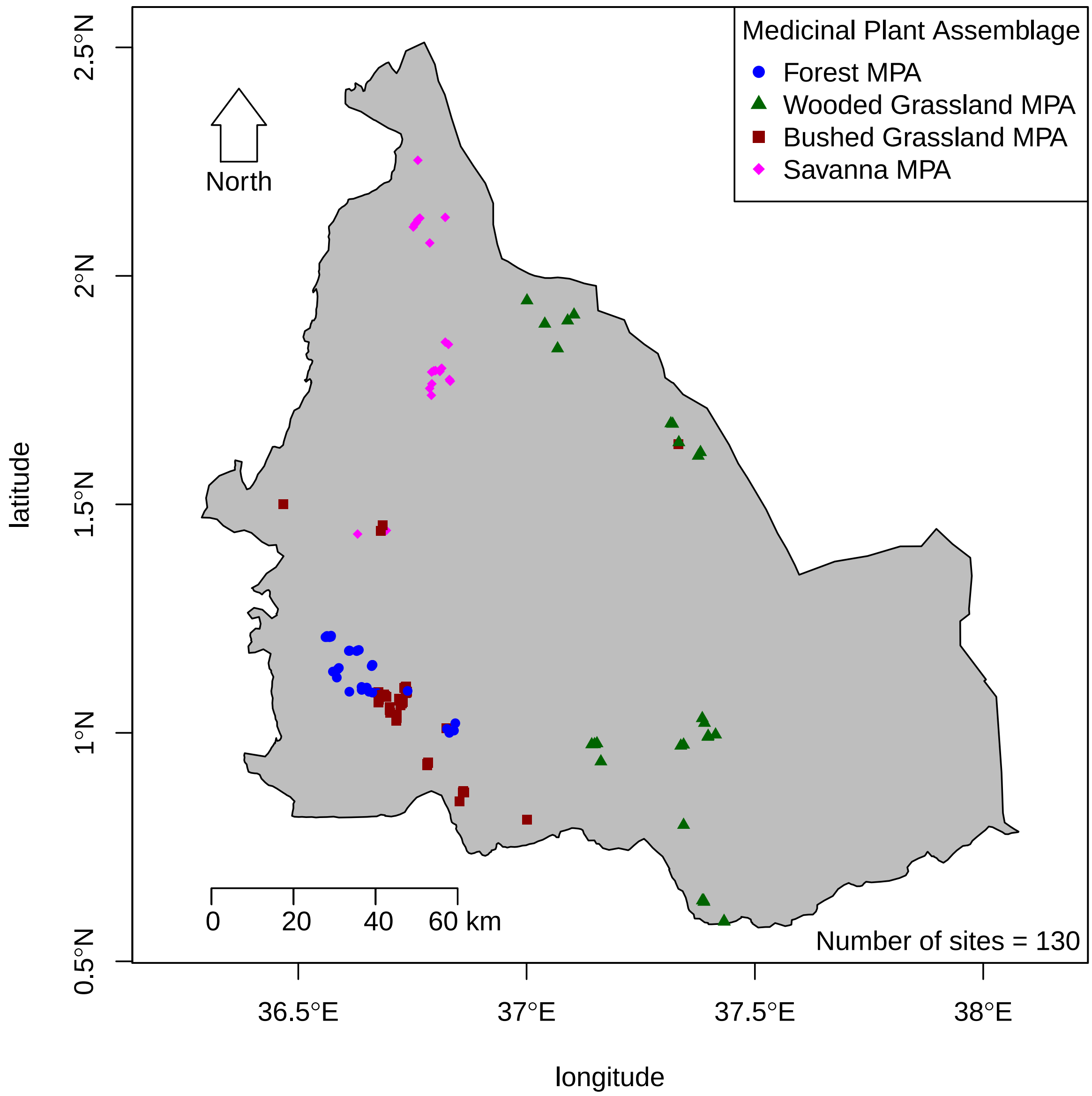


Figure 2.1.: Map of the study area and sites labeled according to MPA.

2.2.2. Vegetation survey

A plant survey of the Samburu area was conducted during periods of peak vegetation cover (July 2016 and September 2016, March 2017 and May 2017). Stratified random sampling was applied to select sites, with strata based on land cover (Anderson et al., 1976), soil type (Dewitte et al., 2013) and protection status (KWS, 2010). A total of 68 sites was selected within a buffer distance of not more than 5 km from the main roads due to logistic constraints. These sites were distributed across the strata and are referred to as "primary sites".

In the event of a nearby corral (within 900 m), we placed two sub-plots at fixed distances from that corral (at 1500 m and 2000 m). Corral and all the three sites where placed on a straight line. Distance from corral served as a proxy for grazing intensity. 19 sites were situated next to the corrals and they were well distributed across the strata. If we noted signs of recent wildfires (deposits of ash on the soil and fire scars on plants) we added a pair of sites (at a distance of 700 m from the primary site and in opposite direction) to assess effects of fire on the occurrence of medicinal plants. One of these sites showed no signs of burning; the other was placed in an area with signs of severe burning. 12 sites were severely burnt and 12 unburnt sites; both types were well distributed across the strata. The plots measured 80 m by 80 m. Within plots, we recorded all occurrences of medicinal plants from a checklist of 133 medicinal plant species present in the Samburu dryland (Bussmann, 2006; Kokwaro, 2009; Dharani and Yenesew, 2010; Omwenga et al., 2014; Gafna et al., 2017).

Additional 17 plants that were commonly identified as medicinal by the research assistants were taken to the traditional herbalists who certified their use for medicinal purposes. The taxonomy of the plants followed Heine et al. (1988). Scientific identification and validation of the local names of the collected medicinal plant species was done at the East Africa Herbarium (EA). The flora of Tropical East Africa was used for identification (Hurskainen, 1994). Verification of the plants was done by Dr. Ombori Omwoyo, from Kenyatta University.

Additionally, the conservation status of all the study taxa was checked from the available relevant literature (Dharani and Yenesew, 2010; Dharani, 2011; Gafna et al., 2017) and the IUCN database (Version 14, (IUCN, 2021). For instances where the conservation status of a given species differed, the highest assigned conservation status was used.

2.2.3. Environmental variables

At each site, aspect, elevation, slope and cover of dead plant matter were recorded. Soil moisture was measured in the field using a theta probe at five different points of a plot at a depth of 10 cm. The values were later averaged. In each plot, soil samples were collected from five points (four at the corner and one at the center). The soil samples were extracted using a soil corer (7 cm diameter x 10 cm deep). The soil samples were stored in polythene bags and deposited at the Kenya Agricultural Research Institute laboratory for analysis. Soil texture was estimated using the hydrometer method, soil pH was measured using a pH meter, while the soil salinity was measured using a hand held salinity meter (Beretta et al., 2014). The percent cover of dead plant material was visually estimated.

Corrals within a radius of 900 m of each site (primary and secondary) were searched and their positions recorded. Grazing intensity was measured as the distance from corrals, while expert assessment of recent grazing pressure was applied (Linstädter et al., 2014) by counting of dung and signs of trampling within 200 m radius in each site.

In addition to the field survey data, we used climatic data from WORLDCLIM for the annual precipitation and temperature sums (Hijmans et al., 2005), historical monthly precipitation data covering 2004-2016 (Essenfelder, 2016; KMD, 2019) and population density data from KNBS (2019).

2.2.4. Data analysis

We used a classification approach to find characteristic co-occurrences of medicinal plants. The resulting classes were assigned to broad plant formations and used as reference for our estimates of supply security and supply diversity. Direct ordination was used as a complementary approach to reveal gradients in co-occurrence patterns with linear relations to the included environmental variables.

2.2.4.1. Classification of medicinal plant assemblages

The species presence/absence was transformed employing the R function decostand with method "normalize" to realize normality and homogeneity of variance. Isopam clustering, with gray distance measure, was used to categorize our vegetation data into assemblages and portray the floristic features provided by the assemblages (Schmidtlein et al., 2010). Data handling and analyses were conducted with the R packages 'vegan' (Oksanen, 2006) and 'isopam' (Schmidtlein et al., 2010). To better describe the patterns and assess the variability of the vegetation formations, we used the nested design during the analysis. Here, we created dummies of our plots and aggregated to primary sites.

An ordination analysis revealed how the environment triggered the groups found in classification. Redundancy Analysis (RDA) was used to ordinate the species data since gradient lengths were low (Oksanen, 2006).

Based on our hypotheses, existing theories and removal of highly correlated variables, the following environmental variables were selected for analysis: soil pH, soil salinity, grazing pressure, fire history, grazing intensity, population density, drought, slope, aspect, cover of dead plant matter, sand and clay fractions in soils. The choice of our variables was ascertained using the step-wise selection of variables via adjusted R^2. The Palmer Drought Severity Index (PDSI) (Newman and Oliver, 2005) was calculated and calibrated with the package scPDSI in R program.

A linear environmental fit on the axes 1 and 2 was used to determine the statistical relation between grazing pressure, drought, slope, sand fraction, clay fraction and cover of dead matter on medicinal plants variation. Kruskal-Wallis non-parametric test was used to assess the environmental differences among assemblages. For instances when the Kruskal-Wallis test revealed significant differences ($p < 0.05$), we performed the Bonferroni adjusted Dunn's a post-hoc analysis test to determine which plant formation differed from the other(s) (Dunn, 1964). This test incorporates multiple pairwise comparisons for stochastic dominance and was adopted because our plant formations had unequal number of observations (Zar, 2009).

2.2.4.2. Supply security

The N+1 redundancy concept was used to analyze the supply security (Albuquerque and Oliveira, 2007). This concept originates from information technology and is viewed as expression of resilience that ensures that component failure does not compromise system availability. N is the "operational component", for instance a power supply or a computer server system. It is normally N = 1, whereas +1, +2, +3 show the available number of backup systems which performs the same function as N. A backup system could be on standby status, active or passive. In our study, N is a given plant species used against a particular disease whereas +1, +2, +3 represent the number of other plant species which treat the same disease. In case of disorder, for example the loss of a medicinal plant species, redundant species would be able to take over the functionality of the missing medicinal plant species.

We used the medicinal plant assemblages (hereafter, MPA) resulting from the classification analysis to assess the variability in supply diversity and supply security. The N+1 redundancy was applied to the mean values of medicinal plant species, per disease, in each MPA. The values were categorized as follows: Values less than one were not to be considered, values between one and two were assigned to the category N (not redundant), between two and three to N+1 (low redundancy), between three and four to N+2 (moderate redundancy) and greater than four to N+3 (high redundancy). We calculated the mean of the redundant treatments in all the assemblage to determine the supply security of the assemblages. Besides, we analyzed the key medicinal plant species responsible for the supply security in each MPA. Key medicinal plant species are the species used to treat the highest number of diseases and are well distributed within the MPA. Kruskal-Wallis test was used to assess the possible differences in supply diversity and security among the assemblages. Thereafter, dunn's test was used to identify the difference in supply diversity and supply security among the assemblages. The Pearson correlation between the physical site parameters and supply diversity and supply security in the assemblages was determined. Supply diversity in each assemblage was determined by counting the number of medicinal functions (target diseases) in the assemblages (Albuquerque and Oliveira, 2007).

2.3. Results

2.3.1. Medicinal plants survey

A total of 77 medicinal plant species in 130 plots (68 primary sites and 62 secondary sites) were present in a sampled area of 83 ha (supplementary material, Table 2.3). The study species were categorized into six conservation status: Least concern (18 species), near threatened (9 species), vulnerable (29 species), endangered (10 species), critically endangered (2 species) and data deficient (9 species) (supplementary material, Table 2.3, Fig. 2.6). An average of 14 medicinal plants was found in each site. The most frequent medicinal plant species was *Solanum incanum* with 82 occurrences while the rarest was *Ajuga remota* with 8 occurrences.

2.3.2. Drivers of medicinal plants co-occurrence

The isopam algorithm clustered the records into four MPA which were named according to prevailing growth forms or formations. The identified MPA were: bushed grassland, forest, wooded grassland and savanna grassland. Individual plants differentiated between assemblages using the significance of their contribution to separating a class from the rest (supplementary material, Table 2.4). At a respective 6.8 and 2.9, accounting for 12.8% and 5.6% of the total explained variation in the data set, the eigenvalues of the first two axes were high and were therefore good predictors of medicinal plants co-occurrences (supplementary material, Table 2.5). Additionally, 27% of the variation in medicinal plants co-occurrences were explained by the environmental variables. The permutation test revealed a significant difference between the eigenvalues of the first two ordination axes ($p < 0.05$) and the environmental variables. The high eigenvalues of the first and second axes along with the permutation test results ($p < 0.05$), indicate a strongly significant correlation between environmental variables and the medicinal plants co-occurrences frequency. The arrangement of medicinal plant species along the first ordination axis included species which are vulnerable such as *Euphorbia tirucalli* and *Aloe secundiflora* among others (Fig. 2.2). The gradient depicted by the second axis was created by the relation of plants that are considered endangered like *Gutenbergia cordifolia* and *Fuerstia africana* among others within the environment.

The natural site characteristics with the highest impact on ordination axes were drought ($r^2 = 0.48$, $p < 0.005$), slope ($r^2 = 0.37$, $p < 0.005$) and sand fraction in soils ($r^2 = 0.09$, $p < 0.005$) (Fig. 2.2). Grazing pressure was the most important anthropogenic factor ($r^2 = 0.71$, $p < 0.05$). Dead matter cover and fraction of clay in soils were also important but not as the other three (supplementary material, Table 2.6). Contrarily, pH, aspect and fire history were irrelevant. The environmental fit on the ordination indicated that parameters related to sand and clay fractions in soils varied across the first axis. Cover of dead matter had a higher loading on the second axis. The correlations among the physical site parameters were depicted in the environmental overlays. Slope and clay fraction were strongly positively correlated in their influence on medicinal plants co-occurrences while drought, grazing pressure and sand fraction were strongly negatively correlated to these variables (Fig. 2.2). The bushed grassland MPA was characterized by high grazing pressure and high population density. The forest MPA was located in areas with relatively steep slope and high clay fraction in soils. The wooded grassland MPA was distributed at dry areas with high sand fraction (Fig. 2.2, Fig. 2.3). The RDA results indicate that the occurrence of *Acacia tortilis* (reported as of least concern) was strongly associated with drought, whereas *Carissa edulis* and *Lippia javanica*, reported as vulnerable, were strongly associated with high slope and were mainly found in the forest MPA. Grazing pressure played a significant role in the occurrence of *Acacia nilotica*, which is considered to be near threatened. Contrastingly, plants that were classified as of least concern such as *Croton dichogamus*, *Solanum incanum* among others were not influenced by any of the environmental factors.

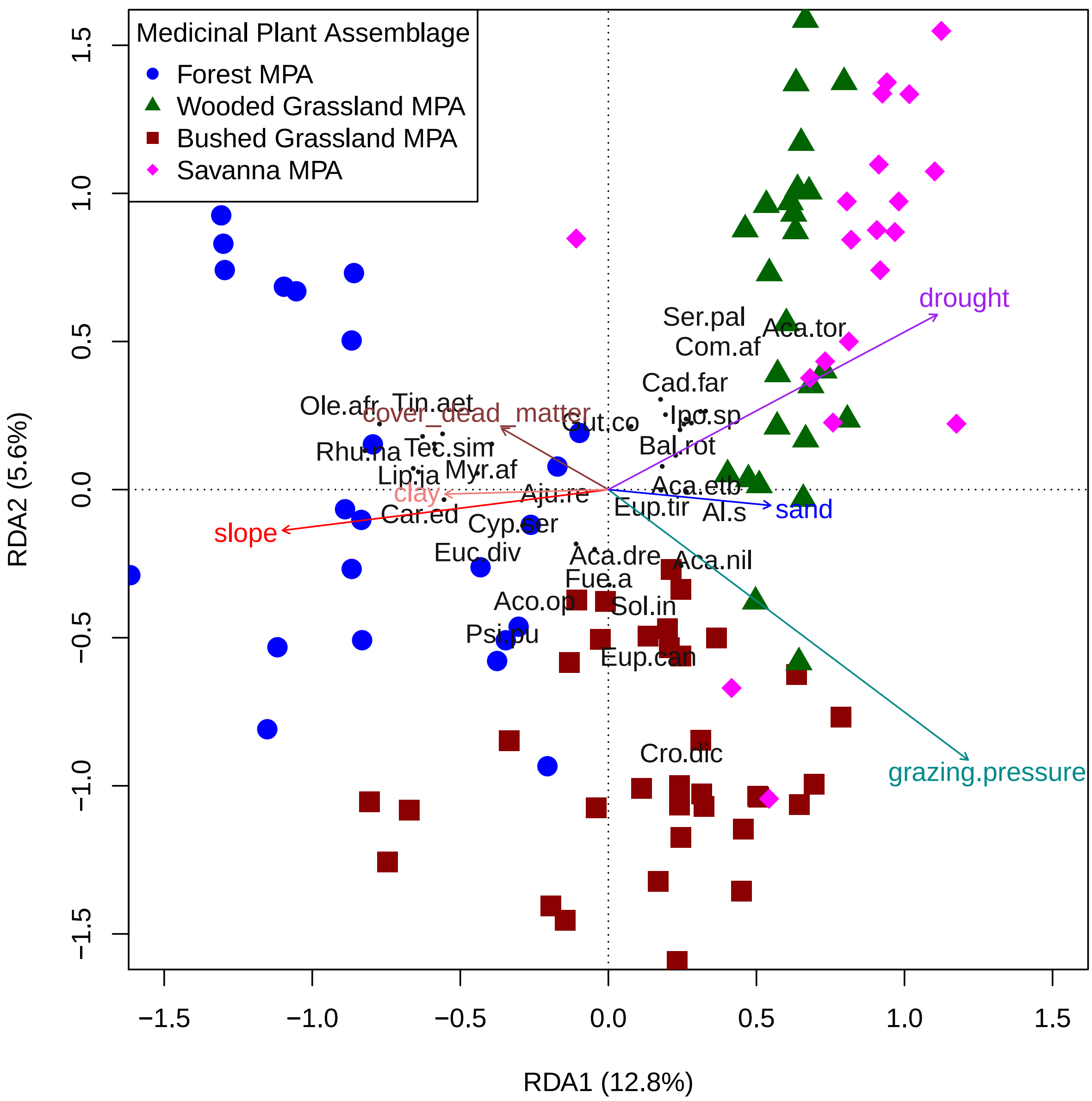


Figure 2.2.: RDA ordination with environmental fit for some variables. The arrow represent the strength of correlation and direction of variation of the significant variables that determine medicinal plants co-occurrences among the MPAs. Species codes: Aca.dre- *Acacia drepanolobium*; Aca.etb- *Acacia etbaica*; Aca.nil- *Acacia nilotica*; Aca.nub- *Acacia nubica*; Aca.tor- *Acacia tortilis*; Aco.op- *Acokanthera oppositifolia*; Aju.re- *Ajuga remota*; Bal.rot- *Balanites rotundifolia*; Car.ed- *Carissa edulis*; Cro.dic- *Croton dichogamus*; Com.af- *Commiphora africana*; Cyp.ser- *Cyphostemma serpens*; Euc.div- *Euclea divinorum*; Eup.can- *Euphorbia candelabrum*; Fue.a- *Fuerstia africana*; Gut.co- *Gutenbergia cordifolia*; Ipo.sp- *Ipomoea spathulata*; Lip.ja- *Lippia javanica*; Myr.af- *Myrsine africana*; Ole.afr- *Olea africana*; Psi.pu- *Psiadia punctulata*; Rhu.na- *Rhus natalensis*; Sal.per- *Salvadora persica*; Ser.pal- *Sericocompsis pallida*; Sol.in- *Solanum incanum*; Tec.sim- *Teclea simplicifolia*; Tin.aet- *Tinnea aethiopica*.

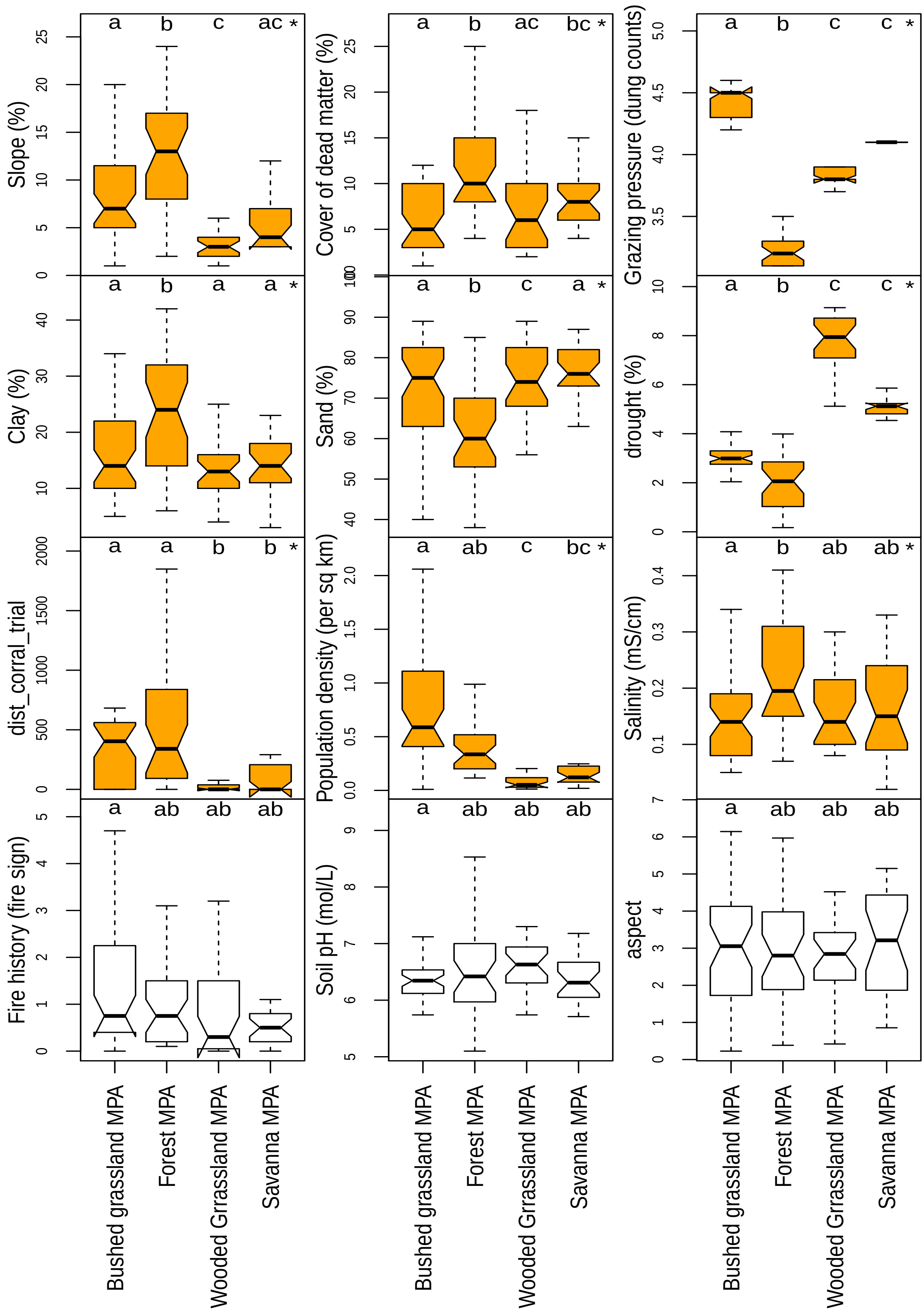


Figure 2.3.: The distribution of environmental variables across MPA as derived from species composition. One star indicates significant differences between groups according to a Kruskal-Wallis test, while groups sharing a letter are not significantly different according to Dunn's test.

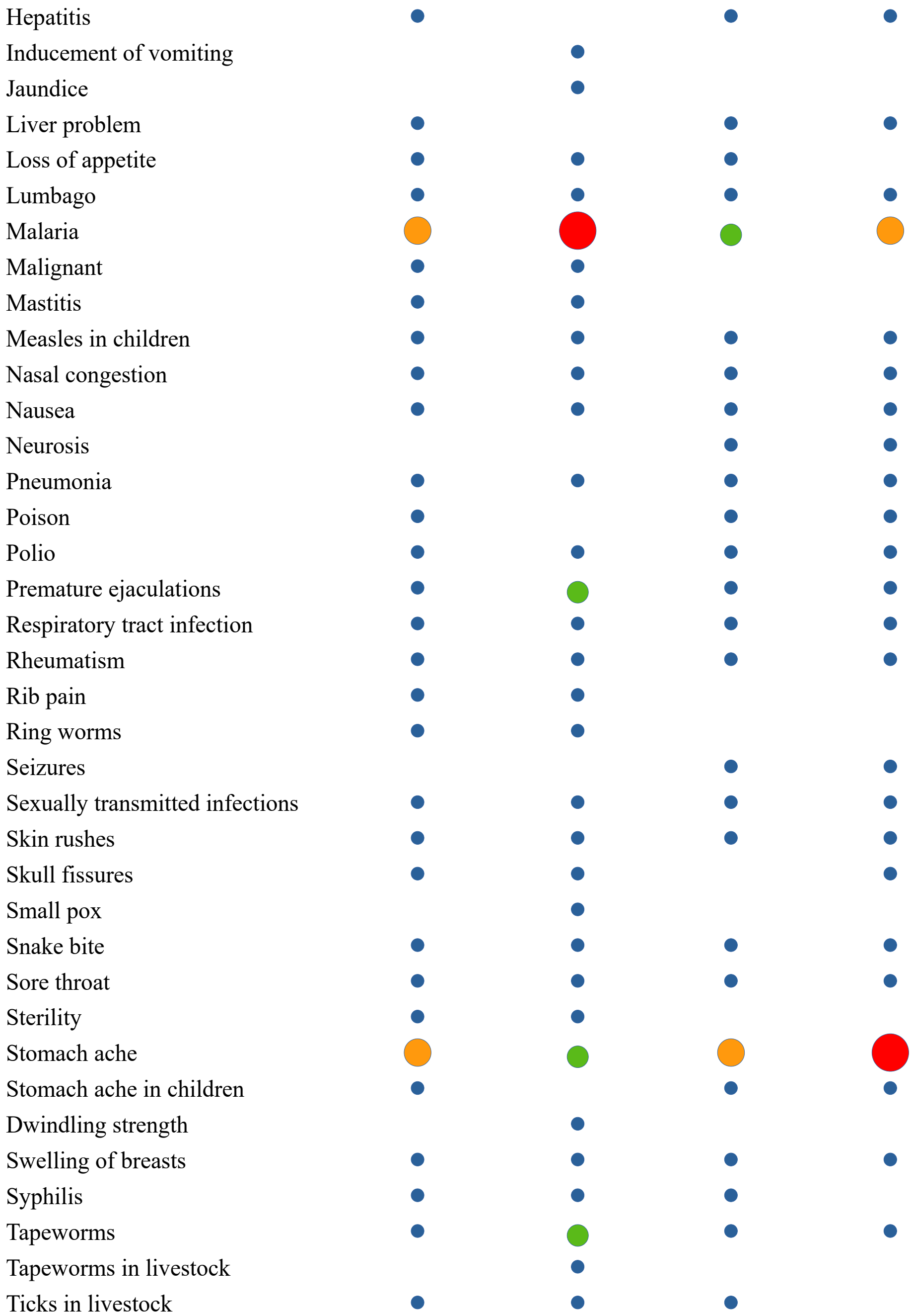
A weak overlap was found between wooded grassland and savanna MPA, while the forest and bushed grassland MPA were clearly separated from the other assemblages. Strongly differentiated medicinal plants were associated with the forest and bushed grassland. For instance species that were classified as endangered like *Olea africana* and *Fuerstia africana* respectively. Many medicinal plants were present in the forest and bushed grassland MPA. Moreover, few medicinal plants were held in common by the MPA. The difference in composition of savanna and the forest MPA can be attributed to drought, while the difference in composition between the wooded grassland and forest MPA can be attributed to grazing pressure and sand fraction (Fig. 2.2). A Kruskal-Wallis test showed that there was a significant difference in drought, population density, slope, grazing intensity and grazing pressure among others among the MPA ($p < 0.001$). Surprisingly, there was no significance difference in aspect, fire history and pH among our assemblages (Fig. 2.3). Post-hoc analysis using Dunn's test indicated that there was a significant deference in drought, grazing pressure, sand fraction and slope among the forest, wooded grassland and bushed grassland MPA. Besides, there was a significance difference in grazing pressure, population density and cover of dead matter between the bushed grassland and savanna MPA. A significance difference in sand and clay fractions was noted between the savanna and forest MPA.

2.3.3. Environmental site conditions as drivers of medicinal service supply diversity

The study revealed that the occurring medicinal plants were used to treat 102 diseases. Kruskal Walis tests showed a significant difference in the number of diseases treated by the plants from different assemblages ($x^2 = 59.52$, df= 3, $p < 0.001$). Dunn's post-hoc procedure identified a significant difference in the number of diseases treated by the plants from the bushed grassland, forest and wooded grassland MPA ($p < 0.001$). The forest MPA had the highest supply diversity with plants used against 67 diseases (Table 2.1) .

Table 2.1.: N + 1 redundancy of all diseases in alphabetic order for each MPA. Blue dots indicate treatments that were available but had no redundant medicinal plants while the green, orange and red dots of various sizes show varying level of redundancy with the largest depicting high redundancy. (Color used in table)

Disease	Bushed Grassland MPA	Forest MPA	Wooded Grassland MPA	Savanna MPA
Abortion			🔵	🔵
Acheing joints	🔵	🔵		
Acne		🔵		
Anaplasmosis in livestock	🔵	🔵	🔵	
Anthrax in livestock			🔵	🔵
Antihelmintic		🔵	🔵	
Arrow poison	🔵	🔵	🔵	
Arthritis	🔵	🔵	🔵	🔵
Asthma	🔵	🟠	🔵	🔵
Bilharzia	🔵		🔵	🔵
Bleeding stomach	🔵	🔵		🔵
Body ache	🔵	🔵		
Bronchitis	🔵	🔵	🔵	🔵
Brucellosis				
Burns	🟢	🔵	🔵	🔵
Cerebral malaria	🔵	🔵	🔵	
Chest congestion	🔵			
Chest pain	🔵	🔵	🔵	🔵
Cleansing of blood	🔵	🔵	🔵	
Colds	🔵	🟢	🔵	🔵
Collibacillosis	🔵			
Constipation in children				🔵
Diarrhoea	🔵	🔵	🔵	🟢
Diarrhoea in livestock		🔵		
Ear ache	🔵	🔵	🔵	🔵
Ectoparasites in livestock	🔵	🔵	🔵	🔵
Eye problems	🔵	🔵	🟢	🟠
Fever	🟠	🔴	🟢	🔴
Fungal infection				
Gastrointestinal complications	🔵	🔵	🔵	🔵
Giardiasis	🔵	🔵	🔵	
Gonorrhoea	🔵	🔵	🔵	🟢
Head ache	🔵	🔵	🔵	🔵
Heart water	🔵	🔵		
Helmithosis	🔵	🔵	🔵	


Hepatitis
Inducement of vomiting
Jaundice
Liver problem
Loss of appetite
Lumbago
Malaria
Malignant
Mastitis
Measles in children
Nasal congestion
Nausea
Neurosis
Pneumonia
Poison
Polio
Premature ejaculations
Respiratory tract infection
Rheumatism
Rib pain
Ring worms
Seizures
Sexually transmitted infections
Skin rushes
Skull fissures
Small pox
Snake bite
Sore throat
Sterility
Stomach ache
Stomach ache in children
Dwindling strength
Swelling of breasts
Syphilis
Tapeworms
Tapeworms in livestock
Ticks in livestock

Tonic in children	●	●		
Tooth ache	●	●	●	●
Trypanosomiasis in livestock		●	●	●
Tuberculosis	●	⬤	●	●
Ulcers				●
Umblical cord healing	●	●		
Wounds	⬤	⬤	⬤	⬤
Yellow fever			●	
Legend				
● (1-2) Not redundant				
⬤ (2-3) Low redundancy				
⬤ (3-4) Moderate redundancy				
⬤ (>4) High redundancy				
Mean Redundancy	3.25	3.62	3.04	4.5

The bushed grassland and wooded grassland MPA had moderate supply diversity with the plants used against 65 and 57 disorders respectively. The savanna MPA had the lowest supply diversity with the medicinal plants used to cure only 49 illnesses (Table 2.1).

Accordingly, a negative correlation existed between grazing pressure ($r = -0.44$, $p < 0.005$), fire ($r = -0.03$, $p = < 0.005$), drought, salinity, clay fraction and supply diversity, whereas a positive correlation existed between slope, ($r = 0.45$, $p > 0.005$), sand fraction, population density and supply diversity (Table 2.2).

Table 2.2.: Pearson correlation coefficient (r) between environmental site conditions and supply diversity and supply security. Significance values are denoted by asterisks: *, P < 0.05; **, P < 0.01; ***, P < 0.001.

Site Condition	Supply Diversity	Supply security
Grazing pressure	-0.44***	-0.35***
Fire history	-0.03**	-0.09
Population density	0.05***	0.08**
Drought	-0.48**	-0.35***
Grazing intensity	-0.13	-0.11
Slope	0.45***	0.33***
Aspect	-0.02	-0.07
Clay fraction	-0.18	-0.11
Sand fraction	0.16	0.07
Dead matter cover	0.12	0.09
Salinity	-0.01	-0.26
pH	-0.11	-0.14

Generally the forest MPA, especially those with moderate grazing intensity (intermediate distance to the corrals) had a high supply diversity. The forest MPA, especially those with few signs of fire had a high supply diversity, while savanna MPA with many signs of fire often had a low supply diversity (Fig. 2.4).

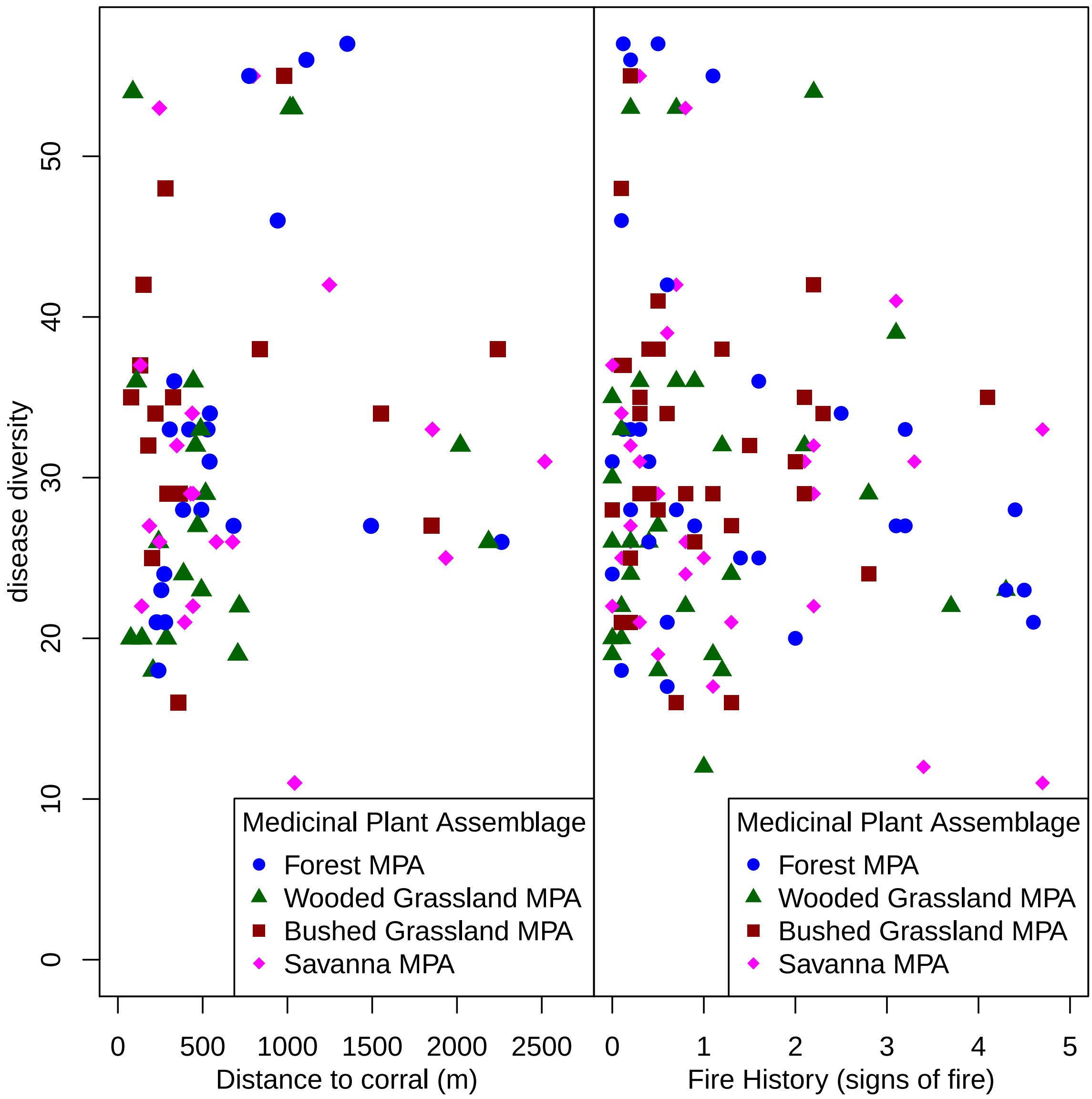


Figure 2.4.: Differences in supply diversity with regard to distance to corral (grazing intensity) and fire history.

2.3.4. Medicinal service supply pattern

Among the diseases treated by plants from the forest MPA were asthma, arthritis, colds and polio. Diseases exclusively treated by forest plants were fungal infection, acne, small pox, dwindling strength, jaundice and diarrhoea in livestock (Table 2.1).

Chest congestion was only treated by plants from the bushed grassland MPA. Other diseases included tuberculosis, pneumonia and gonorrhoea.

Burns and wounds among others were treated by plants from the wooded grassland MPA. Yellow fiver was only treated by plants in this assemblage. Constipation in children and ulcers were only treated by plants from the savanna MPA. Other diseases were tuberculosis and premature ejaculations (Table 2.1).

2.3.5. Environmental site conditions as drivers of medicinal service security

Kruskal Walis tests showed a significant difference in the supply security among the assemblages (x^2 = 45.49, df= 3, $p < 0.001$). Dunn's test identified a significant difference in the supply security among the forest and wooded grassland MPA ($p < 0.001$). The savanna MPA had the highest supply security for all diseases treated by plants growing in this formation (Table 2.1) like stomach ache, fever, wounds and eye problems. Supply security of plants used against diarrhoea and gonorrhoea was only found in this assemblage. The high supply security in the savanna MPA was driven by key species like *Aloe secundiflora* and *Balanites rotundifolia*, each used against 9 diseases and was classified as of least concern.

The forest MPA had a moderate supply security (mean redundant treatments = 3.62) (Table 2.1) and a high supply security of plants used against malaria (mean = 4.72) (Table 2.1). Supply security of plants used to treat colds, tuberculosis and tapeworms was only present in this assemblage (Table 2.1). Low supply security of plants used against stomach ache was found in this assemblage. The bushed grassland MPA had a moderate supply security as well. Medicinal plants used to treat burns were only redundant in this assemblage. *Olea africana* and *Rhus natalensis*, which were both classified as endangered were key to the supply security of the forest MPA. Both species were used to treat 8 illnesses. *Croton dichogamus*, considered as of least concern and used against 6 diseases, was the key species in the bushed grassland MPA.

A negative correlation existed between grazing pressure ($r = -0.35$, $p < 0.005$), fire, drought ($r = -0.35$, $p < 0.005$), salinity, clay fraction, pH and supply security, whereas a positive correlation existed between slope ($r = 0.33$, $p > 0.005$), sand fraction, population density and supply security (Table 2.2).

Wooded grassland MPA had the lowest supply security (Table 2.1) and a low supply security of plants used to cure malaria, wounds and fever (Table 2.1). The assemblage did not have a high supply security of plants used against any disease. Key species in this MPA were *Acacia tortilis*, used against 8 diseases, as well as *Cissus quadrangularis* which was used against 7 diseases. The species were classified as of least concern and vulnerable respectively.

The savanna MPA with low grazing intensity (close to corrals) had high supply security while there was low supply security in the wooded grassland MPA, especially those with low grazing intensity. MPA with high supply security tended to feature few signs of fire (Fig. 2.5).

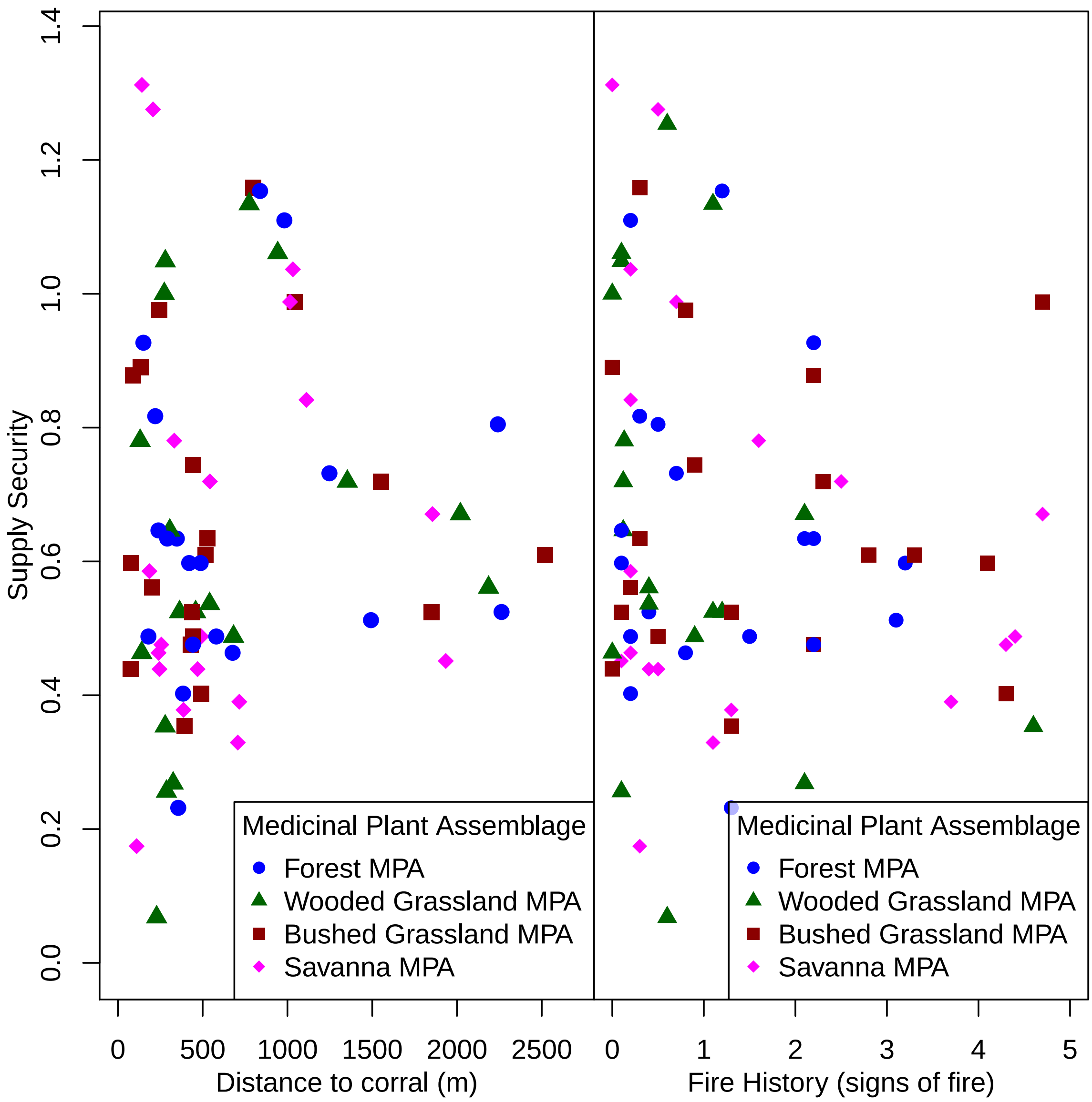


Figure 2.5.: Differences in supply security with regard to distance to corral (grazing intensity) and fire history.

2.4. Discussion

We aimed to identify the effects of environmental site conditions on the occurrence of medicinal plant species in MPA and sought to evaluate the security of medicinal service supply across MPA and individual diseases.

2.4.1. Drivers of medicinal plants co-occurrence

The RDA analysis identified the main environmental variables explaining 27% of the variation in medicinal plants co-occurrences. The following discussion will start with this explained part of variation and we will come back to the rest in the end.

The differentiation of MPA based on medicinal plants was found to be related to variation in grazing pressure, drought, slope and fraction of sand in soils. This is in agreement with results from studies on plant communities in general that have been conducted in nearby Tulu Korma, Ethiopia, (Asfaw et al., 2016) and Narok district, Kenya, (Ogutu, 1996). Here, grazing pressure and slope were reported to determine variation in overall plant community composition. All potential determinants of MPA show correlations that hamper interpretation. For example, even if difference in grazing pressure seems to be a parsimonious explanation for differences between MPA, it is itself related to environmental variables such as the occurrence of sand affecting soil drainage, absence of steep slopes, reduced precipitation and higher temperatures (Eldridge and Tozer, 1997). Most humid places (with lower temperatures and high precipitation) are found at higher elevations that also feature steep slopes and less grazing. Differences in fire history appeared to be insignificant for differences between species co-occurrences although we suspect that the methods used may not have allowed a full assessment of this factor. It would be interesting to conduct further assessment on fire history using both MODIS burned product and ground observations since the ground observations only considered the very recent fire history. Among the factors that were important in RDA (grazing pressure, drought, slope and sand fraction), we hypothesize that drought is the most important trigger as soil water clearly limits plant growth in savanna systems (Sankaran et al., 2005). Together with grazing pressure, it is a determinant of the savanna-forest gradient, which makes up much of the differences between MPA.

Soil salinity has been recorded as having a key role in explaining the distribution of plants in tropical savanna by Dharani and Yenesew (2010). This was not the case in Samburu, probably because crop cultivation, related to fertilizer use and changes in soil salinity, was not a dominant activity in the area. In this study, soil nutrients (K, N, Ca, P) were not directly investigated, but clearly, drought affects nutrients availability (Vanlauwe et al., 2015) and since drought triggered differentiation of MPA, soil nutrients may be considered as a site factor. The role of soil nutrients, as an important element in plant co-occurrence in semi-arid savanna is also described by Eldridge and Tozer (1997) and deserves further investigation.

In ordination space, savanna and wooded grassland MPA were placed in adjacent positions. This is in agreement with our observation that the assemblages were found in areas with similar environmental conditions but different land use. For other MPA, we observed that few medicinal plants were held in common, suggesting strong environmental filtering from the existing pool of medicinal plants. The occurrence of *Acacia nilotica* is associated with high grazing pressure since it protects itself from livestock using thorns and toxins, consistent with Asfaw et al. (2016).

Considering that IPCC (2014) projects that Samburu will experience increased temperatures by 15% and 8% decreased rainfall by 2050, in future, medicinal plants may be under pressure. Because drought is a leading factor for the occurrence of MPA, the mentioned changes can have detrimental effects. Plants that thrive in wetter areas are likely to decline due to reduced rainfall i.e. *Euclea divinorum*, while those that thrive in drier areas may still have a chance to shift to higher elevations i.e. *Acacia tortilis*.

In RDA we used standardized frequency or cover values since it recognizes the quantitative difference within species (Davis, 2000). RDA was helpful because it detected gradients of measured values along which medicinal plants were correlated (Oksanen, 2006). We examined the correlation structure and considered reasons external to our data set in choosing the environmental variables. Temperature, precipitation, soil moisture and drought were highly correlated with correlation > 0.87. The soil moisture was dropped due to high noise caused by weather and time of the day when it was recorded.

2.4.2. Environmental site conditions as drivers of medicinal service supply diversity

We found a significant difference in the number of diseases treated by plants from the bushed grassland, from forests and from wooded grassland MPA. This result shows that supply diversity should be taken into account when prioritizing MPA conservation. The forest MPA had the highest supply diversity, consistent with the results of a study by Gafna et al. (2017) in Samburu County which showed that the locals are dependent on forests for traditional medicine supply. According to these authors, favorable conditions like high precipitation or less pronounced drought events led to high medicinal plants diversity, resulting in high supply diversity. Controlled use of forest products by Kenya Forestry Service (Gafna et al., 2017) may have contributed to this richness. Slope gradient determines plant community structure by influencing the land-use and physicochemical soil properties. A moderate positive correlation existed between slope and supply diversity. The steep slope in the forest MPA may have contributed to the high supply diversity by discouraging locals from accessing and overexploiting medicinal plants. Many trees in this MPA besides reducing high slope erodability may also be related to reduced grazing disturbance, thereby enhancing supply diversity.

Our results show a significant positive correlation between population density and supply diversity. This could partly be caused by a correlative effect as areas with higher precipitation support a denser human population. We would rather expect that dense human population, associated with urbanization, especially in the bushed grasslands MPA, leads to loss of supply diversity, thus weakening the effect of rainfall in the statistics. Still, supply diversity in the bushed grasslands was moderate with the plants used against 65 diseases, which is similar to the number of diseases treated by plants recorded by Heine et al. (1988) in a similar grassland nearby but contrasting that recorded by Nanyingi et al. (2008) in a similar grassland in the same study area.

Despite being found in dry areas, the wooded grassland MPA still had a moderate supply diversity. This result is in agreement with Omwenga et al. (2014) who observed a similar number of diseases treated by plants in a similar grassland of our same study area. If efforts by Namunyak conservancy to establish wild nurseries in areas where this MPA occurs have led to the moderate supply diversity deserves further research.

African savannas provide many services, including firewood collection and bush food (Tsigemelak et al., 2016) but for medicinal plants, the lowest supply diversity was linked to the savanna MPA. One reason could be that medicinal plants are also highly relied upon for non-medicinal uses like firewood collection, construction of housing and bush food (Tsigemelak et al., 2016) but a more parsimonious explanation is drought as the most important driver. Priority conservation, in the savanna MPA, should be given to the medicinal plants that are used against many diseases and were classified as vulnerable like *Salvadora persica*.

Generally, we found a high supply diversity in the forest MPA especially where the intensity of grazing was moderate. This is because moderate grazing intensity within forests can help certain plants through opening up of canopy space (Kikoti and Mligo, 2015). The locals light fire during the honey harvesting process and burn pasture as they move to new areas (Gafna et al., 2017). We found a high supply diversity of plants in the forest MPA where fire intensity was low. According to Hitimana et al. (2011), low fire intensity in forests significantly increases soil fertility because it breaks down nutrients bound in dead plant tissues to forms that are easily available for plants resulting in a high medicinal plants wealth and supply diversity. Savanna MPA, especially those with many signs of fire had a low supply diversity. This is probably because in comparison to other assemblages, the fires in the savanna MPA could have been more frequent due to frequent human use of the savanna, leading to loss of many medicinal plants and low supply diversity. Detailed, larger and long-term data set will undoubtedly give more information on the impact of grazing intensity and fire on MPA.

Given the significance of drought for supply diversity, future climate change may have detrimental effects. IPCC scenarios suggest warmer temperatures and decreased rainfall by 2050 (IPCC, 2014). Therefore, some medicinal plants will shift their ranges or become extinct. This may cause shifts of MPA as well as changes in supply diversity within MPA, due to changes in MPA composition. Drought, due to climate change, will have an impact on medicinal plants co-occurrences.

2.4.3. Medicinal service supply patterns

We found most plants used against malaria and fever in the forest MPA (Bussmann, 2006). This confirms results by Hitimana et al. (2011) for the Kirisia dryland forest, in the same study area. According to Dharani and Yenesew (2010), there is a tendency of plants from the family Apocynaceae, which dominate dryland forests, to stand out in the treatment of malaria, while those from the Asteraceae family, known to dominate the highland forests, stand out in the treatment of coughs e.g. *Vernonia amygdalina*. Amuka et al. (2014) reported that coughs and pneumonia were treated by plants in nearby Mau highland forest, Kenya.

This can for example be shown for plants in the Bushed Grassland MPA that were often used against eye problems and gonorrhoea (Gafna et al., 2017). Also the finding that chest congestion was only treated by plants from this assemblage is important because chest congestion is common in the study area due to the smoky Samburu huts that have poor ventilation, with only a small door or window (Bussmann, 2006). In a similar grassland in the neighboring Nyeri County, Kamau et al. (2016) found plants to be used for the treatment of convulsions and joint pain, whereas Chalo et al. (2016) identified treatments of scabies and tonsillitis as the most prominent applications of plants from a similar grassland in the nearby Kajiado County. This difference in supply identity could be due to differences in floristic composition or due to different approaches (i.e. personal interviews versus literature study for identifying applications of individual plant species). But these discrepancies may also illustrate the importance of differences in local knowledge for the actual use of medicinal plants. When interpreting these pattern we need to keep in mind that they reflect not only biogeographic patterns but also patterns of knowledge: It is possible that we did not consider useful medicinal plants because people had no knowledge on their medicinal use.

Yellow fever was only treated by plants from wooded grassland MPA, consistent with Omwenga et al. (2014) in a similar MPA in the same study area. This is because *Kedrostis pseudogijef*, the only species used against yellow fever in the study area (Omwenga et al., 2014), thrives in gentle slopes with high temperatures which are associated with the wooded grassland MPA (Dharani, 2011). In fact Dharani and Yenesew (2010) showed that the seeds of *Kedrostis pseudogijef* rarely disperse to and germinate in other vegetation types. Considering that the species was classified as endangered, our findings reinforce the need to cultivate and prohibit excessive collection of the species.

Plants used against pneumonia and constipation in children were present in the savanna MPA. This is in contrast to surveys by Nanyingi et al. (2008) who reported plants used against dysentery and joint pain. Such differences in plant applications are likely because, unlike earlier years, species used against constipation in children and pneumonia such as *Santalum album* is presently extensively protected due in part to its use in making perfumes (Dharani and Yenesew, 2010). Plants used against ectoparasites in livestock and tuberculosis were documented for the first time in regards to the medicinal plants present in the savanna MPA, indicating that the plants used against these diseases could be endemic to the study area.

2.4.4. Environmental site conditions as drivers of medicinal supply security

In this study, species richness and not abundance was used in determining the supply security. The N+1 redundancy concept was effective in identifying diseases with functionally redundant medicinal plant species since it did not portray MPA with many sampled sites as having a high redundancy.

The savanna MPA had the highest general supply security, with a focus on plants used against fever and stomach ache. The finding that supply security of plants used against diarrhoea only existed in this assemblage is important because diarrhoea is common in the study area since the locals frequently share unclean water with wild animals and their livestock (Omori et al., 2012). Further research aimed at developing a redundancy model to test whether the high supply security in the savanna MPA is affected by the use of medicinal plants is needed.

The forest MPA had a moderate supply security and a high supply security of plants used against malaria, a major threat to the local population. The high redundancy of anti-malarial plants in this MPA may be due in part to the many occurrences of the disease around the forests, as medicinal plants redundancy correlates with disease occurrence (Albuquerque and Oliveira, 2007). The low supply security for medicinal plants used against stomach ache in this assemblage was most likely caused by logging of plants such as *Juniperus procera* that are used against stomach ache (Ngari et al., 2010). Conservation priority should therefore be given to *Juniperus procera*, since it was also classified as vulnerable. To improve the supply security in this MPA, effective conservation of vulnerable medicinal plant species in the MPA, key for the moderate supply security should be conducted i.e. *Carissa edulis* and *Olea africana*. The steep slope in the forest MPA enhanced its supply security since a weak positive correlation existed between slope and supply security. Despite this positive correlation which should have led to a high supply security in the forest MPA, deforestation in this MPA led to the moderate supply security. Hence, it is challenging for ecologists and policy makers to enhance medical supply in semi-arid areas where deforestation is still practiced. The high salinity in this assemblage may have also lowered the supply security, since a weak negative correlation existed between salinity and supply security. This suggests that curbing salinization could increase supply security.

The bushed grassland MPA had a moderate supply security and was the only MPA with supply security of plants used against burns. The weak negative correlation between grazing pressure and supply security is due to the nomadic lifestyle of the Samburu people who move to the neighboring counties in search of pasture (Bussmann, 2006). Despite the positive influence of precipitation in this MPA, the utilization of some medicinal plants used against individual diseases as livestock fodder may have led to the moderate supply security. Therefore, reduction of the grazing pressure by the local population is vital for the enhancement of medicinal supply security.

Lowest supply security was found in the wooded grassland MPA, with a low supply security of plants used against fever and wounds. According to Dharani and Yenesew (2010) communities that live in humid areas or next to forests tend to use leaves for disease treatment while those in wooded grasslands tend to use roots since plant leaves are not always available due to drought. Due to the location of the wooded grassland MPA in dry areas, it is likely that unsustainable harvesting practices such as uprooting of plants used against individual diseases led to the low supply security. Instead of digging out the main roots, sustainable harvesting in this MPA could be conducted by cutting the offshoots of the main roots to minimize the loss of medicinal plants. Gentle slope in this MPA may have also enhanced accessibility of medicinal plants used against individual diseases leading to low supply security (Kareru et al., 2006). We did not find a high supply security of plants used against any disease in the wooded grassland MPA probably due to its location in dry areas and unsustainable harvesting. This finding reinforces the need to conserve the redundant species in the MPA, especially those that are classified as vulnerable i.e. *Salvadora persica*.

A high supply security existed within the savanna MPA, especially where grazing intensity was low. Low grazing intensity within the savanna MPA allows the soil to gain nutrients which facilitates growth and regeneration of plants used against individual diseases. Conservation measures should be directed to this assemblage so as to enhance medicinal service supply, since it had the highest supply security (Kioko et al., 2012).

Climate change as suggested by current scenarios would also affect supply security due to the projected increase in temperature and decrease in precipitation by 2050. Considering the negative correlation between drought and supply security, increased drought incidences due to climate change will most likely adversely affect the wooded grassland MPA since it had a low supply security and is found in dry areas that are likely to become drier.

2.5. Conclusion

This study shows the impact of environmental conditions on medicinal plants co-occurrences, supply diversity and redundancy. Our data along with climate scenarios suggests possible future loss of medicinal plants, therefore, *exsitu* cultivation of medicinal plants (considering drought and grazing pressure) is advisable. Urgent and highest conservation priority should go toward the savanna grassland MPA that had the highest supply security for traditional medicine. There is a need to adopt sustainable medicinal plants conservation strategies which will enhance sustainable harvesting particularly in the savanna grassland. The adverse effects of climate change on supply diversity and security can be mitigated by conservation of critically endangered, endangered and vulnerable key medicinal plant species. Additionally, the vulnerability of supply security to climate change could be reduced by conservation of redundant medicinal species especially in the savanna grassland MPA. In order to reduce the severity of anthropogenic pressure on medicinal supply, we suggest that the local county government should consider the impact of anthropogenic activities on supply diversity and supply security when formulating medicinal plants management policies and legislation.

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2.6. Supplementary material

Table 2.3: Medicinal plant species list, species code name, local names, the diseases they treat and their conservation status.

Scientific Name	Species Code	Local Name	Disease	Conservation Status
Acacia mellifera	Aca.mel	Iti	malaria	Least concern
Acacia etbaica	Aca.etb	Lchakwai	stomach ache, gonorrhoea, skin diseases	Least concern
Acacia drepanolobium	Aca.dre	Rangau	retained afterbirth, gastrointestinal complications	Least concern
Acacia nilotica	Aca.nil	Ikiloriti	stomach ache, babesiosis, chest pain, pneumonia, gonorrhea, eye problem, burns, nausea	Near threatened
Acacia nubica	Aca.nub	L-depe	fever, stomach ache, diarrhoea, liver problem, hepatitis, menstruation in women	Data deficient
Acacia senegal	Aca.sen	Lterekesi	abortion, diarrhoea, stomach ache	Data deficient
Acacia tortilis	Aca.tor	L-tepes	malaria, stomach ache, fever, polio, colds, burns, malaria, polio	Least concern
Acacia xanthophloea	Aca.xan	Lerai	stomach ache, malaria	Least concern
Acokanthera oppositifolia	Aco.op	L-morijioi	arrow poison, snakebite, stomach ache, syphilis, ectoparasites	Vulnerable
Adenium obesum	Ade.ob	L-perentai	poison, ectoparasites	Least concern
Ajuga remota	Aju.re	L-menangi	retained afterbirth, gastrointestinal complications, anaplasmosis, mastitis, fever	Data deficient
Aloe secundiflora	Al.s	Sukuroi	ectoparasites, eye problem, wounds, burns, tuberculosis, fever, lumbago, sterility, sore throat	Vulnerable
Albizia gummifera	Alb.gu	Lese	strength	Least concern
Balanites aegyptiaca	Bal.aeg	Lowaai	wounds, burns, malaria, bilharzia, chest congestion, bronchitis, pneumonia, snakebite, eye problem	Least concern
Balanites rotundifolia	Bal.rot	Sorai	eye problem, stomach ache, tonic in children, sore throat, joint pains, skin rashes, retained afterbirth, anthrax, gum pain	Vulnerable

Continued on next page

Table 2.3: Medicinal plant species list, species code name, local names, the diseases they treat and their conservation status. (Continued)

Barleria spinisepala	Bar.sp	Sucha	polio, fever, constipation in children	Vulnerable
Boscia angustifolia	Bos.ang	Lororai	malaria, diarrhoea, gonorrhea, stomach ache	Data deficient
Boscia coriacea	Bos.cor	Serijioi	malaria, burns, stomach ache, gonorrhoea	Vulnerable
Cadaba farinosa	Cad.far	Larasoro	fever, gonorrhoea	Vulnerable
Capparis elaegnoides	Cap.e	Larurdei	wounds, burns	Near threatened
Carissa edulis	Car.ed	Lamuriei	polio, gonorrhoea, collibacillos, tuberculosis, malaria, gastrointestinal complications, diarrhoea, heart water	Vulnerable
Cissus rutundifolia	Cis.rut	Raraitit	stomach ache	Vulnerable
Cissus quadrangularis	Cis.qua	Sukurtuti	wounds, fever, diarrhoea, ulcers, neurosis, asthma, liver problem	Vulnerable
Clerodendrum myricoides	Cle.my	Lmak	gastrointestinal complications, lumbago, headache, diarrhoea, polio, sexually transmitted infections, chest pain	Near threatened
Commelina imberbis	Com.im	N-kaiteteyyai	child cough	Least concern
Commiphora africana	Com.af	Lchen	diarrhoea, tooth ache, stomach ache in children, eye problem, gum pain, wounds	Least concern
Cordia monoica	Cor.m	Seki	diarrhoea, retained after birth, wounds	Vulnerable
Croton dichogamus	Cro.dic	Lakir	malaria, chest pain, coughs, chest congestion, fever, stomach ache	Least concern
Croton megalocarpus	Cro.m	Lmargwet	malaria,fever, tapeworms, chest pain, stomach ache, throat infection, coughs, cold	Least concern
Cyphostemma adenocaule	Cyp.ad	Lordo	tuberculosis, arthritis, sterility	Vulnerable
Cyphostemma serpens	Cyp.ser	Wanto	gonorrhea, syphilis, tonic in children	Near threatened
Dodonea angustifolia	Dod.an	Saramunai	stomach ache	Endangered
Ekebergia capensis	Eke.ca	Lmin	diarrhoea in livestock, tapeworms in livestock, common cold	Vulnerable
Enteropogon macrostachyus	Ent.mac	Lkujitaongo	trypanosomiasis in livestock	Endangered

Continued on next page

Table 2.3: Medicinal plant species list, species code name, local names, the diseases they treat and their conservation status. (Continued)

Euclea divinorum	Euc.div	Lchingei	malaria, fever	Vulnerable
Euphorbia candelabrum	Eup.can	Mpopongl	respiratory track infection, gastrointestinal complications	Least concern
Euphorbia heterochroma	Eup.h	Lpara	malaria, gonorrhea, wounds	Critically endangered
Euphorbia tirucalli	Eup.tir	Loile	sore throat, stomach ache,	Least concern
Flueggea virosa	Flu.v	Letomia	common cold	Vulnerable
Fuerstia africana	Fue.a	Lkaria le muny	eye problem	Endangered
Gardenia jovis-tonantis	Gar.to	Lmur	malaria	Vulnerable
Gloriosa superba	Glo.su	Lerubat	joint pains	Vulnerable
Grewia tembensis	Gre.tem	Irii	skull fissures	Vulnerable
Gutenbergia cordifolia	Gut.co	Lodw	ticks, giardiasis	Endangered
Heliotropium steudneri	Hel.st	Lmasikirai	fleas	Data deficient
Hilderbrantia sepalosa	Hil.sep	Nyirman	retained afterbirth, gastrointestinal complications	Vulnerable
Ipomoea spathulata	Ipo.sp	Lokitengi	eye problem	Data deficient
Juniperus procera	Jun.pr	L-tarakwai	sore throat, stomach ache, tape worms	Vulnerable
Kedrostis pseudogijef	Ked.ps	Saku	malaria, stomach ache, diarrhoea, yellow fever	Endangered
Lippia javanica	Lip.ja	Sinoni	measles in children, malaria, nasal congestion	Vulnerable
Lippia kituiensis	Lip.kit	Sunoni	wounds, coughs	Vulnerable
Lycium europaeum	Lyc.eur	Lokii	malaria, rheumatism, swelling of breasts	Vulnerable
Maerua triphylla	Mae.tri	Loitaakine	wounds, headache, snakebite, burns	Data deficient

Continued on next page

Table 2.3: Medicinal plant species list, species code name, local names, the diseases they treat and their conservation status. (Continued)

Maytenus heterophylla	May.h	Ika	poor appetite	Data deficient
Myrsine africana	Myr.af	Seketet	malaria, wounds, tuberculosis, gastrointestinal complications, tapeworms	Near threatened
Ocimum basilicum	Oci.ba	Nketurai	retained afterbirth in livestock	Critically endangered
Olea africana	Ole.afr	Lgeriyoi	helmithosis, asthma, tapeworms, lumbago, rheumatism, skin rashes, diarrhoea, fever	Endangered
Olinia rochetiama	Oli.roc	Lkireny	malaria	Vulnerable
Osyris abyssinica	Osy.aby	Loisesyai	swollen breasts, diarrhoea	Data deficient
Pentarrhinum inspidum	Pen.ins	Lkisuchie	anaplasmosis	Vulnerable
Plectranthus igniarius	Ple.ign	saali	stomach ache, bleeding stomach	Endangered
Podocarpus falcatus	Pod.falc	Masa	measles in children	Least concern
Prunus africana	Pru.afr	Nkaibilish	acheing joints, umbical cord healing	Vulnerable
Psiadia punctulata	Psi.pu	Laabai	burns, ectoparasites, abdominal pain, cold	Endangered
Rhamnus stado	Rha.st	L-kukulai	polio, malaria, common cold, gonorrhea	Near threatened
Rhus natalensis	Rhu.na	L-misigyo	malaria, fevers, tuberculosis, stomach ache in children, diarrhoea, coughs, wounds, tuberculosis	Endangered
Salvadora persica	Sal.per	Sekotei	retained afterbirth, ulcers, seizures, anthrax, trypanosomisis, malaria, brucellosis, stomach ache	Vulnerable
Scutia myrtina	Scu.myr	Sananguri	retained afterbirth, body ache, ring worms	Vulnerable
Senna didymobotrya	Sen.di	Senetoi	malaria, fever, gonorrhoea, measles	Least concern
Sericocompsis pallida	Ser.pal	L-turkan	stomach ache	Near threatened
Solanum incanum	Sol.in	L-tulelei	sore throat, diarrhoea, fever, malaria, polio, stomach ache, ectoparasites, snakebite, wounds	Least concern

Continued on next page

Table 2.3: Medicinal plant species list, species code name, local names, the diseases they treat and their conservation status. (Continued)

Solanum renschii	Sol.re	N-aiba layyok	stomach ache	Least concern
Teclea simplicifolia	Tec.sim	Lgelai	cerebral malaria, fever, diarrhoea, clensing of blood	Vulnerable
Tinnea aethiopica	Tin.aet	Lokildia	eye infection, small pox	Endangered
Zanthoxylum usambarense	Zan.usa	Loisuk	retained afterbirth, malaria, malignant	Near threatened
Viscum tuberculatam	Vis.tub	Laru	retained afterbirth	Least concern
Ximenia caffra	Xim.ca	Ledat	respiratory track infection, stomach ache	Near threatened

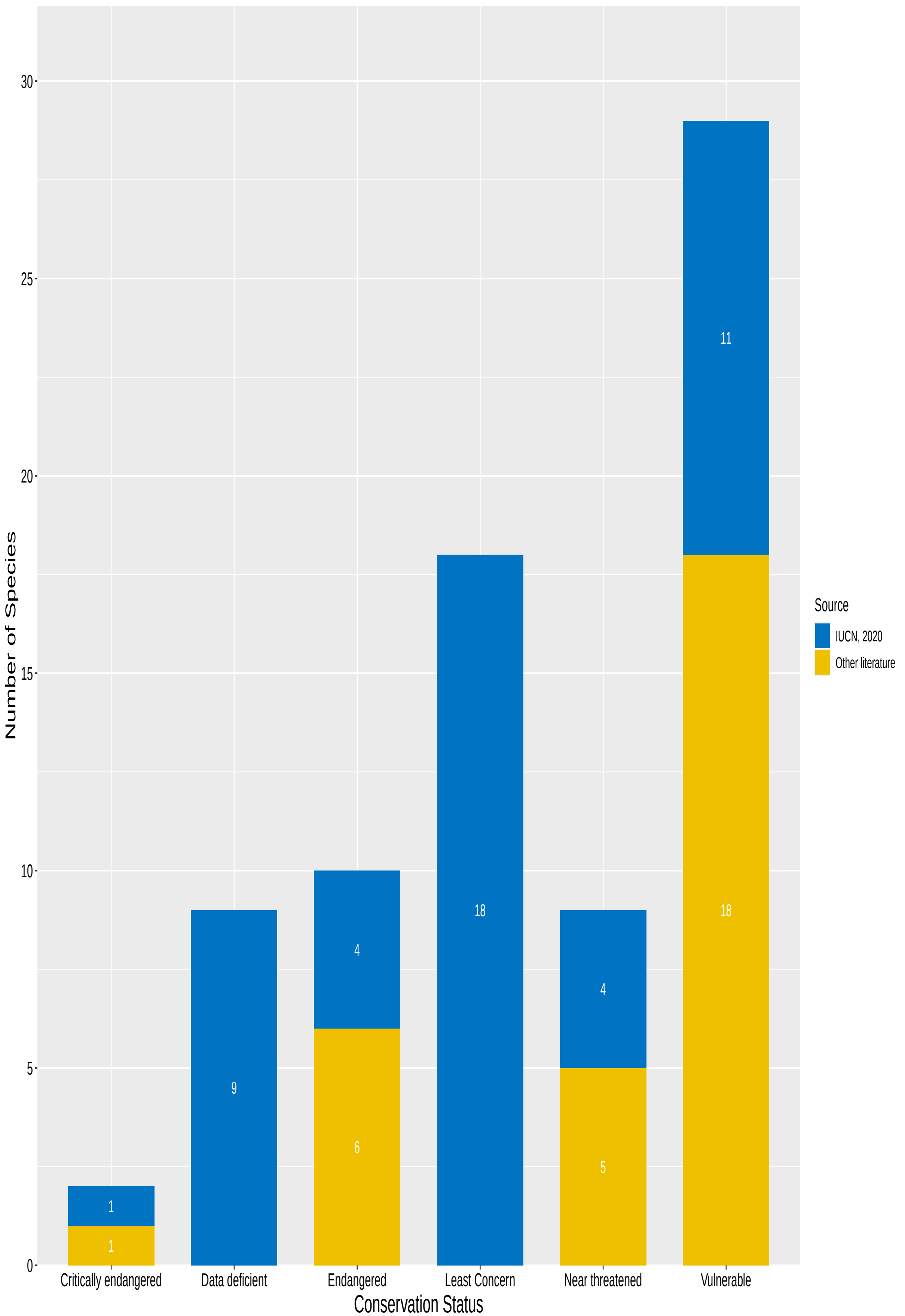

Figure 2.6.: Stacked barplot showing the conservation status of medicinal plant species as reported by IUCN and other literature sources.

Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 *

Medicinal Plant Assemblage with number of sites	Characteristic Species	Value	Other Species	Value
Bushed Grassland MPA (42 sites)	*Croton dichogamus*	98***	*Solonum incanum*	93*
	Psiadia punctulata	96***	*Aloe secundiflora*	52
	Euphorbia candelabrum	66***	*Akokanthera oppositifolia*	59***
	Cyphostemma adenocaule	52***	*Lippia javanica*	44
	Acacia drepanolobium	41***	*Cyphostemma serpens*	50**
	Fuerstia africana	36***	*Pronus africana*	39**
			Ximenia caffra	23
			Acacia tortilis	16***
			Acacia nilotica	36
			Olea africana	18*
			Myrsine africana	0*
			Acacia mellifera	0***
			Rhus natalensis	20
			Ipomoea spathulata	14
			Euphorbia tirucalli	16
			Juniperus procera	30
			Comiphora africana	2***
			Teclea simplicifolia	14
			Podocarpus falcatus	7
			Solonum incanum	93***
			Adenium obesum	5*
			Cissus quadrangularis	0***
			Balanites rotundifolia	0***
			Acacia etbaica	9*
			Tinnea aethiopica	0**
			Ekebergia capensis	0*
			Ajuga remota	7
			Croton megalocarpus	25*

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Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

			Viscum tuberculatam	27
			Cordia monoica	23
			Salvadora persica	40***
			Cordia monoica	23
			Croton megalocarpus	25*
			Clerodendrum myricoides	14
			Balanites aegyptiaca	11
			Viscum tuberculatam	27
			Acacia nilotica	36
			Cyphostemma serpens	50***
			Euclea divinorum	43
			Grewia tembensis	7**
			Cissus rutundifolia	0*
			Comiphora africana	2***
			Barleria spinisepala	2***
			Commelina imberbis	0***
			Acacia nubica	2*
			Sericocompsis pallida	0**
			Scutia myrtina	0**
			Rhamnus stado	7*
			Maytenus heterophylla	5*
			Lippia Kituiensis	30
			Clerodendrum myricoides	14
Forest MPA (26 sites)	*Olea africana*	98***	*Croton dichogamus*	38**
	Ximenia caffra	90***	*Psiadia punctulata*	85***
	Lippia javanica	83***	*Euphorbia candelabrum*	3***
	Rhus natalensis	83***	*Cyphostemma adenocaule*	18

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Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

		Juniperus procera	79***	*Acacia drepanolobium*	9
		Teclea simplicifolia	76***	*Sericocompsis pallida*	0*
		Maytenus heterophylla	62***	*Acacia tortilis*	0***
		Plectranthus igniarius	59***	*Scutia myrtina*	38***
		Myrsine africana	55***	*Acacia nubica*	0*
		Rhamnus stado	55***	*Euphorbia tirucalli*	6*
		Tinnea aethiopica	41***	*Cissus rutundifolia*	0*
		Solanum renschii	28***	*Comiphora africana*	0***
		Ekebergia capensis	34***	*Cadaba farinosa*	0*
		Podocarpus falcatus	35***	*Plectranthus igniarius*	53***
		Lippia kituiensis	71***	*Maerua triphylla*	6
				Prunus africana	32
				Ajuga remota	24***
				Viscum tuberculatam	50***
				Grewia tembensis	24
				Cordia monoica	0***
				Salvadora persica	40***
				Croton megalocarpus	21
				Clerodendrum myricoides	29*
				Balanites aegyptiaca	0***
				Acacia nilotica	6***
				Cyphostemma serpens	47*
				Akokanthera oppositifolia	50*
				Euclea divinorum	68***
				Balanites rotundifolia	0**
				Comiphora africana	0***

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Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

			Acacia etbaica	0***
			Barleria spinisepala	0***
			Ipomoea spathulata	0***
			Commelina imberbis	0**
			Acacia mellifera	0***
			Aloe secundiflora	24***
Savanna MPA (32 sites)	*Gardenia jovis-tonantis*	32***	*Euphorbia cande-labrum*	20
	Acacia tortilis	46***	*Croton dichogamus*	72
	Ipomoea spathulata	76***	*Acacia drepanolo-bium*	0*
	Commiphora africana	64***	*Cyphostemma adenocaule*	0**
	Acacia mellifera	81***	*Myrsine africana*	12
	Barleria spinisepala	74***	*Scutia myrtina*	0
	Euphorbia tirucalli	52***	*Acacia tortilis*	96***
	Acacia etbaica	56***	*Acacia nubica*	8
	Balanites rotundifo-lia	83***	*Podocarpus falcatus*	4
	Gardenia jovis-tonantis	32***	*Solonum incanum*	92
	Commelina imberbis	76***	*Euclea divinorum*	8***
	Adenium obesum	48***	*Carissa edulis*	0**
	Aloe secundiflora	96***	*Akokanthera opposi-tifolia*	0***
	Cissus quadrangu-laris	44***	*Ajuga remota*	0*
	Grewia tembensis	56***	*Juniperus procera*	28
	Cissus rutundifolia	56***	*Lippia kituiensis*	0***
	Cadaba farinosa	44***	*Plectranthus igniar-ius*	16
	Hilderbrantia sepa-losa	22***	*Viscum tubercu-latam*	20
	Heliotropium steud-neri	22***	*Sericocompsis pall-ida*	0
	Salvadora persica	40***	*Tinnea aethiopica*	0
			Euclea divinorum	8***

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Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

			Acacia nilotica	32
			Cyphostemma serpens	0***
			Croton megalocarpus	4
			Ekebergia capensis	0
			Euphorbia heterochroma	24**
			Maytenus heterophylla	0
			Cordia monoica	16
			Clerodendrum myricoides	4
			Balanites aegyptiaca	36
			Lippia javanica	20*
			Myrsine africana	12
			Plectranthus igniarius	16
			Grewia tembensis	56***
			Rhamnus stado	0**
			Olea africana	0***
			Psiadia punctulata	8***
Wooded Grassland MPA (30 sites)	*Acacia nubica*	44***	*Euphorbia candelabrum*	22
	Sericocompsis pallida	64***	*Croton dichogamus*	15***
	Acacia tortilis	100***	*Psiadia punctulata*	22***
	Cissus quadrangularis	76***	*Cyphostemma adenocaule*	0***
			Acacia drepanolobium	0**
			Teclea simplicifolia	4
			Rhamnus stado	7
			Aloe secundiflora	63
			Euclea divinorum	11**
			Acacia nilotica	41

Continued on next page

Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

Gutenbergia cordifolia	11
Euphorbia heterochroma	4
Prunus africana	0**
Acacia nilotica	41
Croton megalocarpus	0*
Viscum tuberculatam	0**
Tinnea aethiopica	0
Carissa edulis	0**
Cyphostemma serpens	0***
Croton megalocarpus	0*
Ipomoea spathulata	26
Lippia javanica	0***
Euphorbia tirucalli	0**
Plectranthus igniarius	7*
Podocarpus falcatus	0*
Cadaba farinosa	30*
Commelina imberbis	0*
Ekebergia capensis	0
Euphorbia heterochroma	24**
Salvadora persica	40***
Grewia tembensis	0**
Cissus rutundifolia	4
Balanites rotundifolia	19
Cordia monoica	19
Clerodendrum myricoides	11
Balanites aegyptiaca	48***

Continued on next page

Table 2.4: Isopam classification results showing medicinal plant species occurrence per medicinal plant assemblage (%). Significance codes: < 0.0001 ***, < 0.001 **, <0.01 * (Continued)

Akokanthera oppositifolia	0***
Comiphora africana	56***
Acacia mellifera	0**
Ajuga remota	0
Scutia myrtina	0
Maytenus heterophylla	4
Lippia kituiensis	0***
Olea africana	0***
Acacia etbaica	22
Barleria spinisepala	11
Myrsine africana	11

Table 2.5.: Results of redundancy analysis (RDA), showing the eigenvalues and proportions of explained variation by the first two RDA axes. Also shown is the correlation between environmental variables and the axes.

Variable	**RDA Axis 1**	**RDA Axis 2**
Eigenvalues	6,8	2,9
Percentage of explained variance	12	5
Percentage of cumulative variance	12	17
Correlations of the environmental variables		
Salinity	-0,12585	0,113505
pH	0,09133	0,039157
Slope	-0,72179	-0,198903
Cover of dead matter	-0,22604	0,138362
Grazing pressure	0,73856	-0,638746
Clay	-0,36218	-0,058335
Sand	0,35948	0,003644
Drought	0,7256	0,524772
Aspect	0,05057	0,031082
Fire history	-0,02581	-0,217025
Grazing intensity	0,09331	0,163538
Population density	0,03559	-0,024581

Table 2.6: Results of the environmental fit on RDA axes 1 and 2 with 999 permutations. Significance levels: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1.

Site Parameter	RDA1	RDA2	r2	Pr(r)
Salinity	-0.78	0.63	0.02	0.26
pH	0.96	0.28	0.01	0.67
Slope	-0.99	-0.12	0.37	0.001 ***
Cover of dead matter	-0.86	0.5	0.05	0.032 *
Grazing pressure	0.8	-0.6	0.71	0.001 ***
Clay	-1	-0.02	0.09	0.001 ***
Sand	0.99	-0.11	0.09	3/1/00
Drought	0.88	0.47	0.48	0.001 ***
Exposition_rad	0.93	0.38	0	0.87
Fire history	-0.61	-0.79	0.02	0.21
Grazing intensity	0.53	0.85	0.02	0.24
Population density	0.78	-0.62	0	0.89

3. Climate Change Impacts on the Availability of Anti-malarial Plants in Kenya

Dikko Jeff Gafna, Joy A. Obando, Jesse M. Kalwij, Klara Dolos, Sebastian Schmidtlein

Abstract

In many rural East African areas, anti-malarial plants are commonly used as first-line treatment against malaria. Efficient conservation planning supporting the availability of such plants requires a sound understanding of the current and future intersections between their distributions and that of malaria itself. In this study we 1) model the distribution of anti-malarial plant and malaria vector species and assess the drivers of their distributions taking the example of the Samburu dryland in Kenya, 2) map the modeled overlap in this area, 3) assess the impact of future climate change on anti-malarial plant and malaria vector species and 4) report their future overlaps. Our results show that mean temperature of warmest quarter, precipitation of wettest quarter and mean temperature of coldest quarter were the most important environmental variables that affected the distribution of anti-malarial species. The effects of climate change will be detrimental, since most areas will witness huge losses in anti-malarial species suitable habitat while only a few gained or remained stable under both SSP2-4.5 and SSP5-8.5 climate change scenarios by 2050s and 2070s. According to most of our scenarios, more than half of the anti-malarial species will become threatened by 2050s and 2070s. A comparison between distribution patterns of future anti-malarial species richness and malaria vector species suitable habitat suggests that the former will decrease considerably while the later will increase. Because the availability of anti-malarial species will decrease in the areas affected by malaria vectors, geographically targeted conservation strategies and further control measures against malaria vectors are all the more important.

3.1. Introduction

A world free of malaria is a common vision for the health community worldwide (Ryan et al., 2020). In 2015, the World Health Organization developed the Global Technical Strategy for malaria, which announced the target of lowering global malaria incidences by at least 90% by 2030 (WHO, 2015). Earlier initiatives such as the Roll Back Malaria program (Nabarro, 1999) and Bill and Melinda Gates Malaria Foundation (McCoy et al., 2009) also seek to eradicate the disease. Backed by these initiatives, many countries developed their own malaria control programs which resulted in only a slight decrease in malaria infections (Kimuyu et al., 2017), due in part to the spread of drug-resistant malaria strains and declining efficacy of the cheapest and most widely used anti-malarial drugs (Nabarro, 1999). Therefore, innovative strategies to fight the disease need to be urgently formulated (Acheson et al., 2015). With the growing unavailability of conventional anti-malarial drugs and the discovery that combining anti-malarial drugs with anti-malarial plant species lowers the treatment failure risk (Dharani and Yenesew, 2010), many traditional healers; even medical practitioners prescribe the use of anti-malarial species to treat malaria (Dharani et al., 2010). Apart from the direct use of the wild anti-malarial species, they also provide a broad reservoir upon which potential conventional anti-malarial drugs can be developed (Malahlela et al., 2019). Consequently, their conservation could benefit populations that rely on them and guide the discovery of new generation conventional anti-malarial drugs (Dharani et al., 2010).

In Kenya, around 80% of the population (especially rural communities) still rely on anti-malarial plant species to fight malaria (Mukungu et al., 2016). This has been attributed to cultural acceptability of traditional anti-malarial herbs, inaccessibility of modern healthcare centers and high cost of conventional anti-malarial drugs (Dharani et al., 2010; Omara, 2020). Plant species in Kenya used for malaria control are either orally consumed Omara (2020) or used as mosquito repellents (Seyoum et al., 2002). Communities in the country use different plant parts from *Ajuga remota*, *Harrisonia abyssinica*, *Carissa edulis* and *Azadirachta indica* to treat malaria (Mukungu et al., 2016; Omara, 2020). Screening of the pharmacological action of some of the plant parts of these species found that the root back extracts of *Harrisonia abyssinica* (Kirira et al., 2006), *Carissa edulis* (Koch et al., 2005), and whole herb of *Ajuga remota* (Kuria et al., 2001) are highly effective in malaria treatment because they have high *in vitro* antiplasmodial activity. However, leaves of *Azadirachta indica* are less effective due to their low *in vitro* antiplasmodial property based on studies carried out by Kirira et al. (2006). Consequently, different anti-malarial species are prescribed for malaria treatment depending on the severity of the illness, with the dosage varying depending on the age of the patient (Omara, 2020). Some anti-malarial species such as *Azadirachta indica* and *Caesalpinia volkensii* are singly consumed to treat malaria (Kuria et al., 2001). However, others like *Ajuga remota* (Kuria et al., 2001) and *Cassia didymobotrya* (Kokwaro, 2009) are used in combination with other anti-malarial species; probably to mask their bitter taste (Kuria et al., 2001) or due to the synergistic effect of many compounds that make them only fully active when administered in combinations (Gessler et al., 1994). Whereas most anti-malarial species are consumed, a few are used as mosquito repellents (Omara, 2020). For instance, smoke from burnt leaves of *Corymbia citriodora* is highly effective in keeping away mosquitoes (Seyoum et al., 2002). Apart from their use in malaria control, most anti-malarial species are also used in the management of other diseases (Omara, 2020). In spite of these promising prospects for anti-malarial species in Kenya, overexploitation for medicinal use, trade, and deforestation continue to pose a threat to their population (Dharani et al., 2010).

Because of the importance of anti-malarial species, knowledge on their spatial distribution is crucial. For most anti-malarial plant species, however, there is insufficient information on their distribution (Malahlela et al., 2019). A crucial starting point for the future monitoring and conservation of these species would be to improve knowledge about their ecological requirements and future distribution. This may help conservationists to identify conservation priority areas (Kaky and Gilbert, 2016) or suitable areas for cultivation (Zhao et al., 2021). Consensus has been reached among conservationists that protected areas enhance *in situ* conservation of plant biodiversity (Kaky and Gilbert, 2017). Therefore, one approach to *in situ* conservation of the anti-malarial plant species could be based on planning of the "best" locations of protected areas, depending on a regions distribution of the species, shifts in the species distribution under changing climate and other disturbance factors (Kaky and Gilbert, 2016). However, anti-malarial species distribution maps considering the location of protected areas or their effectiveness in conserving anti-malarial species are still unavailable (Kaky and Gilbert, 2016), even in resource limited African countries where malaria is among the leading causes of death.

With limited resources to combat this disease, policy makers must target and time preventive interventions appropriately to maximize their effectiveness (Ryan et al., 2020). This requires accurate identification of regions that are most vulnerable to malaria and timely delivery of interventions to mitigate and prevent the disease in these regions (Kulkarni et al., 2010), but most models lack accurate identification of malaria vulnerability areas. Malaria is caused by the spread of the *Plasmodium* parasite to people through bites of infected *Anopheles* mosquitoes. The potential threat of malaria distribution can be assessed by predicting the distribution of malaria vectors (Acheson et al., 2015). Earlier studies modelled malaria vectors distribution at regional scale (e.g., West Africa; Kleinschmidt et al., 2001) or national level (e.g. Kenya; Kimuyu et al., 2017). Worrisomely, recent malaria vectors distribution maps depict their spatial expansion (KMS, 2019). This fact presents an evolving and fresh threat for malaria control initiatives. Despite this threat, health organizations continue to rely merely on national and regional malaria distribution maps to target anti-malarial resources (Acheson et al., 2015). Such malaria risk maps are of limited practical use for guiding intervention efforts since they do not consider the local overlap between malaria vectors and anti-malarial plant species distributions, which is critical in directing the malaria control and anti-malarial species conservation measures appropriately.

To design future malarial control and anti-malarial species conservation measures, knowledge on the impact of climate change is crucial. With unprecedented rate of climate warming due to human activities, climate change has already reshaped species distributions, including malaria vectors and their associated parasites (Kimuyu et al., 2017). This has raised great concern about the potential availability of anti-malarial plant species (Dharani et al., 2010) and the ramifications of changing climate on future malaria risk (Tonnang et al., 2010). Drylands as water-limited environments are considered to be most prone to the effects of climate change (Ryan and Elsner, 2016). Global drylands have experienced warming at the rate of 0.06°C/year, as compared to the global warming rate of 0.03°C/year in the past two decades (Ryan and Elsner, 2016). Consequently, dryland species have shifted their geographical ranges or become extinct (Mariem and Chaieb, 2017). Previous studies documented possible shifts and extinction of medicinal plants (Mariem and Chaieb, 2017), and re-distribution of malaria vectors (Kimuyu et al., 2017) due to climate warming in African drylands. However, spatially explicit information about the future availability of anti-malarial species and its relation to future suitable habitat for malaria vectors is needed for targeted conservation and management actions. Because this information is largely missing (Malahlela et al., 2019), this paper aims at providing it.

In this study, to improve the knowledge base for planning of anti-malarial plants recovery programs and malaria control actions, we address the following key questions: (1) What is the geographic distribution of anti-malarial plant species and malaria vector species and what are the main drivers of their distributions? 2) What is the modeled overlap? 3) What is the impact of climate change on anti-malarial plant species and on malaria vector species? 4) What is their future overlap in the Samburu dryland, Kenya? We selected Samburu dryland in Kenya as our study area as it has a high malaria burden (Kimuyu et al., 2017). Although the region is a stronghold for anti-malarial plants (Gafna et al., 2021) and has been the focus of medicinal plants research in the past few decades (Nanyingi et al., 2008), there is still an apparent lack of information regarding the distribution of both anti-malarial species and malaria vectors. This has hindered malaria control initiatives and efforts to conserve anti-malarial species.

3.2. Material and methods

3.2.1. Study area

Samburu County extends over a 20,183 km^2 area of the Rift Valley from approximately 0.5°N to 3°N and 36.3°E to 38.1°W (Fig. 3.1). In 2019, the region was home to 310,327 people, with a density of 11 people/km^2 (KNBS, 2019). It has an arid and semi-arid climate and receives an annual rainfall of 694 mm which is clearly delineated bimodally from October to November (short rain) and March to April (long rain) (Fig. 3.2). The dry season extends from December to March and June to September. The region experiences a mean annual temperature of 22.6°C which varies spatiotemporally depending on elevation. Elevation of the area ranges from 339 to 2795 m a.s.l. The county's vegetation is characterized by shrubs, forests, wooded grassland and savanna (Gafna et al., 2021). The distribution of these vegetation types follows variations in altitude, geological and climatic conditions. The area has two protected areas: Maralal Sanctuary and Samburu National Reserve.

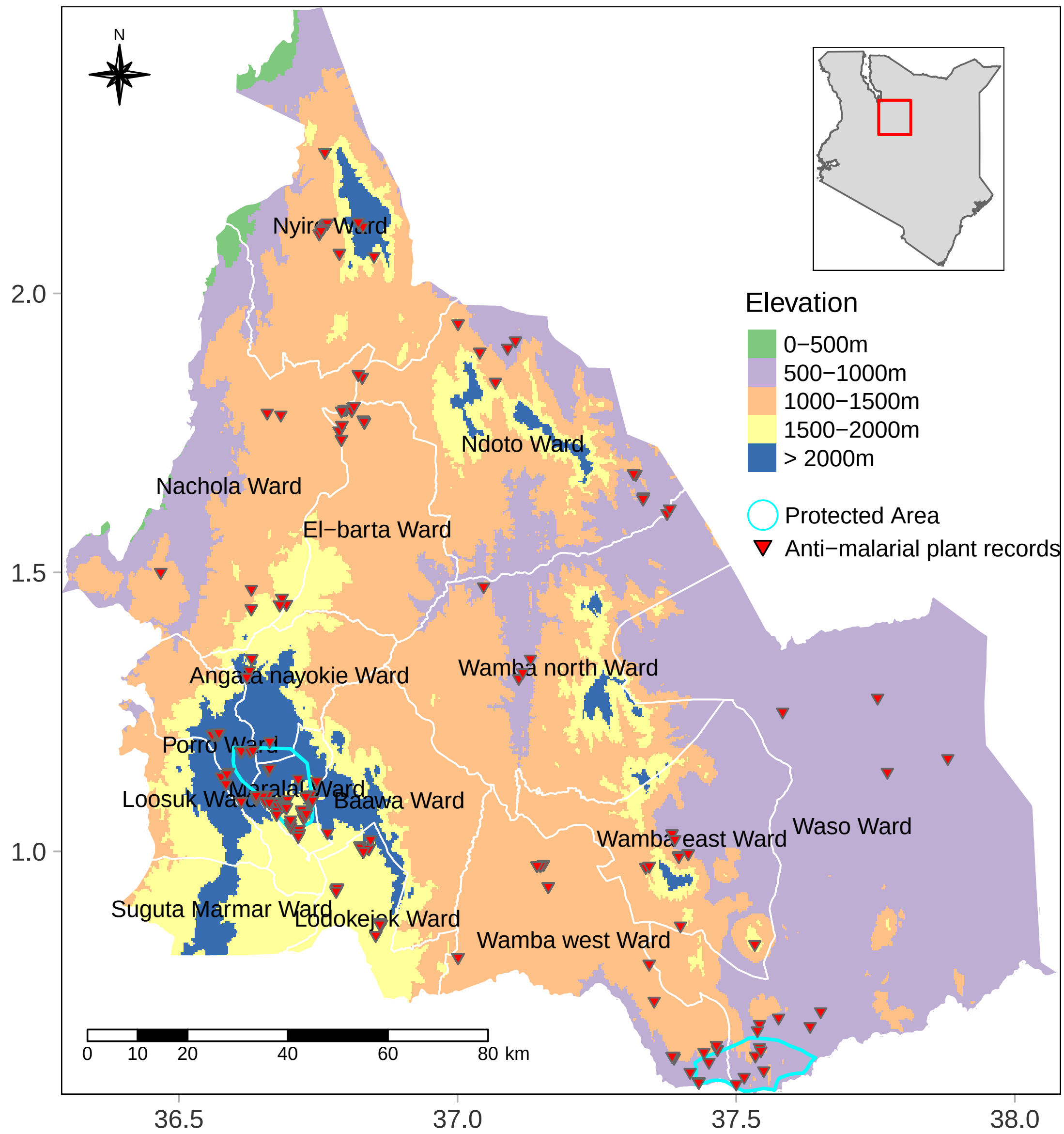

Figure 3.1.: Map of Kenya showing the location of our study area. Map of Samburu County showing the 15 administrative wards, elevation, protected areas and distribution records of all anti-malarial plants recorded during the field survey.

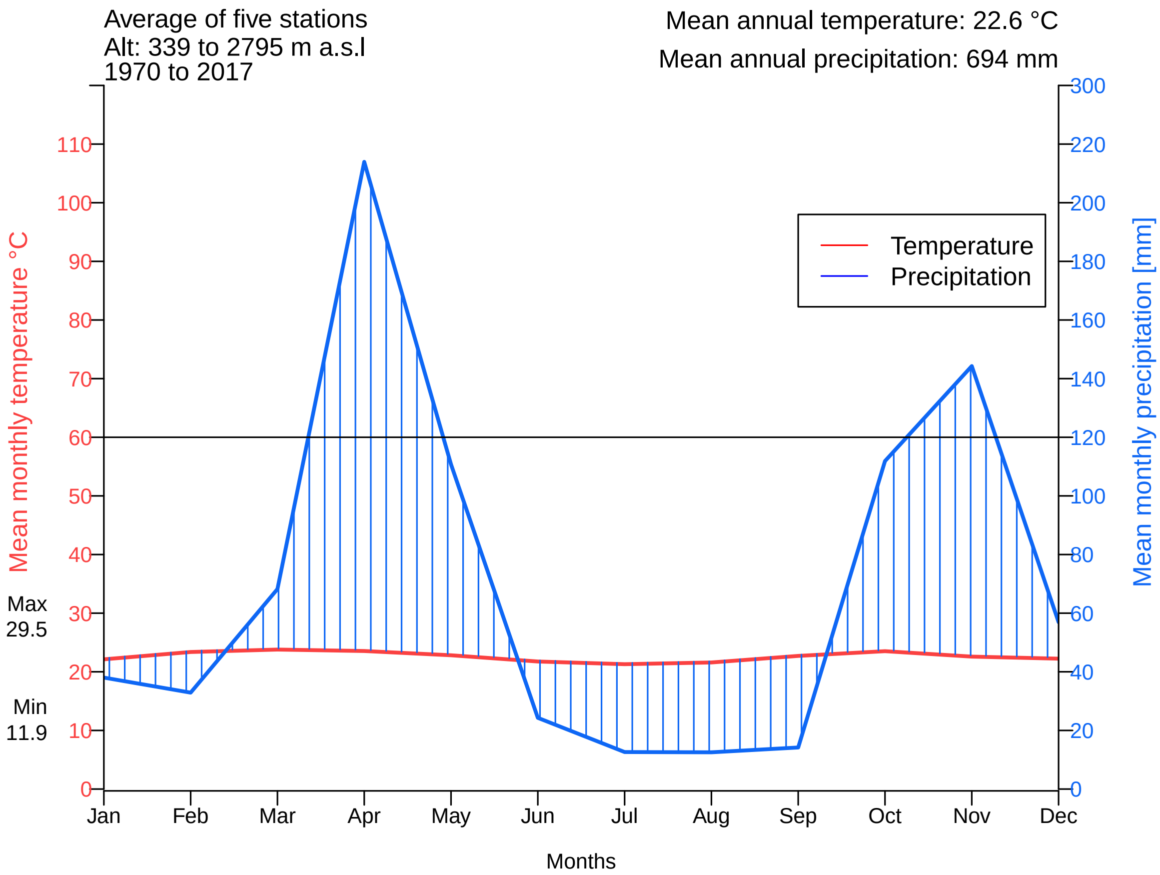

Figure 3.2.: Climate diagram of Samburu County according to Walter and Lieth (1980), based on Climatic Research Unit Gridded Time Series data (Harris et al., 2020). The blue shaded-area that overcuts the red line indicates the rainy season while the blue-shaded area that undercuts the red line indicates the dry season.

3.2.2. Occurrence data

Distribution records for all anti-malarial plant species used by the locals in Samburu County were collected from Global Biodiversity Information Facility (GBIF.org, 2019), and supplemented with records from the East Africa Herbarium (EA) and our field survey data. During our field survey, we visited 90 sites selected by random stratified sampling based on soil type (Dewitte et al., 2013), protected area status (KWS, 2010) and land cover type (Anderson et al., 1976), and recorded all anti-malarial plant species in 80 × 80 m plots (supplementary material Table 3.2). Stratification was based on land cover and soil type because they are thought to affect plant distribution in Samburu (GOK, 2016), which would help to cover the full environmental space that can be occupied by the anti-malarial species (Gaikwad et al., 2011). In addition, protected area status was used for stratification so as to capture sites inside and outside the protected areas (Gray et al., 2016).

The malaria vector species data were obtained from the MARA/AMRA database (MARA/ARMA, 1996), Global Biodiversity Information Facility (GBIF.org, 2019), contacts with local malariologists and recent scientific publications (Kimuyu et al., 2017). These data consisted of geographically referenced locations of the three main malaria vector species in Africa: *Anopheles arabiensis*, *Anopheles gambiae* and *Anopheles funestus* (Tonnang et al., 2010) surveyed from 1996 to 2017.

We removed duplicated or poorly georeferenced observations (i.e. those found in areas where plant species are not normally found such water bodies) before the analysis. To reduce spatial-autocorrelation in our occurrence records, we used the spThin package in the R language environment (Aiello-Lammens et al., 2015) to spatially thin each species' records to a distance of 3 km, which is a value bigger than the grid cell size of our variables (Zhao, Deng, Xiang, Chen,, and Ouyang, 2021). Thereafter, only species with more than 30 occurrence records were considered to ensure accurate predictions (Wisz et al., 2008). We therefore ended up with 21 anti-malarial plant species and three malaria vector species.

3.2.3. Environmental variables

We used 19 bioclim variables from the WorldClim database version 2.1 (in 30 arc-second resolution) as candidate predictors (Table 3.1 (Fick and Hijmans, 2017); http://www.worldclim.org, accessed on 10th August 2022). This data layers are derived from monthly rainfall and temperature recordings from weather stations worldwide (1950-2000) and have proven to support informative models of plant and invertebrate distributions due to close association with growth and development (Yang et al., 2013; Kimuyu et al., 2017). In addition to the bioclim variables, we used Digital Elevation Model (DEM) downloaded from Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007), sand, clay and soil pH data downloaded from the Google Earth Engine (GE; Gorelick et al., 2017) platform for modeling the anti-malarial species. We also supplemented the bioclim variables with gridded human density population data (Lloyd et al., 2017), Digital Elevation Model (DEM) (Farr et al., 2007) and NDVI calculated from sentinel 2 image acquired from Google Earth Engine (GE; Gorelick et al., 2017) for modeling malaria vector species. All predictors with coarse resolution were resampled to bioclim variables to harmonize them with the bioclimatic variables.

We downloaded the climate change data from worldclim version 2.1 (http://www.worldclim.org) at 30 arc-second resolution (Fick and Hijmans, 2017, http://www.worldclim.org, accessed on 10th August 2022). The future climate data were based on the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016), which has models that tend to be highly sensitive to climate (Eyring et al., 2016). We selected two Shared Socioeconomic Pathways (SSPs): SSP5-8.5 and SSP2-4.5 for 2050s (2050 averaged over a 20 year period) and 2070s (2070 averaged over a 20 year period). SSP2-4.5 represents an optimistic climate scenario of mitigation and adaptation, characterized by moderate population growth and insignificant changes of socio-economic and technological trends from the historical patterns. On the other hand, SSP5-8.5 represents a pessimistic scenario of many challenges for mitigation and few challenges for adaptation, characterized by high exploitation of fossil fuels and emission of GHGs (see IPCC, 2021, for detailed explanation). These two scenarios were adopted to assess the impacts of climate change on species under both extreme and optimistic climate change scenarios. To reduce the uncertainty of reliance on a single Global Climate Model (GCM), we used an ensemble of various GCMs. For the two SSP scenarios, we used a mean ensemble of five CMIP6 models: ACCESS-CM2, BCC-CSM2-MR, HadGEM3-GC31-LL, CNRM-CM6-1 and MIROC6. The models have been widely used to examine the impact of climate change on African species (Asase and Peterson, 2019), and have indicated better performance.

Table 3.1: Table of variables with those used in modeling highlighted in gray.

Variable	Description	Resolution	Unit
Bio1	Annual Mean Temperature	30 arc s	Degrees Celsius
Bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	30 arc s	Degrees Celsius
Bio3	Isothermality (BIO2/BIO7) (* 100)	30 arc s	Percentage
Bio4	Temperature Seasonality (standard deviation *100)	30 arc s	Degrees Celsius
Bio5	Max Temperature of Warmest Month	30 arc s	Degrees Celsius
Bio6	Min Temperature of Coldest Month	30 arc s	Degrees Celsius
Bio7	Temperature Annual Range (BIO5-BIO6)	30 arc s	Degrees Celsius
Bio8	Mean Temperature of Wettest Quarter	30 arc s	Degrees Celsius
Bio9	Mean Temperature of Driest Quarter	30 arc s	Degrees Celsius
Bio10	Mean Temperature of Warmest Quarter	30 arc s	Degrees Celsius
Bio11	Mean Temperature of Coldest Quarter	30 arc s	Degrees Celsius
Bio12	Annual Precipitation	30 arc s	Millimeters
Bio13	Precipitation of Wettest Month	30 arc s	Millimeters
Bio14	Precipitation of Driest Month	30 arc s	Millimeters
Bio15	Precipitation Seasonality (Coefficient of Variation)	30 arc s	Fraction
Bio16	Precipitation of Wettest Quarter	30 arc s	Millimeters
Bio17	Precipitation of Driest Quarter	30 arc s	Millimeters
Bio18	Precipitation of Warmest Quarter	30 arc s	Millimeters
Bio19	Precipitation of Coldest Quarter	30 arc s	Millimeters
Sand	Proportion of sand in the soil	250m	Kg/Kg

Continued on next page

Table 3.1: Table of variables with those used in modeling highlighted in gray. (Continued)

Clay	Proportion of clay in the soil	250m	Kg/Kg
Soil pH	Proportion of pH in the soil water	250m	Kg/Kg
NDVI	Normalized Difference Vegetation Index	10m	Nil
Human Population	Human population as pixel density	30 arc s	~ 1km
DEM	Digital Elevation Model	30 arc s	Meters

3.2.4. Statistical analysis

SDMs are well-established tools in predicting species' spatial occurrence, habitat suitability and geographical distribution (Asase and Peterson, 2019). To date, SDM have been widely applied in ecology including: predicting areas for re-introduction of threatened species (Yang et al., 2013) and identification of suitable habitats (Malahlela et al., 2019). They correlate occurrence data (presence or presence/absence data) to the prevailing environmental conditions to estimate the relative suitability of a given habitat, thereby providing a prediction of the species' potential distribution. However, occurrence records of many species are often few and spatially clustered, which makes it difficult to model their suitable habitat since such data give limited information for determining the association between the species and their environment. In such cases, MaxEnt models are an interesting option because they have been demonstrated to work well with few presence records (Malahlela et al., 2019), tend to have high predictive power and relies on background points to contrast observed occurrences (Phillips et al., 2006). MaxEnt estimates a species probability distribution (interpreted as a relative index of habitat suitability) by finding probability distribution of maximum entropy, subject to a set of environmental constraints (Phillips et al., 2006). MaxEnt modeling has been extensively used in the field of conservation i.e. to predict the distribution of medicinal plants (Kaky and Gilbert, 2016).

3.2.4.1. Variable reduction

For each species, bioclim variables 8,9,18 and 19 were excluded because they have spatial artifacts which generate abrupt differences between neighboring pixels (Hijmans et al., 2005). Next, from the remaining candidate variables, we calculated pearson correlation coefficient and removed variables with correlation $r \geq \pm 0.7$ to avoid redundancy within the variables which may affect prediction accuracy (Yang et al., 2013). The variable with the greatest ecological relevance (based on our knowledge and literature analysis) was retained among the correlated variables.

3.2.4.2. MaxEnt model optimization, calibration and validation

The potential distribution of each species was predicted using the MaxEnt algorithm (Phillips et al., 2006) available within the dismo R package version 1.3-8 (Hijmans et al., 2022). MaxEnt model has two fundamental modifiable parameters: (1) Regularization Multiplier (RM) and (2) FC (Feature Class). Besides, the model has five FC, namely, hinge (H), linear (L), quadratic (Q), product (P) and threshold (T) (Phillips et al., 2006). MaxEnts default parameters are FC = LQHPT and RM=1 (Phillips et al., 2006). In our case, the two parameters of RM and FC were adjusted by the *ENMeval* R package of Muscarella et al. (2014). To optimize the model, we increased the RM from the default value of 1, with selected range from 0.5 to 4, by 0.5 each time, resulting in 8 RM parameters (Zhao et al., 2021) and used six feature combinations, namely, L, H, LQ, LQH, LQHP and LQHPT (Muscarella et al., 2014). The occurrence record of each species (in Africa) was sub-divided into 4 equal groups by the *ENMeval* package using the block technique, of which three groups were used for training and the remaining one was used for testing (Muscarella et al., 2014). We then used the *ENMeval* package to assess the 48 (6 FC $\times$8 RM) aforementioned parameter combinations. Here, we assessed two performance statistics to select the optimal model parameters. First, we selected the parameter combinations of models which had the lowest average omission rate based on the 10% training presence omission rate (OR10) (Kass et al., 2020). In cases where multiple models had the same OR10, we chose the model with the highest average validation AUC (Kass et al., 2020).

We imported the distribution records of our species into MaxEnt. Each species model was trained using occurrence records all over Africa to take account of conditions that are currently not encountered in our study area. 80% of the occurrence data was used to calibrate models while 20% was used for validation. The selected parameter combination of FC and RM was used in model fitting. To ensure that both the background points and occurrence records had the same geographical bias, we created a bias file for use in MaxEnt modelling (Syfert et al., 2013). For each species, we stacked the selected variables and used the raster stack to rasterize the occurrence records to estimate a two-dimensional kernel density (Khan et al., 2022). In the MaxEnt model, 10,000 background points (across Africa) which also captures the full extent of accessible environmental conditions were used. During modelling, we used the cross-validation method with 5 repeats and averaged the results. The MaxEnt output format was set as logistic and the number of iterations was increased to 3000 to enable the model to have enough time to converge, thereby preventing over-prediction or under-prediction (Abrha et al., 2018). We also used the “fade-by-clamping option” to avoid extrapolations that are outside the environmental range of the species (Phillips et al., 2006). Additionally, the Jackknife importance and the response curves of the model variables were developed. Moran's I was used to test for spatial auto-correlation in models residuals with the ‘spatstat’ package (Baddeley and Turner, 2005) in program R. The models were later transferred to Samburu County under present and future scenarios.

We evaluated the model performance using three different approaches, based on the testing dataset. First, we used the adapted Area Under the Receiving Operator Curve (ROC) according to Phillips et al. (2006). Second, we calculated the True Skill Statistics (TSS), as a threshold dependent measure. TSS compares the difference between the number of correct predictions and those that are attributed to random guesswork, to that of the hypothetical perfect predictions (Allouche et al., 2006). We used TSS because it considers both commission and omission, is independent of occurrence prevalence and is not affected by the validation dataset size (Allouche et al., 2006). Third, we used the Kappa statistic with binary maps since it considers both commission and omission errors, resulting in a less biased predictability measure (Baldwin, 2009). TSS and Kappa values range from -1 to +1, where values of zero or less are considered as performance no better than random while values close to 1 (TSS>0.3) indicate a good predictive power (Allouche et al., 2006).

3.2.4.3. Variables contribution, current and future distribution areas for anti-malarial plant and malaria vector species

We determined the factors affecting the distribution of the understudy species using the scores of the jackknife of test gain (Phillips et al., 2006). This test excludes one environmental variable each time when running the model and subsequently shows the variables which reduced model test AUC most when omitted and how much unique information each variable provides (Baldwin, 2009). Those environmental variables are presumed to be the most important in explaining the distribution of the species (Baldwin, 2009). We then ranked the environmental variables for each species in terms of their order of importance and identified the most dominant environmental variables across all the species considering their ranking (Cahyaningsih et al., 2021). The response curve of each species was further examined to explain the effect of each environmental variable on species suitable habitat. For generating binary range maps for each species under current and future climate scenarios, we used the maximum sensitivity plus specificity threshold. This threshold maximizes sensitivity (true positive rate) and specificity (true negative rate) (Liu et al., 2013) and proved to outperform other thresholds because it is sensitive to the selection of pseudo-absences and optimizes discrimination within the presence-absence records (Liu et al., 2016). The final anti-malarial species richness maps for current and future scenarios were generated by combining the binary maps of the 21 species and counting the total number of species in each pixel (Kaky and Gilbert, 2016). To generate the final malaria vector species distribution map under current and future scenarios, we selected the pixels which had species presences in any of the three malaria vector species binary maps (Kulkarni et al., 2010).

For present and future climate scenarios, we created a 9-km buffer zone around each protected area and assessed the pixels that lay within each buffer zone and inside the protected areas (Kaky and Gilbert, 2016). The 9 km distance was a trade-off between a large value (to ensure that as many pixels lay within each protected area) and a small value (to ensure that the area outside the protected area is as similar as possible to that inside it) (Kaky and Gilbert, 2017). Thereafter, we calculated the mean species richness based on anti-malarial species count in each pixel within the buffer area (outside protected area) and within the protected areas (inside). Using the t-test, we compared the mean species richness values outside and inside the protected areas. Here, we sought to test whether Samburu's protected areas are effective in conserving the region's anti-malarial species (Kaky and Gilbert, 2016).

3.2.4.4. Current overlap between malaria vector species and anti-malarial species richness

The current anti-malarial species richness and binary malaria vector maps were overlaid. We then identified the regions that had an overlap between malaria vectors and high (15-21), moderate (8-14) and low (1-7) anti-malarial species richness respectively.

3.2.4.5. Impact of climate change on anti-malarial species

The potential impact of climate change on anti-malarial species in Samburu was analysed applying species richness, gain and loss of species, turnover rate and threat level based on the IUCN (2021). We calculated the loss of climatically suitable habitat, gain in suitable habitat and turnover rate using methods by Thuiller et al. (2005). Gain was measured when the species was present in future binary prediction but absent in the current binary prediction. Loss was calculated based on the species being absent in future binary prediction but present in the current binary prediction. Loss has a negative value, gain has a positive value, while stable has a value of 0.

3.3. Results

3.3.1. Model performance

The mean of AUC, TSS and Kappa for all models are given in supplementary material Table 3.2 and Table 3.3. The worst model had an average AUC of 0.74, while the best model had an average AUC of 0.96. Maps resulting from the models are provided in supplementary material, Fig. 3.9, while the ROC curves are given in supplementary material, Fig. 3.10 and Fig. 3.11. No significant spatial autocorrelation was found in the model residuals.

3.3.2. Environmental drivers of anti-malarial plant species distributions

Each anti-malarial species was influenced by a different combination of environmental variables (supplementary material Fig. 3.12, Table 3.4). Accordingly, the main variables shaping the distribution of anti-malarial species included bio10 (mean temperature of warmest quarter), bio16 (precipitation of wettest quarter), bio11 (mean temperature of coldest quarter) and elevation (supplementary material Fig. 3.12 and Table 3.4). In contrast, sand and clay content were least influential variables. Highest anti-malarial species richness was predicted in areas with low mean temperature of warmest quarter, precipitation of wettest quarter, mean temperature during the coldest quarter and high elevation (see response curves in supplementary material; Fig. 3.14). Anti-malarial species richness is predicted to range from a low of 1 species per 1 km^2 cell to a high of 20 species per cell (Fig. 3.3). The highest richness was predicted in the south-western region, pockets of north-eastern and central regions i.e. Loosuk and Nyiro wards, while the lowest was found in north west and south east. Besides, paired t-test showed that the mean species richness was significantly higher inside the protected areas than outside (supplementary material Table 3.6 and Fig. 3.18).

3.3.3. Variables contribution and distribution areas of malaria vector species

Each malaria vector species was influenced by a different combination of variables (supplementary material Fig. 3.13 and Table 3.5). The key environmental variables affecting the distribution of malaria vectors were bio4 (temperature seasonality), elevation, population density and Bio13 (precipitation of wettest month, supplementary material Fig. 3.13 and Table 3.5). NDVI did not add any information for increasing the performance of the models. Highest malaria vectors distribution is predicted in areas with moderate temperature seasonality, low elevation, high population and moderate precipitation of wettest month (supplementary material Fig. 3.17). Currently, 37% of Samburu is prone to malaria due to high habitat suitability for malaria vectors (Fig. 3.3). However, most of the southern region and a few scattered pockets of the south eastern are predicted to have no suitable habitat for malaria vectors.

3.3.4. Current anti-malarial plant species richness and malaria vector species habitat

The predicted coincidence of malaria vectors suitable habitat and high anti-malarial species richness is located in the south-western, pockets of north-eastern and central regions i.e. Porro and Ndoto wards (Fig. 3.3). These regions were classified as ‘low vulnerability’ malaria areas. However, parts of the north western and south eastern regions are currently predicted to have suitable habitat for malaria vectors while anti-malarial species richness is low. These areas were classified as ‘high vulnerability’ malaria areas (e.g. Nyiro and Waso wards). Most of the southern region (i.e. Wamba west) is predicted to have moderate species richness and unsuitable habitat for malaria vectors, and were classified as ‘monitored’ . The current scenario shows few high vulnerability malaria areas (Fig. 3.3).

3.3.5. Impact of climate change on anti-malarial plants

The overall patterns of loss, gain and stable areas are almost similar in Samburu. For all climate change scenarios, most regions will lose anti-malarial species (Fig. 3.4, Fig. 3.5). The loss will be more pronounced in the anti-malarial species-rich area in south western region (Angata Nanyokie ward; 13-16 species for SSP2-4.5 and SSP5-8.5 in 2050s and 2070s). The absolute numbers of anti-malarial species loss in the south east were lower than for the south western region. Species loss is predicted to be greater

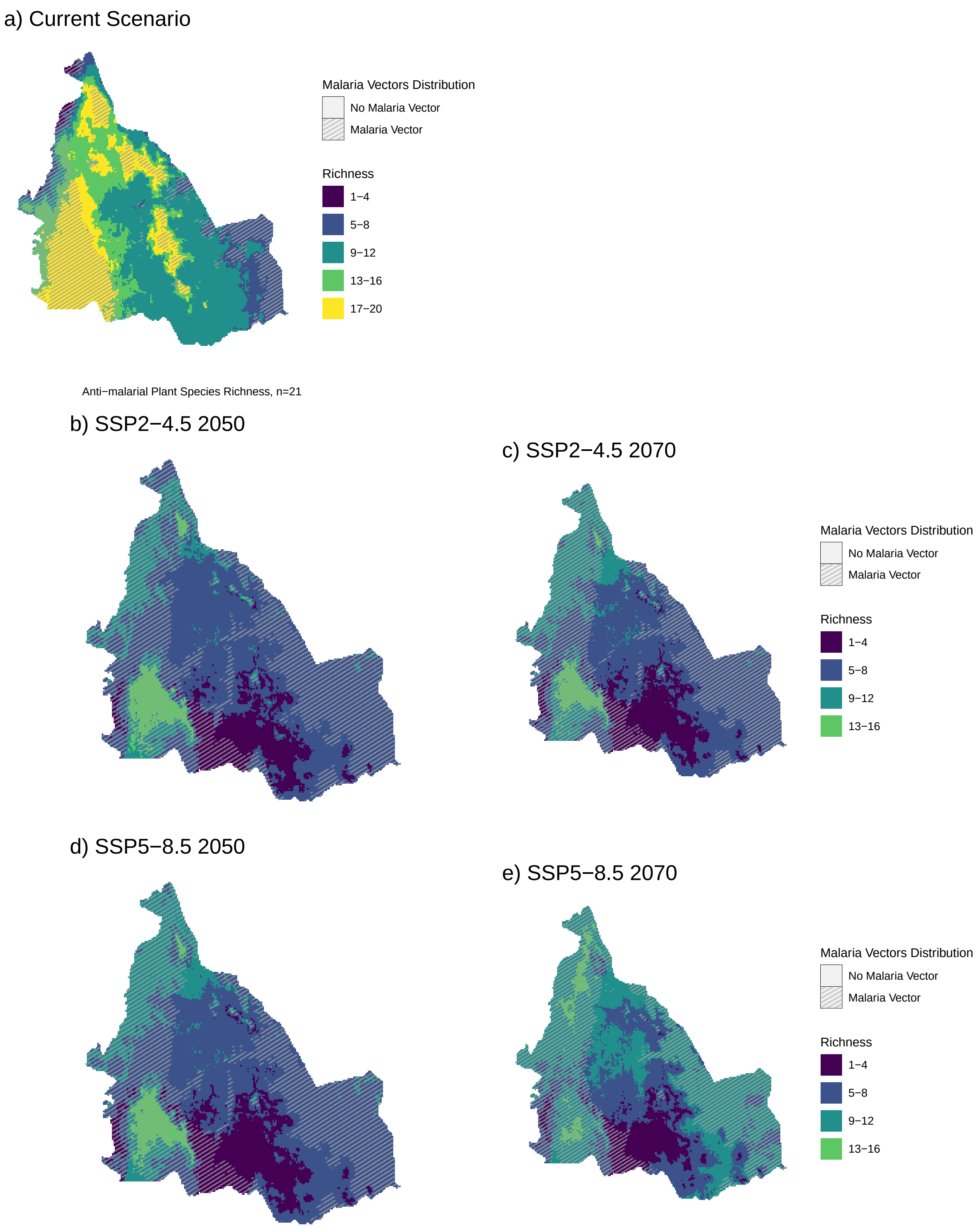

Figure 3.3.: Predicted malaria vectors suitable habitat and anti-malarial plant species richness under the current scenario and future climate scenarios. Results show that north western and south eastern regions currently have suitable malaria vectors habitat but the anti-malarial species richness in these regions is low. The overlap between malaria vectors suitable habitat and areas of low anti-malarial species richness will increase under future climate scenarios.

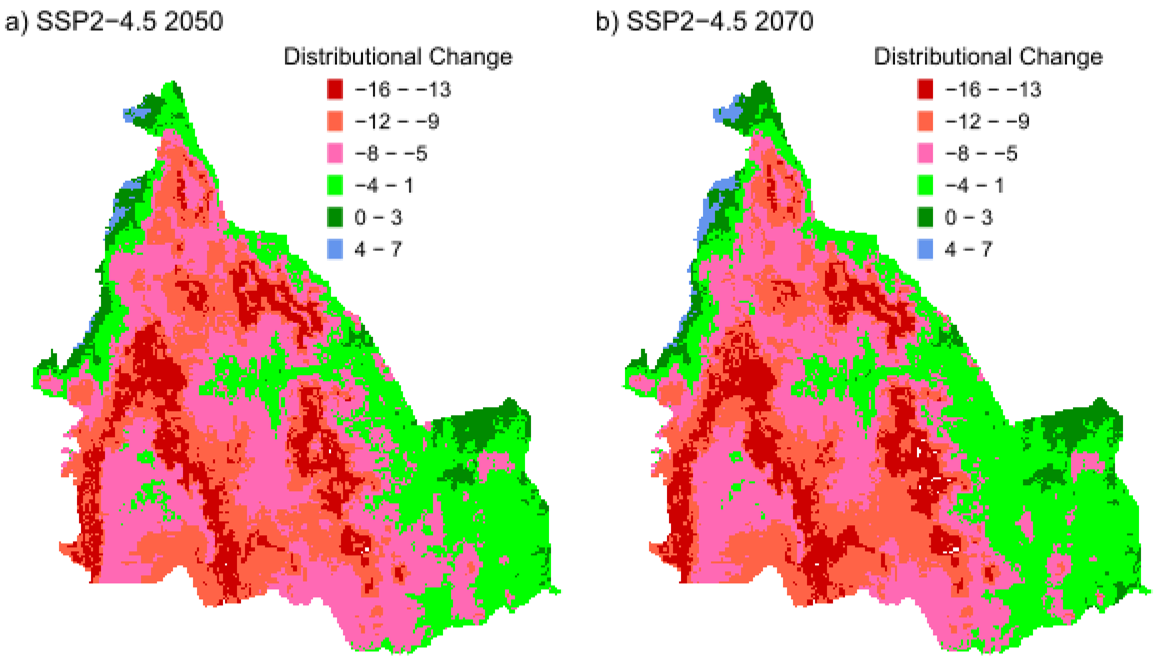

Figure 3.4.: Predicted distributional change of 21 anti-malarial species in Samburu under SSP2-4.5 2050s and SSP2-4.5 2070s.

in areas with low current mean temperature of warmest quarter and precipitation of wettest quarter (Fig. 3.4, Fig. 3.5, supplementary material Fig. 3.16).

On the contrary, gains in anti-malarial species is predicted in a few areas (north west and south east), with the north western region exhibiting the highest gain. Gains are predicted to occur in areas which may have more suitable habitat for the species in future. For all future scenarios, climate change would lead to stable numbers in parts of the south eastern and central regions (Fig. 3.4, Fig. 3.5).

Under climate change scenarios, the turnover rate is expected to range from 14% -76%, with all areas undergoing some changes in anti-malarial species composition (see Fig. 3.6, Fig. 3.7). The highest change is expected in the south western and southern regions (i.e. Porro and Wamba east wards), which have low current temperature. Besides, high turnover rate in anti-malarial species-poor area will occur in the north west, including Nyiro ward.

Compared to the current scenario, mean anti-malarial species richness will decrease for future scenarios (supplementary material Fig. 3.19). The richness is expected to range from a low of 1 species per 1 km^2 cell to a high of 16 species per cell (Fig. 3.3). Specifically, the southern western and north eastern regions will still have the highest anti-malarial species richness, although it would be fewer compared to the current. Parts of the south western region which currently have high anti-malarial species richness areas will have low richness in future (Fig. 3.3). These parts have high current temperature and low precipitation. The mean species richness was predicted to be significantly higher outside the

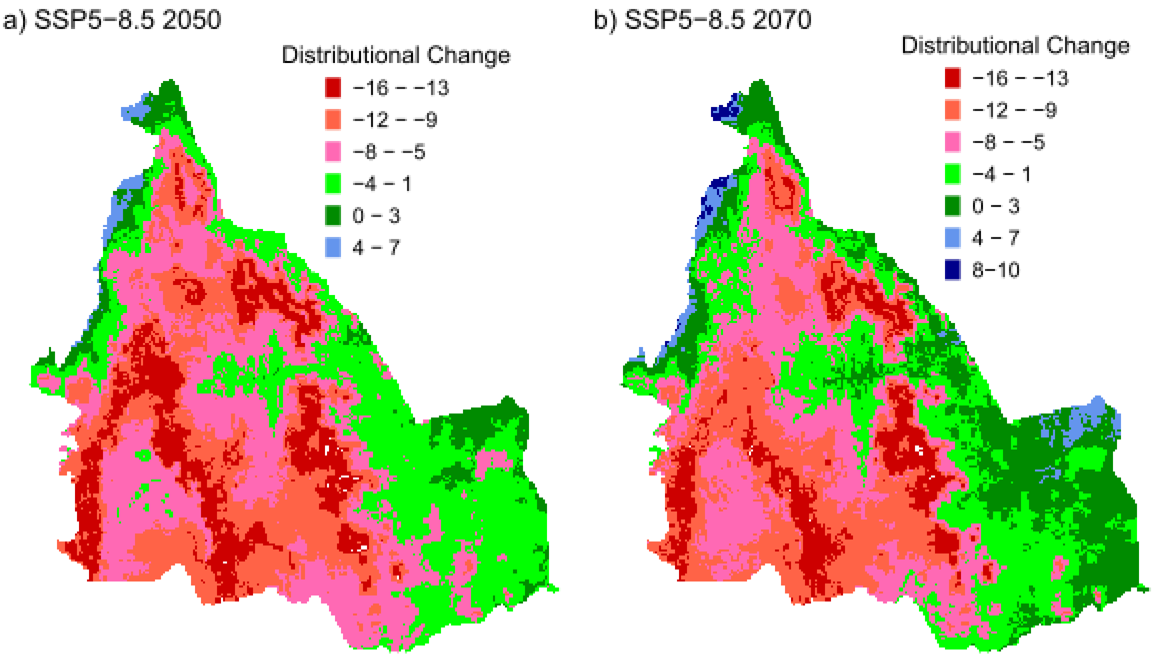

Figure 3.5.: Predicted distributional change of 21 anti-malarial species in Samburu under SSP5-8.5 2050s and SSP5-8.5 2070s.

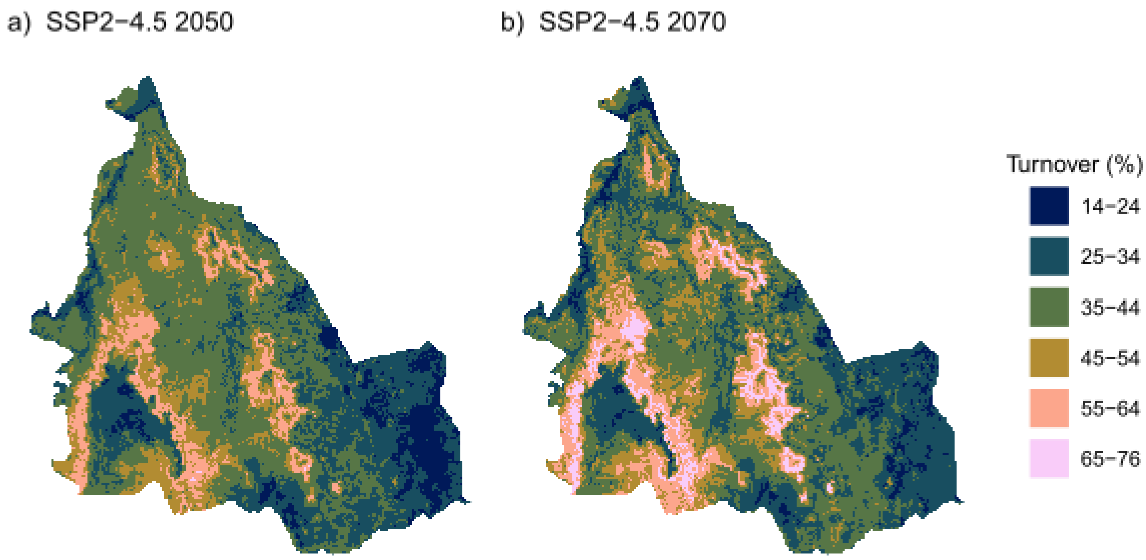

Figure 3.6.: Predicted anti-malarial species turnover rate in percentage under SSP2-4.5 2050s and SSP2-4.5 2070s.

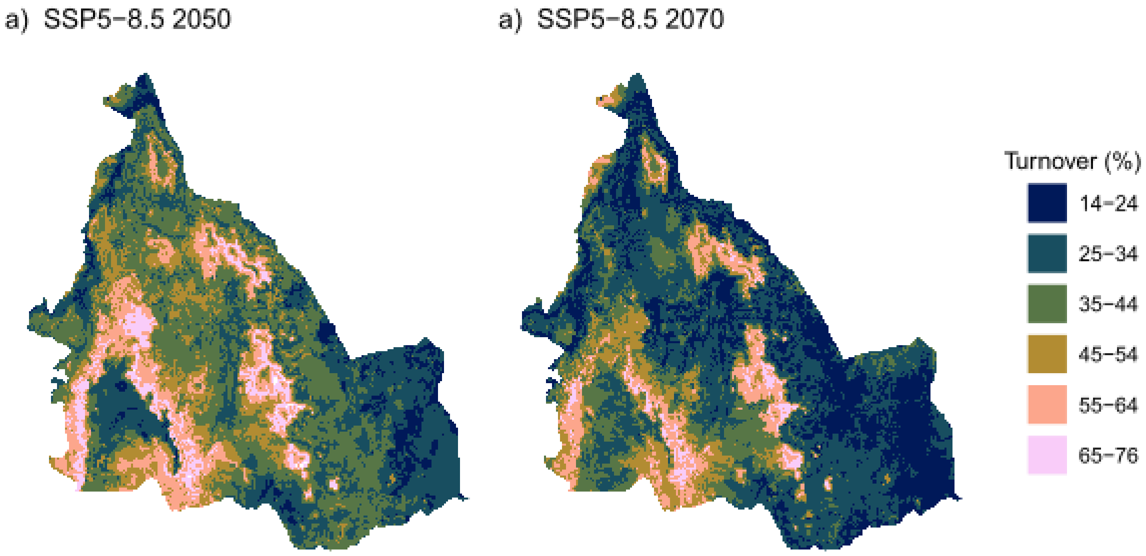

Figure 3.7.: Predicted anti-malarial species turnover rate in percentage under SSP5-8.5 2050s and SSP5-8.5 2070s.

protected area than inside, regardless of the climate change scenarios (supplementary material Table 3.6 and Fig. 3.18).

Our application of the IUCN Red List criterion revealed that under all future scenarios, 14-24% of the species will be CR (Fig. 3.8). Species that will be CR under all scenarios include *Salvadora persica* and *Acacia xanthophloea* (supplementary material Table 3.8). Besides, up to 29% of the species appeared EN by future climate change under SSP2-4.5 by 2050s. Between 33% and 43% of the species will suffer a loss of <30% and were classified as NT for SSP5-8.5 by 2050s and 2070s. Very few species were classified as VU under all climate change scenarios, while 14-19% of the species will be of LC under all scenarios i.e *Harrisonia abyssinica* and *Euclea divinorum*.

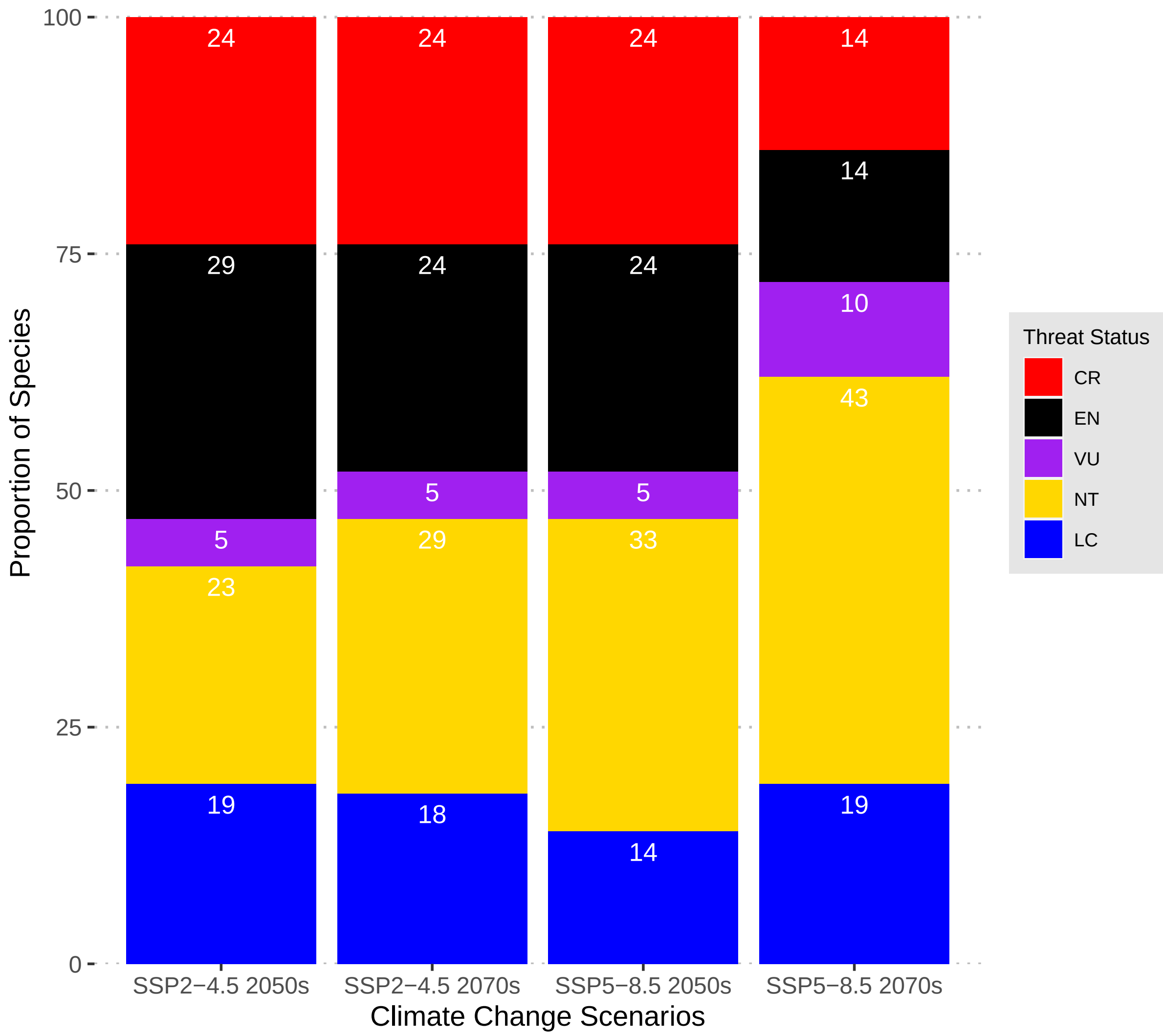

Figure 3.8.: Proportion of anti-malarial species threat level under different future climate scenarios.

3.3.6. Impact of climate change on malaria vector species distribution

Suitable habitat for malaria vectors is predicted to expand to most areas that are currently unsuitable and cover between 58-65% of Samburu (Fig. 3.3), as compared to the current 37%. These areas are mostly situated in the south eastern and southern regions, featuring low current temperature seasonality and high precipitation. Most areas in Samburu which currently have suitable habitat for malaria vectors are expected to remain habitable, while a few pockets of the southern eastern region are predicted to be converted from suitable habitat to unsuitable habitat.

3.3.7. Relating future anti-malarial species richness to malaria vector species distribution

Worrisomely, the overlap between suitable habitat for malaria vectors and areas with low anti-malarial species richness (high vulnerability malaria areas) will increase especially in areas with low current precipitation and temperature seasonality e.g. south east (Fig. 3.3, supplementary material Fig. 3.16, Fig. 3.17). For the southern region, which currently has no suitable habitat for malaria vectors and moderate anti-malarial species richness, our predictions show that the area will have suitable habitat for malaria vectors and low anti-malarial species richness. Besides, the overlap between suitable habitat for malaria vectors and high anti-malarial species richness (low vulnerability malaria areas) is expected to shrink especially in areas with low current temperature i.e. south west. Generally, the future scenarios will witness an increase in high vulnerability malaria areas, compared to the current scenario (Fig. 3.3).

3.4. Discussion

In the current study, the impact of climate change on anti-malarial plant and malaria vector species is explored. To the best of our knowledge, this is the first study to have predicted the future distribution of both anti-malarial plant species and suitable habitat for malaria vector species, and their future overlap.

3.4.1. Numbers of anti-malarial plant species and their environmental drivers

The most important variables shaping the distribution of anti-malarial species were mean temperature of warmest quarter, precipitation of wettest quarter, mean temperature of coldest quarter and elevation. This makes ecological sense because precipitation and temperature influence many ecological processes like seedling growth, flowering and fruiting, and consequently change the composition of species in a community (BAK, 2017), thereby shaping anti-malarial species distribution. Importantly, (Kaky and Gilbert, 2016) in Egypt and (Silva et al., 2022) in Brazil showed that mean temperature of the coldest month and elevation are the major drivers of medicinal plant species distribution in drylands. Therefore, it is not surprising that the two were also the driving forces behind the distribution of the anti-malarial species in Samburu dryland. However, some variables like sand and clay content were the least important for anti-malarial species distribution, even though (Gafna et al., 2021) found otherwise.

Regions with high anti-malarial species richness are currently the high elevation and low temperature regions of Samburu i.e. south-west. Low temperatures ensure availability of soil water which leads to high anti-malarial species richness (Silva et al., 2022). The elevation gradient influences temperature, radiation, precipitation and soil characteristics (Dharani and Yenesew, 2010), which, in concert, drive anti-malarial species numbers. A positive effect of elevation on medicinal plant species in water-limited areas has been previously found for Samburu by Gafna et al. (2021) and this follows a general pattern in plant species richness in Kenya (BAK, 2017).

Protected areas are considered as beneficial for *in situ* conservation of medicinal plants by limiting ecosystem degradation (Kaky and Gilbert, 2016). It is apparent that the predicted anti-malarial species richness is currently significantly higher inside the protected areas than outside, as Kaky and Gilbert (2016) found for medicinal plants in Egypt. Consequently, Samburu's protected areas are currently effective in conserving anti-malarial species and may be considered as possible areas for high priority anti-malarial species conservation. Many protected areas in the world are located in land of little value; which are not necessarily suited for biodiversity conservation (Kaky and Gilbert, 2017). Samburu's protected areas are rather new and seem to have been well chosen to support the area's biodiversity. Much could still be done because considerable human pressure presence was observed during fieldwork despite the laws regulating resource extraction, and the north eastern region which has many anti-malarial species is not covered by the protected areas. The region should be prioritized when extending existing protected areas.

3.4.2. Environmental drivers of malaria vectors and their distribution

The distribution of malaria vectors was influenced by temperature seasonality (Lindsay and Bayoh, 2004), elevation (Kulkarni et al., 2010), population density (Acheson et al., 2015) and precipitation of wettest month (Valderrama et al., 2021). Mordecai et al. (2020) demonstrated that temperature seasonality affects the life cycle of malaria vectors from egg to adult; and the rate of malaria vectors development increases at moderate temperature seasonality because it is ideal for them. It is likely that elevation shapes malaria vector species distribution due to its influence on temperature. Low temperature at high elevations reduces the development or occurrence of the species at high altitudes (Kulkarni et al., 2010). Our results showed that malaria vectors habitat suitability peaked in densely populated areas. This is justifiable because high human population ensures availability of blood feed for the vectors (Ryan et al., 2020). Consequently, suitable habitat for malaria vectors was found in south west and north west (Kimuyu et al., 2017), characterized by current high population, moderate temperature seasonality and low elevation. NDVI did not add any information for the performance of malaria vectors models (in agreement with Acheson et al., 2015), though it is thought to be a critical predictor of malaria vectors distribution (Machault et al., 2010). NDVI is related to vegetation greenness, moisture availability and vegetation productivity, which are strongly associated with malaria vectors reproduction (Acheson et al., 2015). However, it is likely that NDVI was a poor predictor because most parts of Africa are arid with low values of NDVI (Kaky and Gilbert, 2016). Furthermore, healthy vegetation (i.e. with high NDVI) are found in high elevation areas that are very cold to permit malaria vectors occurrences, eroding NDVI's capacity to differentiate between unsuitable and suitable malaria vectors habitat (Acheson et al., 2015).

Suitable habitat for malaria vectors is currently predicted in 37% of Samburu. However, care should be taken when interpreting these results, since the sheer suitability of a habitat for malaria vectors does not automatically translate into malaria incidences (Tonnang et al., 2010). This is because human population and mosquitoes, which act as reservoirs for the *Plasmodium* parasites must be found in areas with suitable malaria vectors habitat for malaria incidences to be reported (Tonnang et al., 2010). Additionally, other factors such as greater access to medical services, better water management and improved housing may limit malaria cases in an area (Acheson et al., 2015), despite its habitat suitability.

Our malaria vectors models had some limitations. First, we did not incorporate other parameters which determine malaria vectors distribution i.e. land use, humidity, cattle hoof prints and floods. In our case, we used climatic variables, population density and elevation. Our use of these variables does not mean that we were unaware that they are just among the several variables that influence malaria vectors distribution (Tonnang et al., 2010). Rather, we argue that, whereas the other unused variables are likely to influence malaria vectors distribution at a fine scale (Acheson et al., 2015), climatic variables, population density and elevation are likely to determine their distribution at a large spatial scale (Acheson et al., 2015). Second, our models did not incorporate biotic interactions between malaria vector species and other species i.e. Fish (Golding et al., 2015). Competition and predation between species may influence malaria vectors distribution (Tonnang et al., 2010). Previous studies showed that malaria vectors avoid habitats which have competitors (Muturi et al., 2008).

3.4.3. Assessing current malaria vulnerability

The overlap between suitable habitat for malaria vectors and areas of high anti-malarial species richness (low vulnerability malaria areas) is found in south western, north eastern and central regions. The current malaria control actions are low in the south-west, and high in the north-east and central regions (KMS, 2019), while medicinal plant species conservation efforts are currently low in south west and central regions (Gafna et al., 2021). However, we recommend high prioritization of anti-malarial species conservation and malaria control measures in south-west and central regions, as this would ensure utilization of the limited malaria control and anti-malarial species conservation resources (i.e. *ex situ* and *in situ* conservation actions, insecticides spraying, distribution of mosquito nets/anti-malarial drugs). Worrisomely, the north west and south east have suitable habitat for malaria vectors and low anti-malarial species richness (high vulnerability malaria areas). Currently, these regions are under both low malaria control (KMS, 2019) and medicinal species conservation efforts (Nanyingi et al., 2008). We propose prioritization of malaria control in these regions, whereas anti-malarial species conservation efforts should remain low since the anti-malarial species richness is low either way. The southern region was predicted to have no suitable habitat for malaria vectors and moderate anti-malarial species richness. The region currently has high malaria control activities (KMS, 2019), while anti-malarial species conservation efforts are moderate (Nanyingi et al., 2008). We suggest that malaria control measures need to be revisited to low, whereas anti-malarial species conservation should remain moderate.

3.4.4. Distributional change in anti-malarial species

Increased temperatures and decreased precipitation due to climate change in Samburu will lead to loss, gain or no change in suitable anti-malarial species habitat. Most areas will witness huge losses in anti-malarial plants. The loss will be greater in anti-malarial species-rich areas, currently featuring low precipitation and temperature, as future condition in the areas will be unsuitable for anti-malarial species due to shifts in bioclimatic zones. Another plausible reason for the loss of anti-malarial species is that climate change will probably replace the cold adapted anti-malarial species with the warm adapted species (Vesperinas et al., 2001). Many studies reported huge losses of medicinal plant species due to changing climate (Cahyaningsih et al., 2021; Silva et al., 2022), which concurs with our projections. The anti-malarial species loss will have ramifications on the pharmaceutical industries and livelihoods of several vulnerable populations that rely on them (Silva et al., 2022). Therefore, regions that will lose should be given priority for *ex-situ* conservation measures such as collection and storage of anti-malarial species germplasm in seed banks (Asase and Peterson, 2019).

A few anti-malarial species that will be able to track their suitable habitats are expected to gain suitable habitat (Kaky and Gilbert, 2017). The gains were predicted to occur in areas with more future anti-malarial species suitable habitat or where warmer climate will favor them (Cahyaningsih et al., 2021) i.e. north-western region. Notably, the region is well endowed with anti-malarial species which are pre-adapted to water stress (Nanyingi et al., 2008) and can thrive in climate warming. Continuous monitoring of the anti-malarial species is advisable in areas that will gain since an influx of new anti-malarial species could alter the competitive interactions in such areas (Kaky and Gilbert, 2017), and because factors other than climate change may threaten the existence of anti-malarial species (Thuiller et al., 2005). Further, we propose *in-situ* conservation of anti-malarial species alongside sustainable utilization, assisted migration, assisted seedling growth, removal of invasive species in areas that gain and overlap with protected areas (Kokwaro, 2009; Cahyaningsih et al., 2021).

Mean anti-malarial species richness for future scenarios was low, compared to the current scenario; similar findings have been reported in other parts of the world (i.e. studies on medicinal plants; Cahyaningsih et al., 2021; Silva et al., 2022). Most areas of high richness (i.e. south west) are predicted to decrease due to increased warming (Silva et al., 2022), while only a small region in the north west will witness a slight increase in richness. Consequently, climate change will pose a challenge to availability of anti-malarial species. However, regions of future high anti-malarial species richness should be considered as conservation areas for restoration and rewilding under climate change. Contrary to our results, a study in Egypt (Kaky and Gilbert, 2017) reported increased medicinal plant species richness, in most areas, due to climate change. These differences may be due to use of other bioclimatic variables, and climate scenarios. Besides, plants in Egypt may not share the same ecological niche location as those in Samburu. Under future scenarios, the mean anti-malarial species richness outside the protected areas is predicted to be higher than inside, contrary to the findings of Kaky and Gilbert (2017) in a study on medicinal plants. This suggests that due to their placement in unsuitable future climates, the current protected areas may not adequately conserve anti-malarial species in future. They should be complemented through effective management and extension to cover future suitable habitats. Conservationists should also adopt anti-malarial species conservation measures beyond the current protected area network to conserve anti-malarial plants in future.

Assessing the impact of climate change on plant species may be overestimated since it is usually difficult to consider the interactions between the population character or species and their habitat (Thuiller et al., 2005). A species may gain suitable habitat, but may be unable to move to the habitat due to limiting factors like altitude and human activities in the surrounding area (Kaky and Gilbert, 2017). Besides, plant population size may not adequately predict long-term population viability because of the time lag associated with its response to habitat deterioration (Cahyaningsih et al., 2021). However, the patterns of loss and gain in species suitable habitat may remain (Thuiller et al., 2005). Regarding the choice of future variables, our study considered soil factors and elevation as static variables and climatic factors as dynamic. Therefore, soil and elevation were not included in the models for future scenarios.

3.4.5. Turnover

High turnover in anti-malarial species-rich areas may affect the health of locals therein as they will experience many changes anti-malarial species composition (Cahyaningsih et al., 2021). High turnover was predicted in areas with high current precipitation and low temperature, associated with high soil water which enhances anti-malarial species development (Kaky and Gilbert, 2017). For areas with high turnover, systematic monitoring of the species may help to formulate scientific conservation measures to adapt to climate change (Cahyaningsih et al., 2021). Low anti-malarial species turnover will occur in the south eastern region (has low current precipitation and high temperature) probably because of little change in future environmental conditions (Thuiller et al., 2005). The region should nonetheless be continuously monitored, since we suspect that the safety or even quality of anti-malarial species therein may be affected by climate change, as increase in CO_2 concentration and temperature affects plant chemical metabolites (Kokwaro, 2009).

3.4.6. Identifying priority species for conservation

Under all future scenarios, 14-24% of the species will be CR while 14-29% will be EN, which may strongly affect the locals' healthcare. However, only 14-19% of the species will be of least concern. These results are in line with those by Gafna et al. (2021) suggesting that most medicinal plant species in Samburu dryland are threatened by climate change. Drylands such as Samburu are sensitive to climatic changes because they have already reached the threshold of water availability and temperature (Gafna et al., 2021). In agreement with Thuiller et al. (2005), two species with narrow climatic tolerances and limited population size (i.e. *Salvadora persica* and *Acacia xanthophloea*) were listed as CR under all scenarios, since they would have to fully shift their distribution range to keep pace with the changing climate. Both species grow in environments with low temperatures (Kokwaro, 2009), which might make them less likely to adapt to the future climatic conditions. These species should be given the highest conservation priority. Compared to CR non-medicinal plants, CR anti-malarial species are more vulnerable to extinction because they face over-harvesting (Yang et al., 2000). Therefore, we suggest the establishment of plant micro-reserves in concentration areas of the CR anti-malarial species, especially in areas with low future temperatures. Likewise, the population size of CR anti-malarial species with a weak ability to regenerate in the wild could be improved using appropriate artificial intervention (Yang et al., 2000). Such actions aimed at conserving CR anti-malarial species could also benefit other VU species that are inadequately conserved (Warman et al., 2004). As expected *Harrisonia abyssinica* and *Euclea divinorum* were classified as of LC, since they were projected not to lose any suitable habitat. They grow in different environmental conditions, which makes them highly adaptable to environmental stress (Dharani and Yenesew, 2010), and are likely to survive the future changing climate.

3.4.7. Impact of climate change on malaria vector species distribution

Suitable habitat for malaria vectors will expand to most areas that are currently unsuitable, thereby exposing new populations to malaria. This shows the potential challenge to Samburu's ambitious goal of eliminating malaria. Increased temperatures will increase the rate of malaria vectors development and the frequency of blood feeding by mosquitoes, while droughts due to climate change may convert rivers into water pools which provide optimal mosquito breeding sites (Tonnang et al., 2010). In Kenya, (Kimuyu et al., 2017) mapped malaria vectors distribution under climate change. Our findings agree with their study; however, our work displayed a much broader expansion, which may reflect the fact that our occurrence records were drawn from a large area. Pockets in the south east will be converted from suitable malaria vectors habitat to unsuitable, thereby reducing the malaria burden on some populations. Very high temperature and low precipitation in these areas may make it unbearable for malaria vectors to survive in future (Kimuyu et al., 2017). Worrisomely, most areas predicted to have suitable malaria vectors habitat in future are also currently predicted as suitable habitats. This repeated and prolonged exposure to malaria may lead to immunity and development of resistance to anti-malarial species or drugs among populations in these areas (KMS, 2019).

When transferring the malaria vector species models to future conditions, we assumed that the current association between malaria vectors presences and predictor variables based on present day data will still hold true under future climate scenarios (Tonnang et al., 2010), which may not be the case. This is likely because the potential evolution of malaria vectors in response to climate change (i.e. temperature tolerance) may affect their shifts in geographical range (Chaianunporn and Hovestadt, 2015). Whereas the impact of climate change on malaria vector species distribution may be altered by the evolutionary changes (Lawler et al., 2006), many species evolve much slower than the changing climate (Etterson and

Shaw, 2001), or may not even evolve at all. Besides, the lack of future human population data may limit the scope of our models (Tonnang et al., 2010).

3.4.8. Assessing the impacts of climate change on future malaria vulnerability

The overlap between suitable habitat for malaria vectors and low anti-malarial species richness will increase, especially in the eastern and southern regions, potentially exposing locals to increased malaria vulnerability burden (Ryan et al., 2020). In future, malaria control interventions in the south should be revisited from the currently low malaria control measures (KMS, 2019) to high, while the anti-malarial species conservation efforts should be low, as this will take into account how climate change will alter malaria vulnerability. We suggest that, there is need to create awareness in the current low vulnerability malaria areas that are likely to become high vulnerability malaria areas, to enhance preparedness. Besides, concerted efforts to increase resilience among locals in these areas should be scaled up in order to strengthen adaptive capacity and reduce vulnerability. We propose review of resource allocation in the high vulnerability malaria areas that will be converted to low vulnerability areas i.e. north west.

3.4.9. Implications for management

Since our results suggest a possible loss of many anti-malarial plant species, decrease in future anti-malarial species richness, expansion of malaria vectors suitable habitat and thus spread of high vulnerability malaria areas, there is need to urgently initiate more effective anti-malarial species conservation and malaria control interventions. Sustainable harvesting practices, effective enlargement of protected areas and supporting *in-situ* and *ex-situ* conservation (with focus on anti-malarial species of highest conservation priority) can ameliorate the processes. For effective anti-malarial plant species conservation and malaria control actions, interventions should take into account the climatic patterns, for a greater impact. Land managers should monitor the changing trends in precipitation and temperature as they determine the regions ability to hold anti-malarial species and malaria vector species. There is also need to revisit current and future anti-malarial species conservation actions and malaria control interventions as outlined by the current study.

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3.5. Supplementary material

Table 3.2: Modeled anti-malarial species, number of occurrence records and the MaxEnt model evaluation metric.

Species	Efficacy	Samburu name	Occurrence records	Training data AUC	Mean AUC	Mean TSS	Mean Kappa
Acacia etbaica	Moderate	Solit	123	0.95	0.95	0.49	0.48
Acacia mellifera	High	Iti	120	0.86	0.85	0.46	0.41
Acacia tortilis	High	L-tepes	299	0.82	0.84	0.38	0.41
Acacia xanthophloea	Moderate	Lerai	92	0.94	0.95	0.53	0.49
Balanites aegyptiaca	Unknown	Lowaai	333	0.78	0.78	0.34	0.34
Boscia angustifolia	Moderate	Lororai	251	0.87	0.81	0.33	0.36
Boscia coriacea	Low	Serijioi	79	0.8	0.76	0.36	0.35
Carissa edulis	Moderate	Lamuriei	159	0.82	0.9	0.48	0.4
Comiphora africana	High	Laishimi	377	0.77	0.79	0.38	0.36
Cordia monoica	High	Seki	157	0.88	0.85	0.39	0.39
Croton dichogamus	Moderate	Lakirdingai	116	0.92	0.92	0.67	0.54
Croton megalocarpus	Low	Lmargwet	66	0.94	0.83	0.82	0.51
Euclea divinorum	High	Lchingei	360	0.89	0.89	0.56	0.54
Harrisonia abyssinica	Moderate	Lasaramai	270	0.84	0.91	0.47	0.55
Juniperus procera	High	L-tarakwai	176	0.95	0.94	0.48	0.47
Lippia javanica	Low	Sinoni	340	0.92	0.92	0.56	0.51
Myrsine africana	High	Seketet	318	0.95	0.95	0.57	0.54
Olea africana	Moderate	Lgeriyoi	58	0.99	0.96	0.78	0.66

Continued on next page

Table 3.2: Modeled anti-malarial species, number of occurrence records and the MaxEnt model evaluation metric. (Continued)

Salvadora persica	High	Sekotei	388	0.82	0.84	0.57	0.54
Senna didymobotrya	Low	Ndku	231	0.93	0.92	0.61	0.64
Solonum incanum	High	L-tulelei	350	0.75	0.84	0.36	0.39

Table 3.3.: Modeled vector species, number of occurrence records and the MaxEnt model evaluation metric.

Malaria Vector Species	Occurrence records	Training data AUC	Mean AUC	Mean TSS	Mean Kappa
Anopheles arabiensis	363	0.81	0.74	0.37	0.39
Anopheles funestus	270	0.92	0.89	0.65	0.59
Anopheles gambiae	367	0.81	0.83	0.35	0.37

Figure 3.9.: Habitat suitability maps of modeled anti-malarial plant and malaria vector species in alphabetical order.

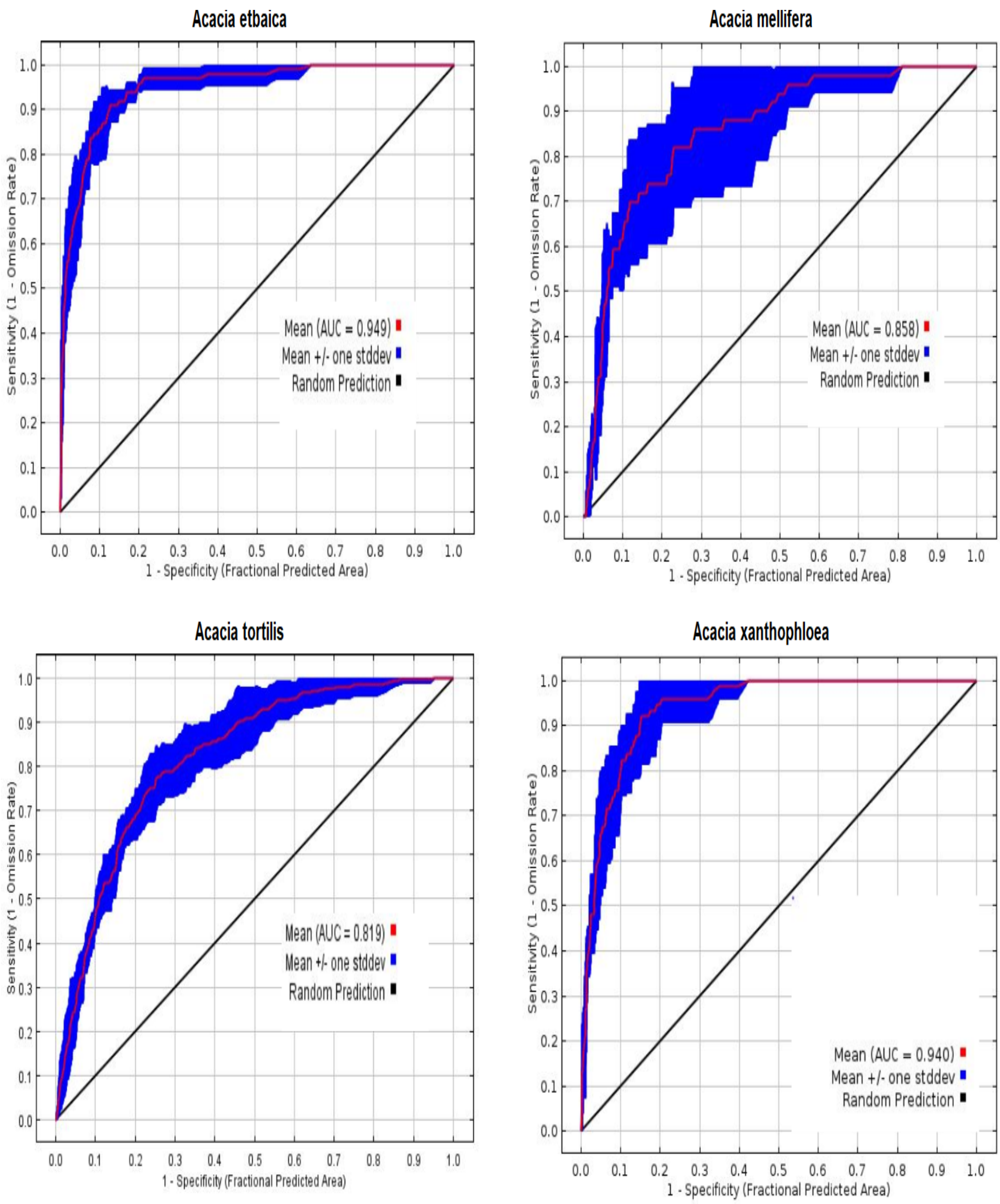

Figure 3.10.: MaxEnt Receiver Operating Characteristics (ROC) curve for anti-malarial plant species in alphabetical order.

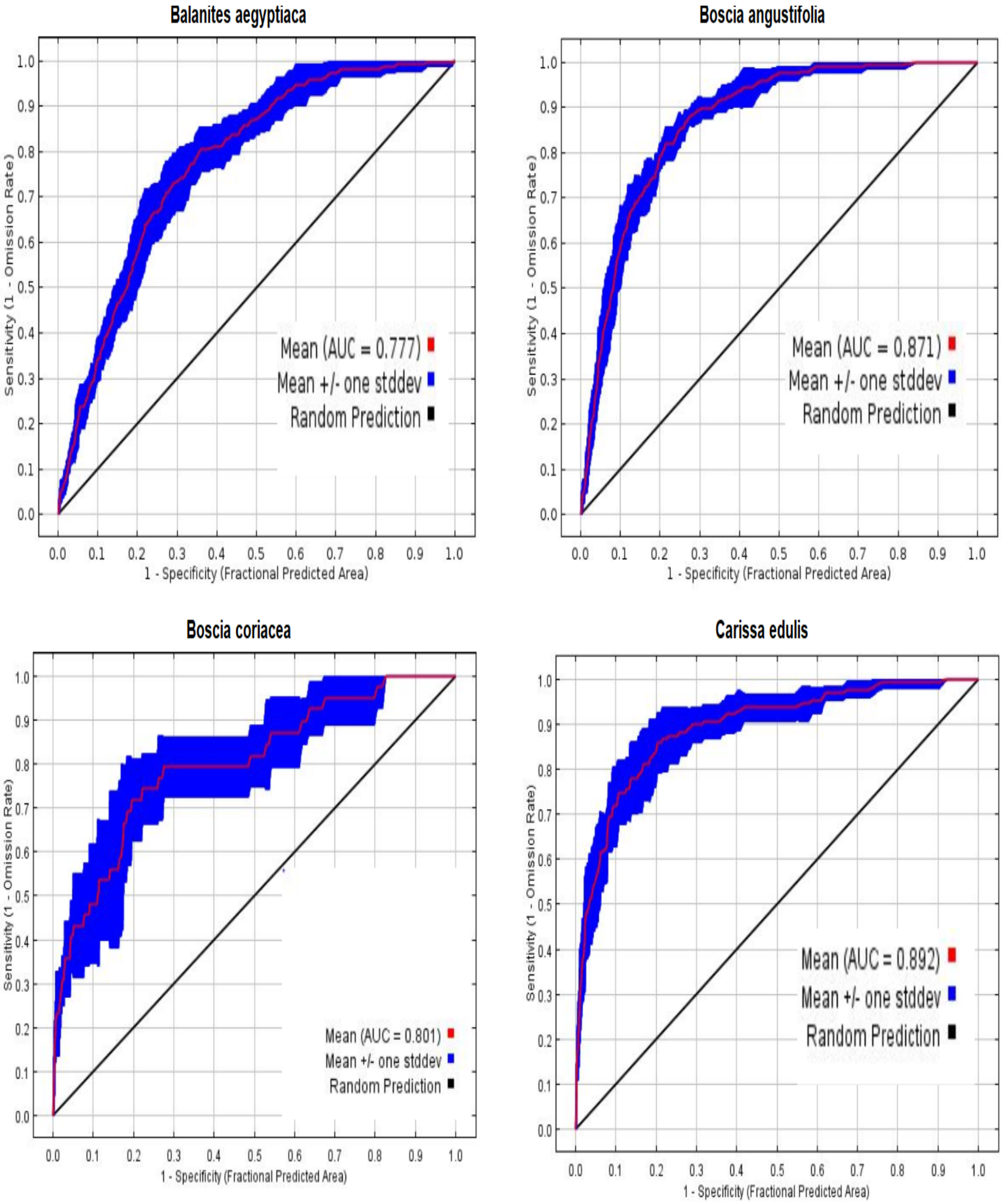

Figure 3.10.: MaxEnt Receiver Operating Characteristics (ROC) curve for anti-malarial plant species in alphabetical order (continued).

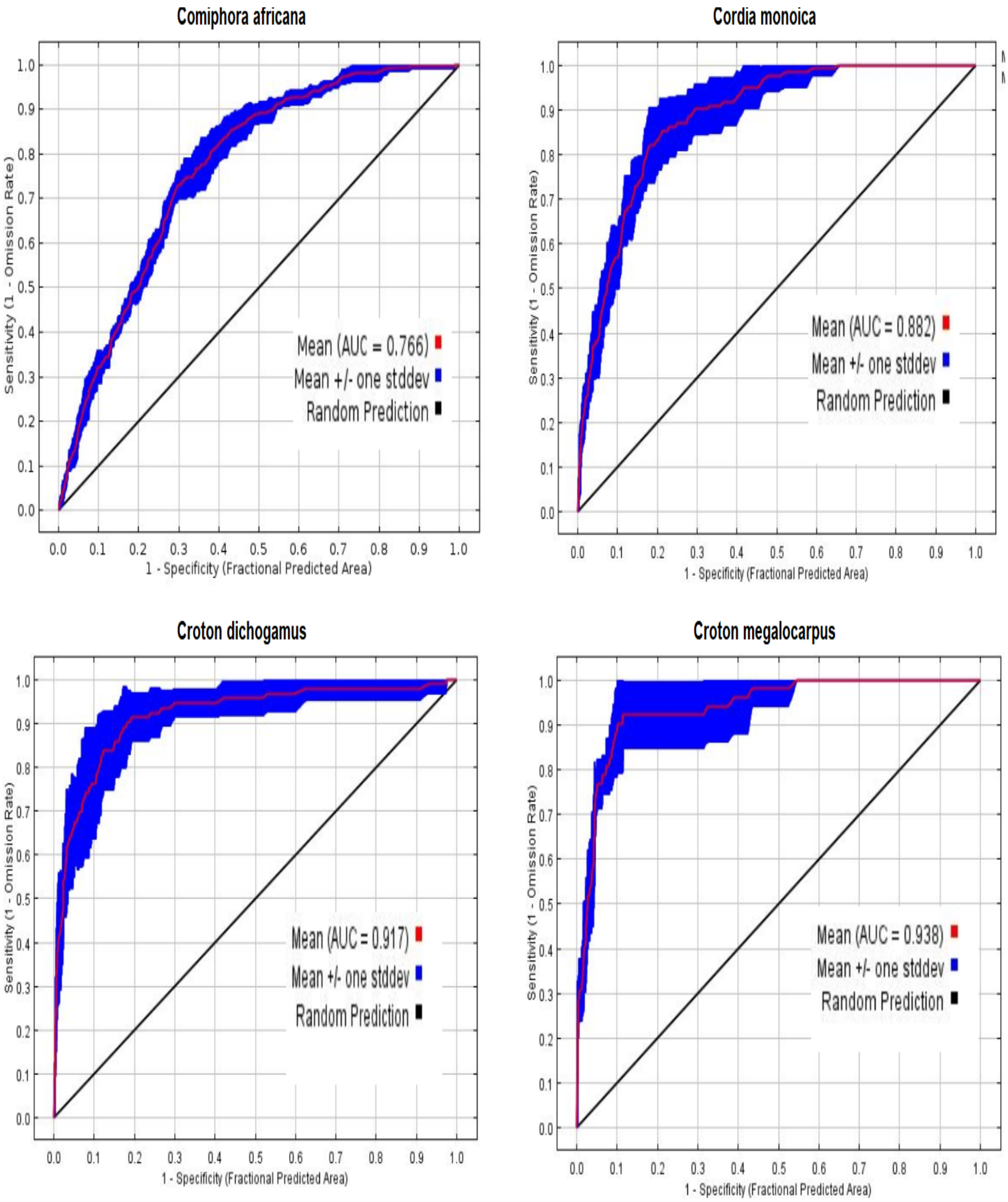

Figure 3.10.: MaxEnt Receiver Operating Characteristics (ROC) curve for anti-malarial plant species in alphabetical order (continued).

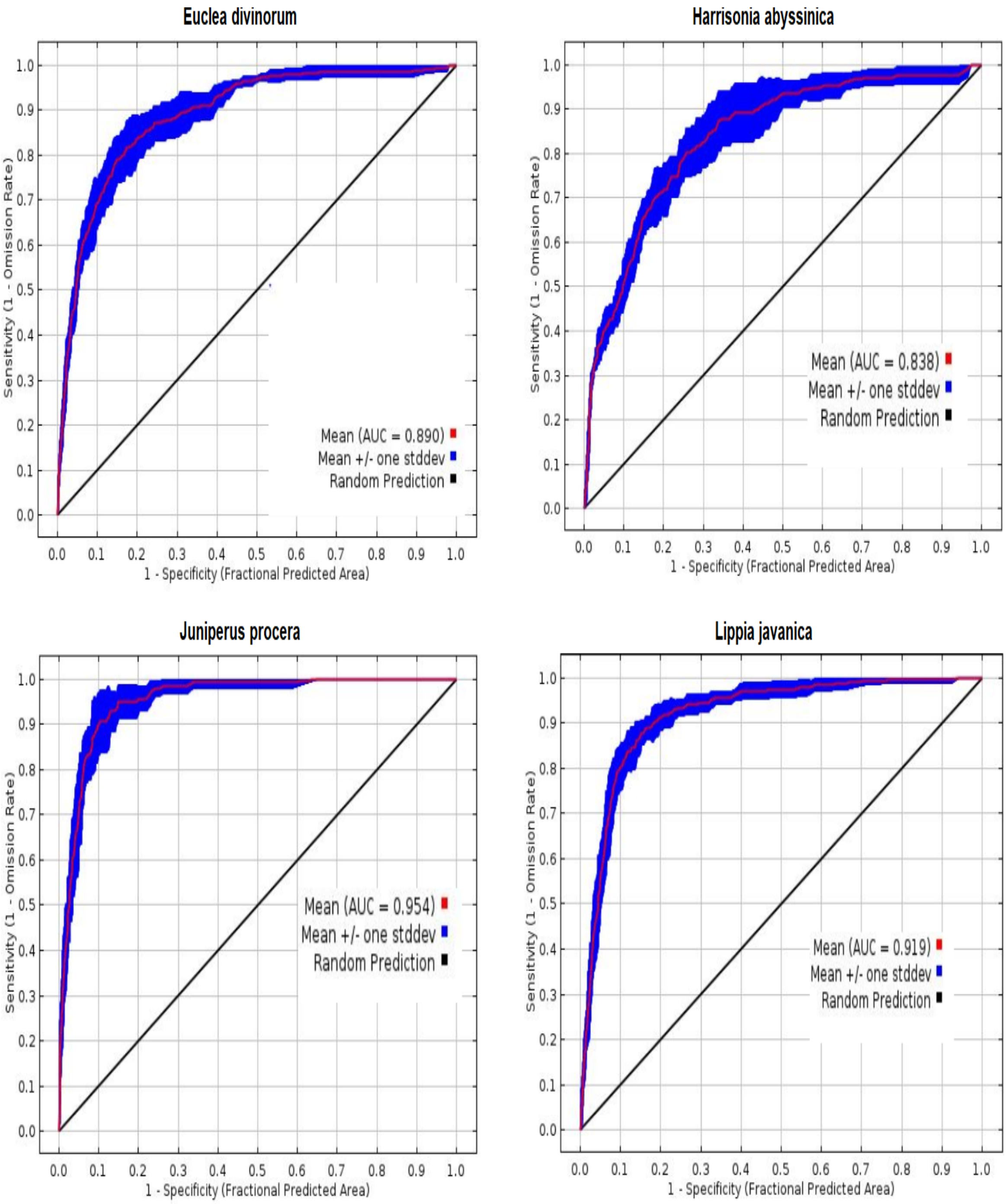

Figure 3.10.: MaxEnt Receiver Operating Characteristics (ROC) curve for anti-malarial plant species in alphabetical order (continued).

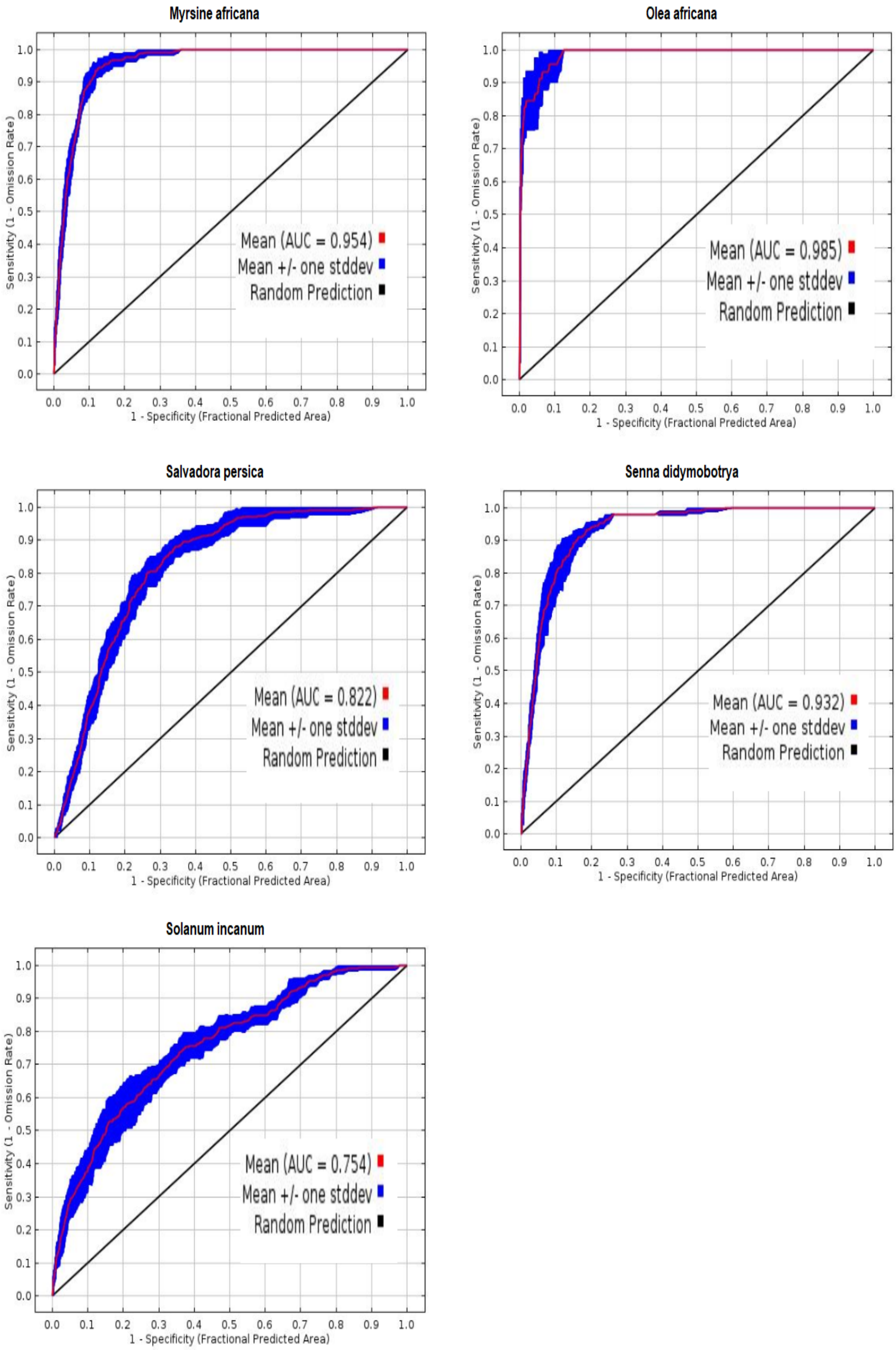

Figure 3.10.: MaxEnt Receiver Operating Characteristics (ROC) curve for anti-malarial plant species in alphabetical order (continued).

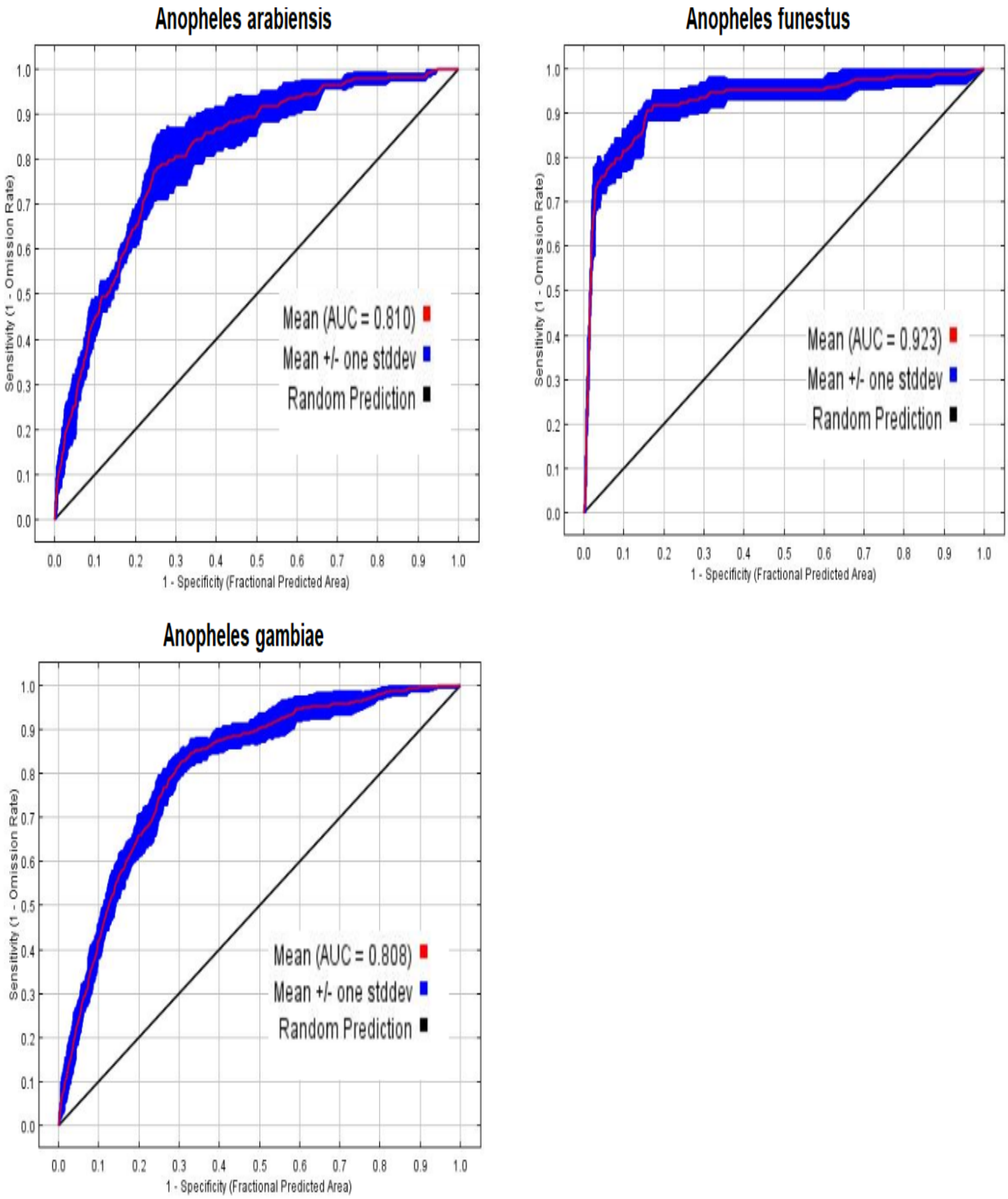

Figure 3.11.: MaxEnt Receiver Operating Characteristics (ROC) curve for malaria vector species in alphabetical order.

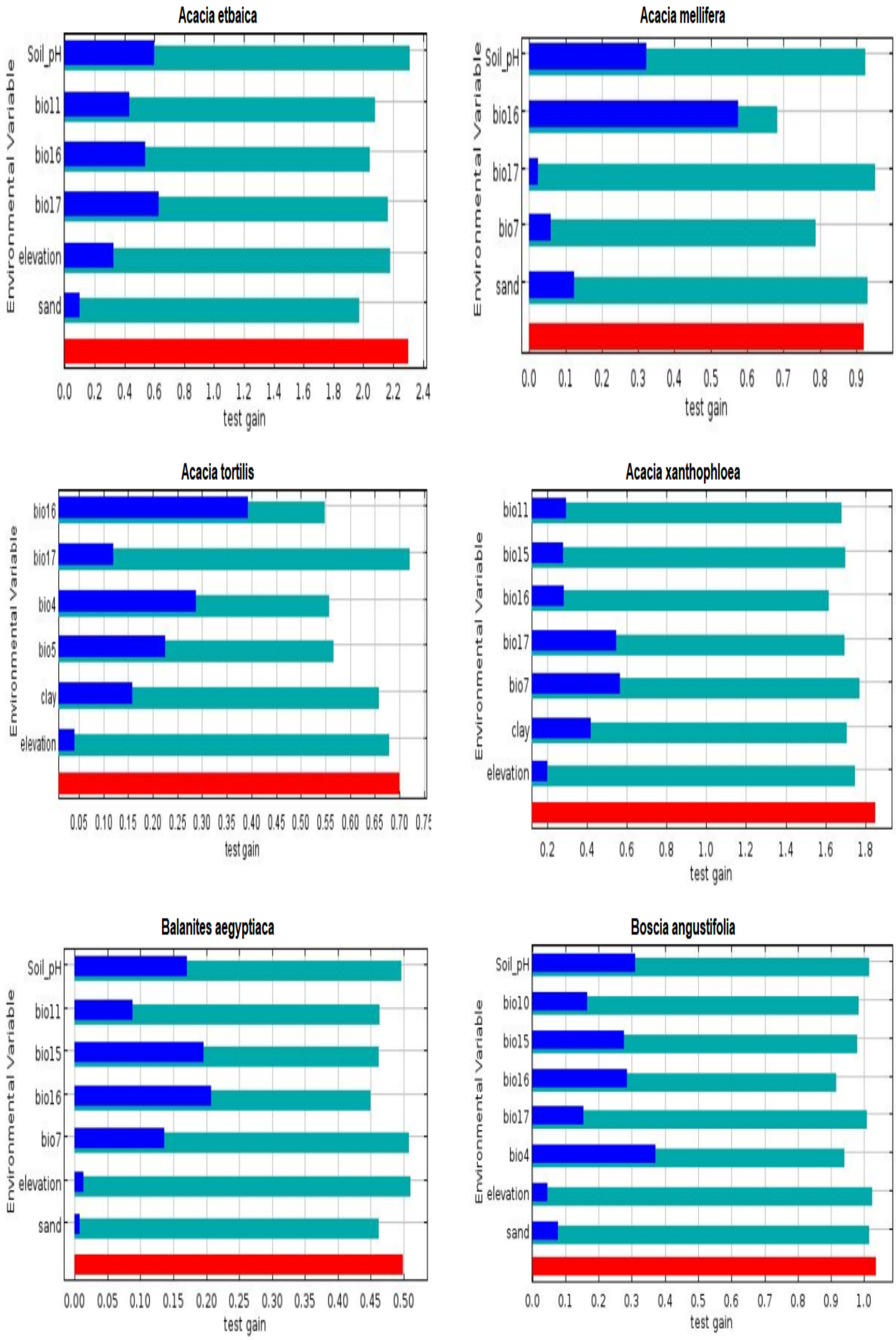

Figure 3.12.: Jackkknife test for modeled anti-malarial plant species in alphabetical order

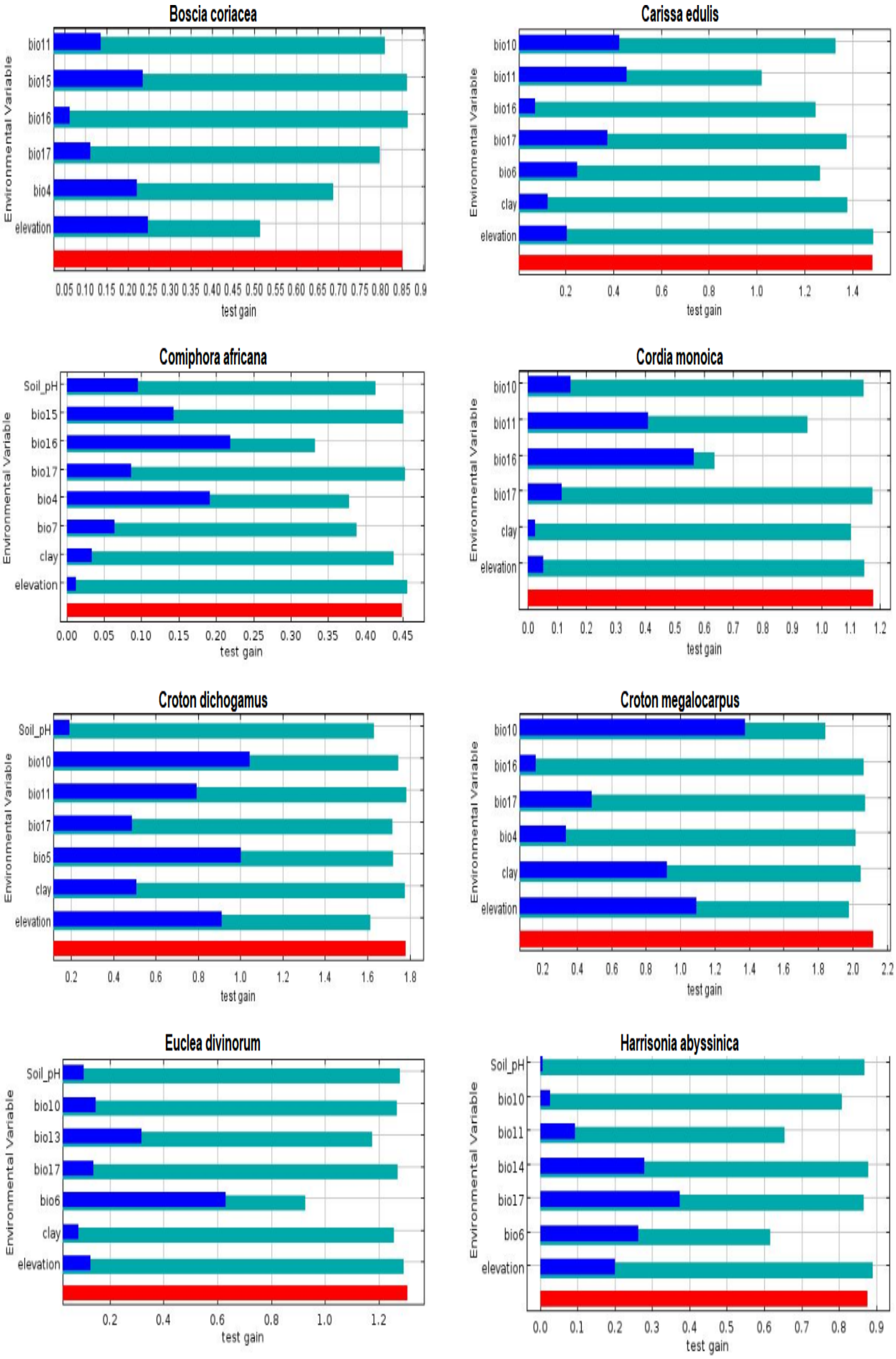

Figure 3.12.: Jackkknife test for modeled anti-malarial plant species in alphabetical order (continued).

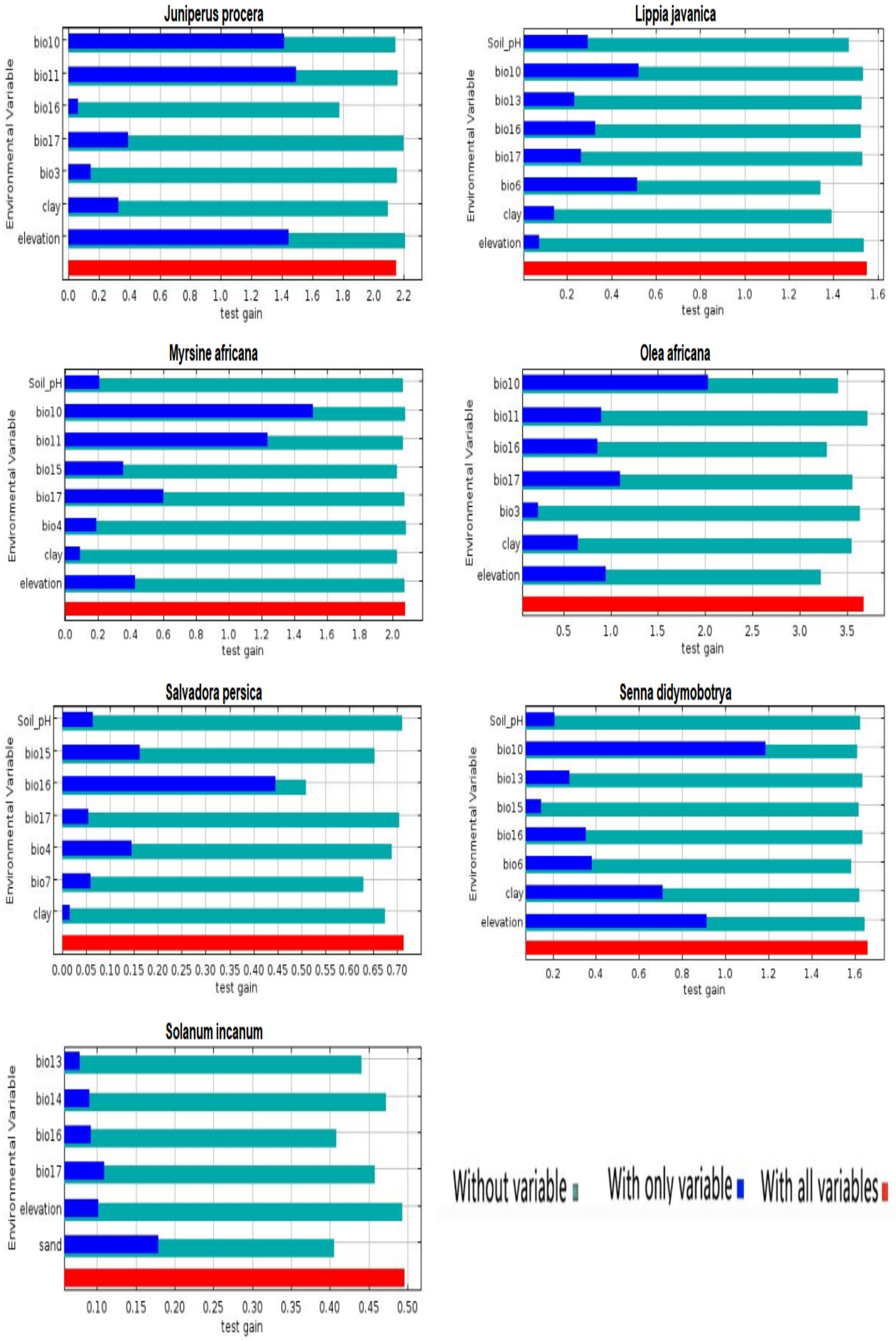

Figure 3.12.: Jackkknife test for modeled anti-malarial plant species in alphabetical order (continued).

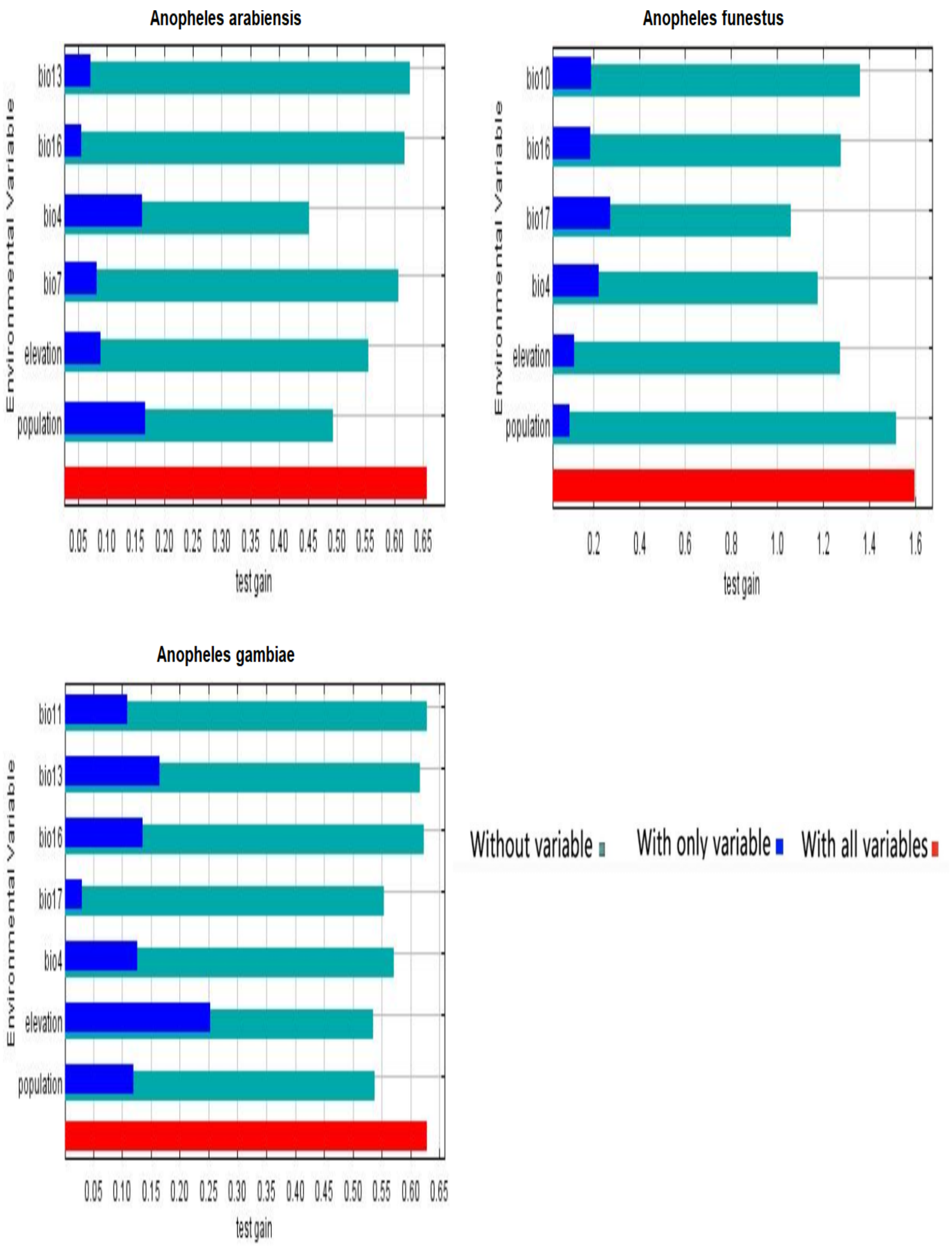

Figure 3.13.: Jackkknife test for modeled malarial vector species in alphabetical order.

Table 3.4: The most important environmental variable is ranked first for anti-malarial plant species.

Species	Variables	Rank
Acacia etbaica	bio17	1
	soil pH	2
	bio16	3
	bio11	4
	elevation	5
	sand	6
Acacia mellifera	bio16	1
	soil pH	2
	sand	3
	bio7	4
	bio17	5
Acacia tortilis	bio16	1
	bio4	2
	bio5	3
	clay	4
	bio17	5
	elevation	6
Acacia xanthophloea	bio7	1
	bio17	2
	clay	3
	bio11	4
	bio16	5
	bio15	6
	elevation	7
Balanites aegyptiaca	Bio16	1
	bio15	2
	soil pH	3
	bio7	4
	bio11	5
	elevation	6
	sand	7

Continued on next page

Table 3.4: The most important environmental variable is ranked first for anti-malarial plant species. (Continued)

Boscia angustifolia	bio4	1
	soil pH	2
	bio16	3
	bio15	4
	bio10	5
	bio7	6
	sand	7
	elevation	8
Boscia coriacea	elevation	1
	bio15	2
	bio4	3
	bio11	4
	bio17	5
	bio16	6
Carissa edulis	bio11	1
	bio10	2
	bio17	3
	bio6	4
	elevation	5
	clay	6
	bio16	7
Comiphora africana	bio16	1
	bio4	2
	bio15	3
	soil pH	4
	bio17	5
	bio7	6
	clay	7
	elevation	8
Cordia monoica	bio16	1

Continued on next page

Table 3.4: The most important environmental variable is ranked first for anti-malarial plant species. (Continued)

	bio11	2
	bio10	3
	bio17	4
	elevation	5
	clay	6
Croton dichogamus	bio10	1
	bio5	2
	elevation	3
	bio11	4
	clay	5
	bio17	6
	soil pH	7
Croton megalocarpus	bio10	1
	elevation	2
	clay	3
	bio17	4
	bio4	5
	bio16	6
Euclea divinorum	bio6	1
	bio13	2
	bio10	3
	bio17	4
	elevation	5
	soil pH	6
	clay	7
Harrisonia abyssinica	bio17	1
	bio14	2
	bio6	3
	elevation	4
	bio11	5
	bio10	6

Continued on next page

Table 3.4: The most important environmental variable is ranked first for anti-malarial plant species. (Continued)

	soil pH	7
Juniperus procera	bio11	1
	elevation	2
	bio10	3
	bio17	4
	clay	5
	bio3	6
	bio16	7
Myrsine africana	bio10	1
	bio11	2
	bio17	3
	elevation	4
	bio15	5
	soil pH	6
	bio4	7
	clay	8
Olea africana	bio10	1
	bio17	2
	elevation	3
	bio11	4
	bio16	5
	clay	6
	bio3	7
Salvadora persica	bio16	1
	bio15	2
	bio4	3
	soil pH	4
	bio7	5
	bio17	6
	clay	7

Continued on next page

Table 3.4: The most important environmental variable is ranked first for anti-malarial plant species. (Continued)

Senna didymobotrya	bio10	1
	elevation	2
	clay	3
	bio6	4
	bio16	5
	bio13	6
	soil pH	7
	bio15	8
Solonum incanum	sand	1
	bio17	2
	elevation	3
	bio16	4
	bio14	5
	bio13	6

Table 3.5: The most important environmental variable is ranked first for malaria vector species.

Species	**Variable**	**Rank**
Anopheles arabiensis	Population	1
	Bio4	2
	Elevation	3
	bio7	4
	bio13	5
	bio16	6
Anopheles gambiae	Elevation	1
	bio13	2
	bio16	3
	bio4	4
	Population	5
	bio11	6
	bio17	7
Anopheles fenestus	bio17	1
	bio4	2
	bio10	3
	bio16	4
	Elevation	5
	population	6

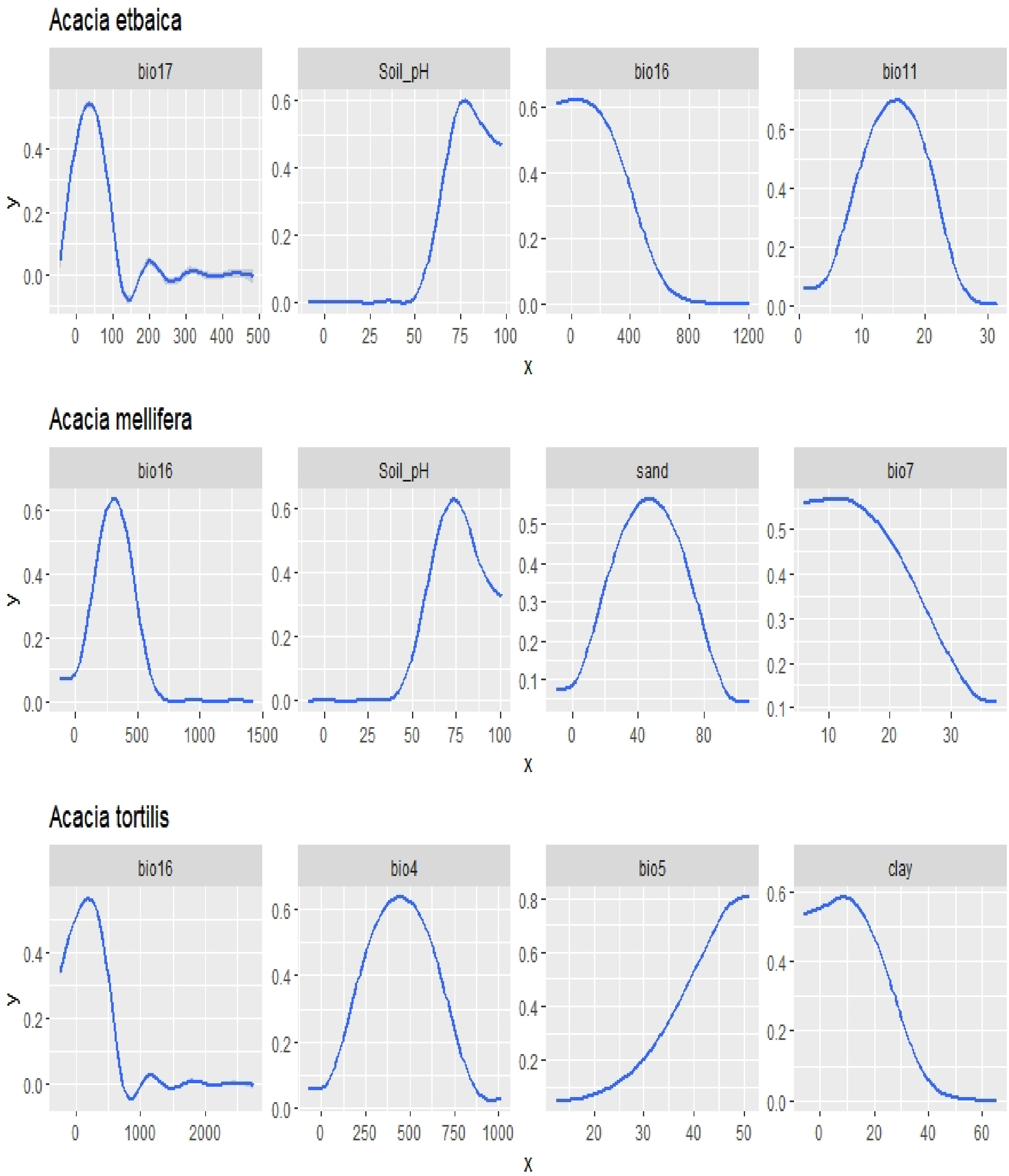

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order.

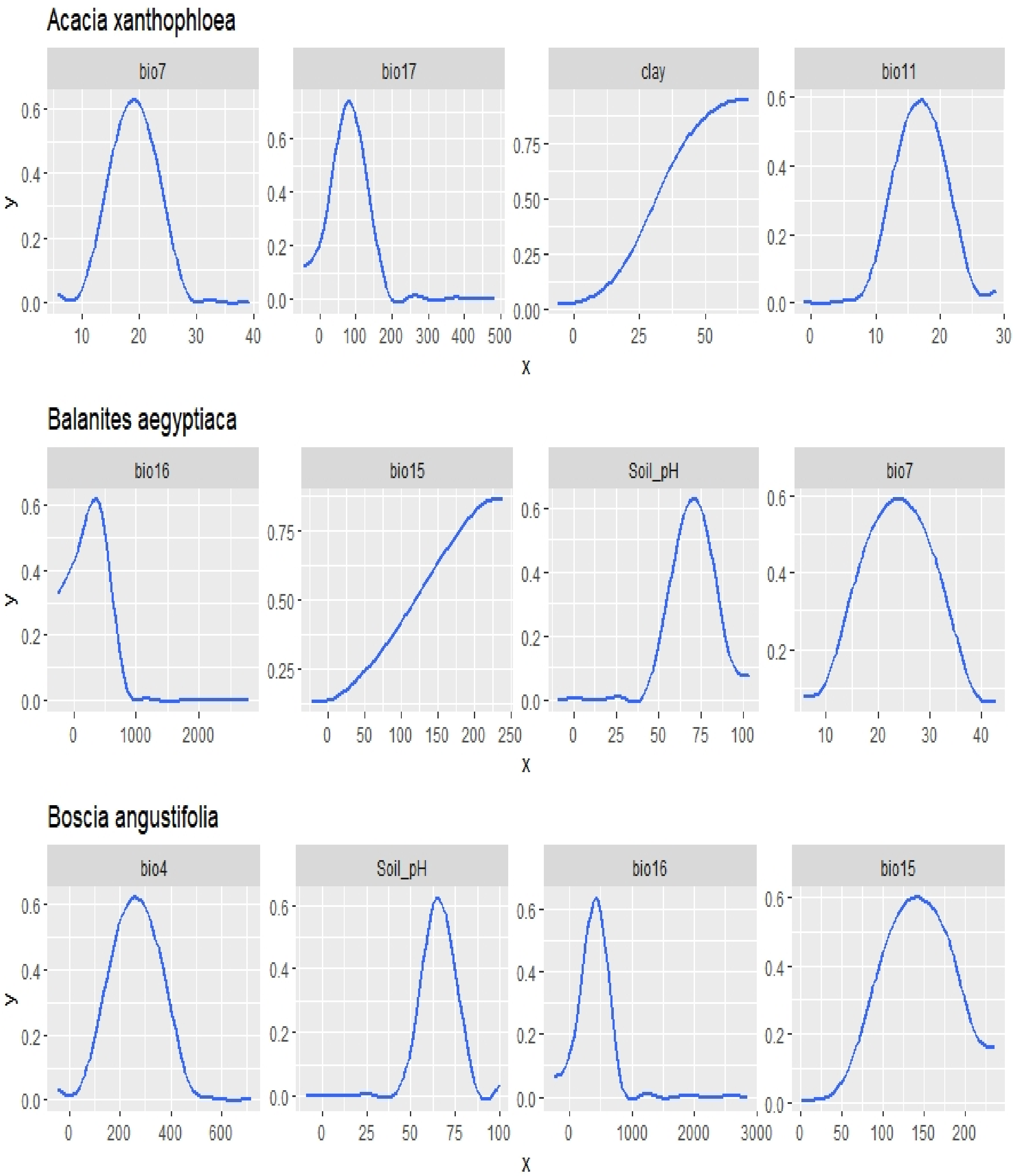

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

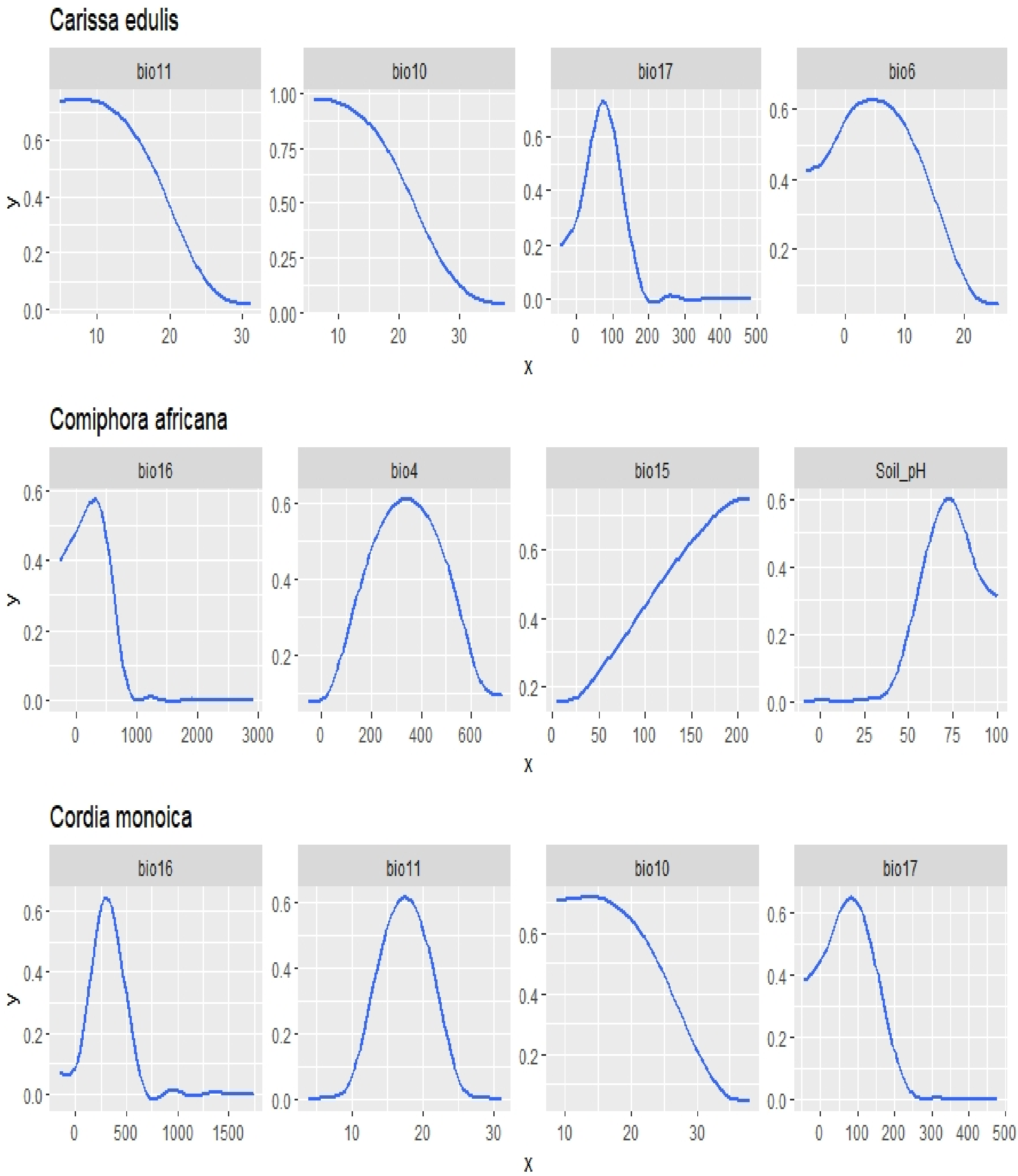

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

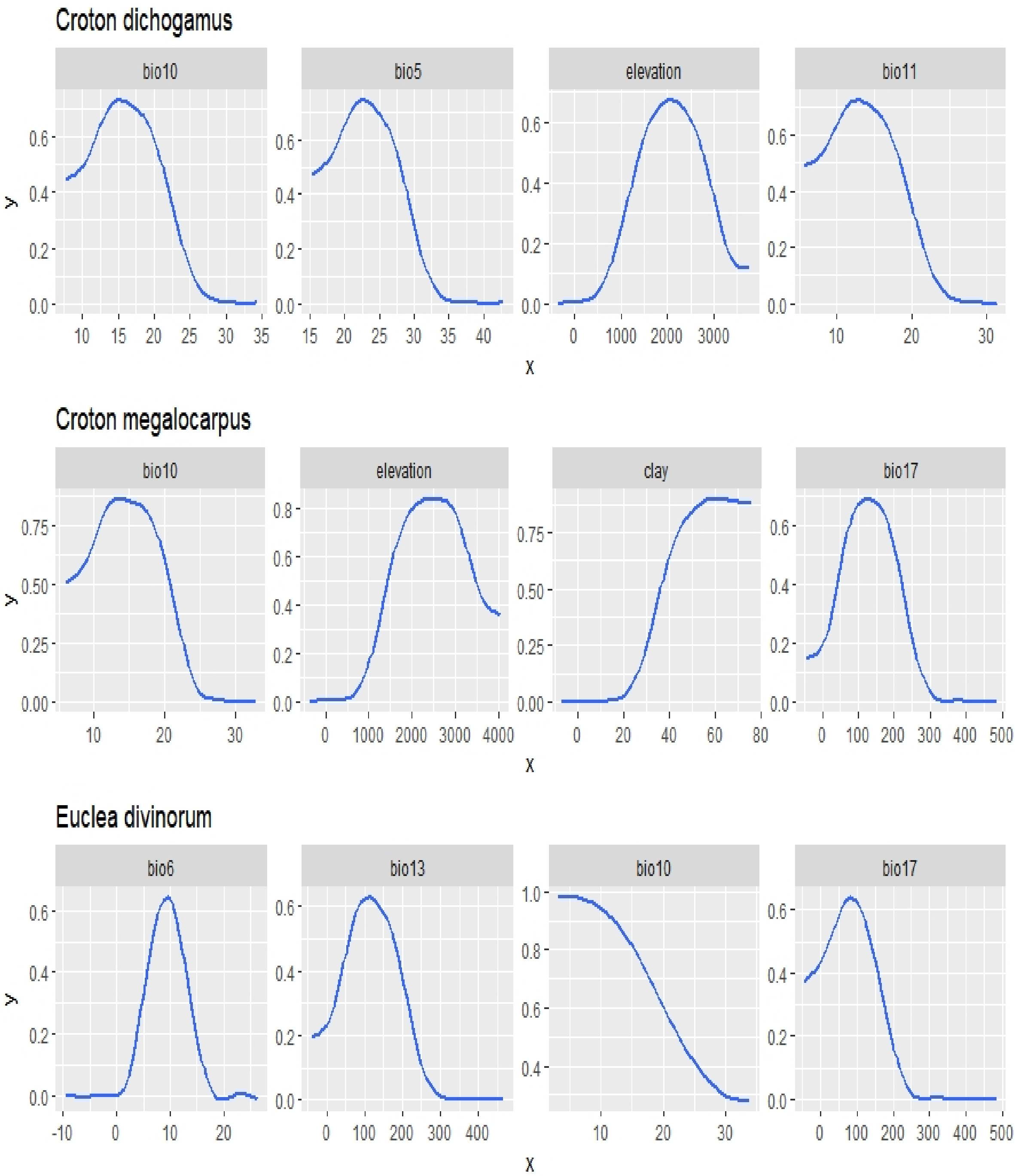

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

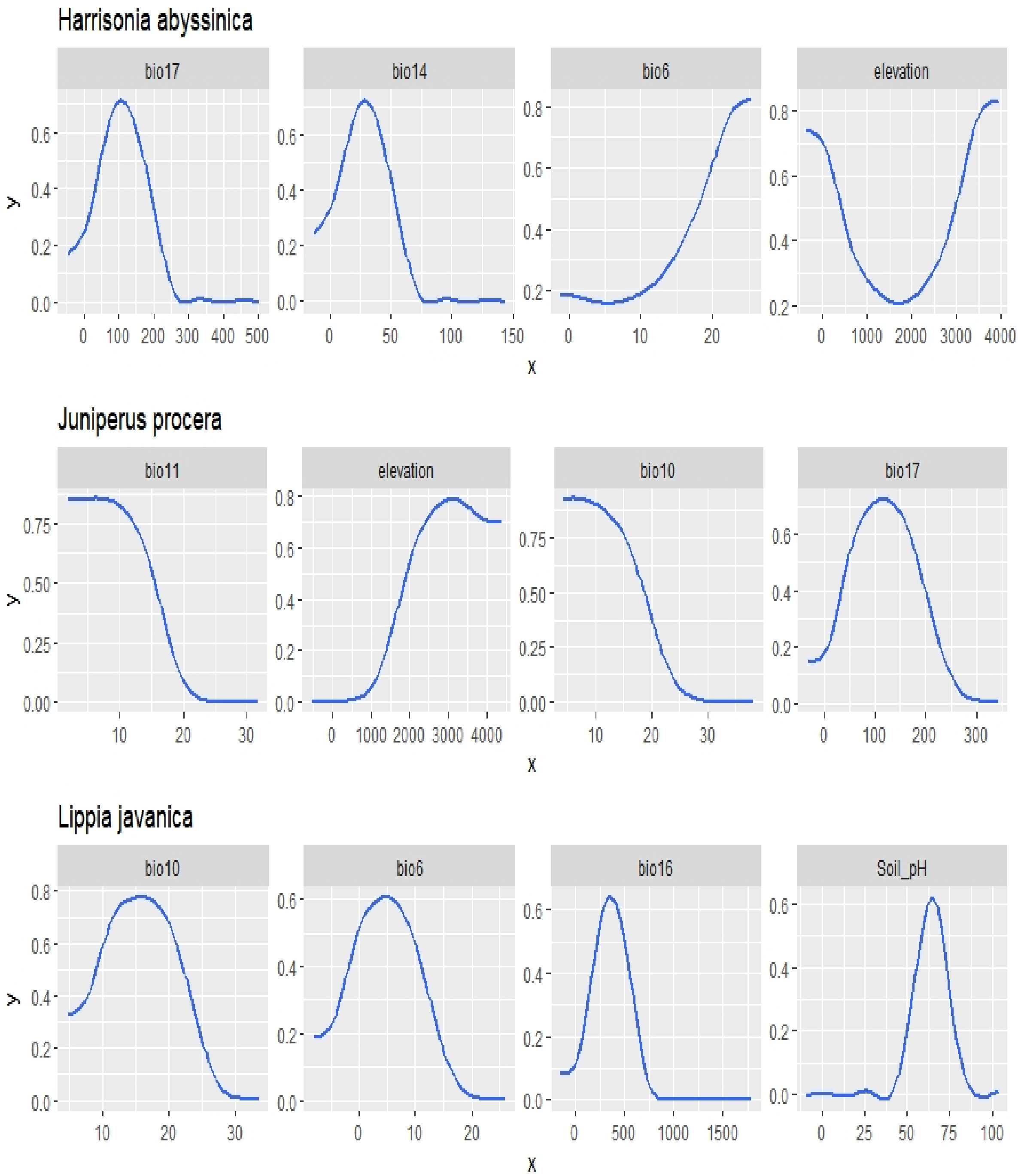

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

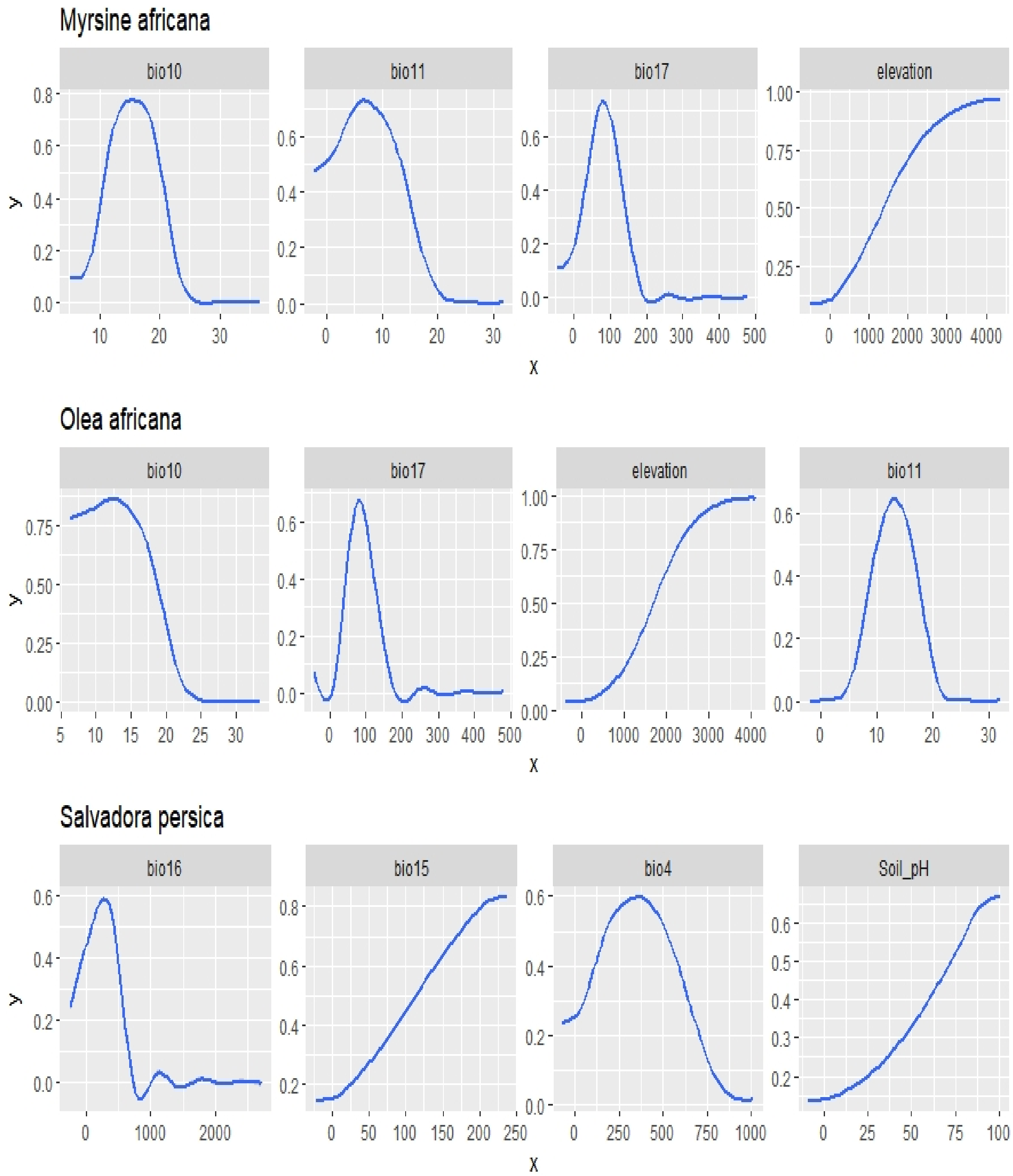

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

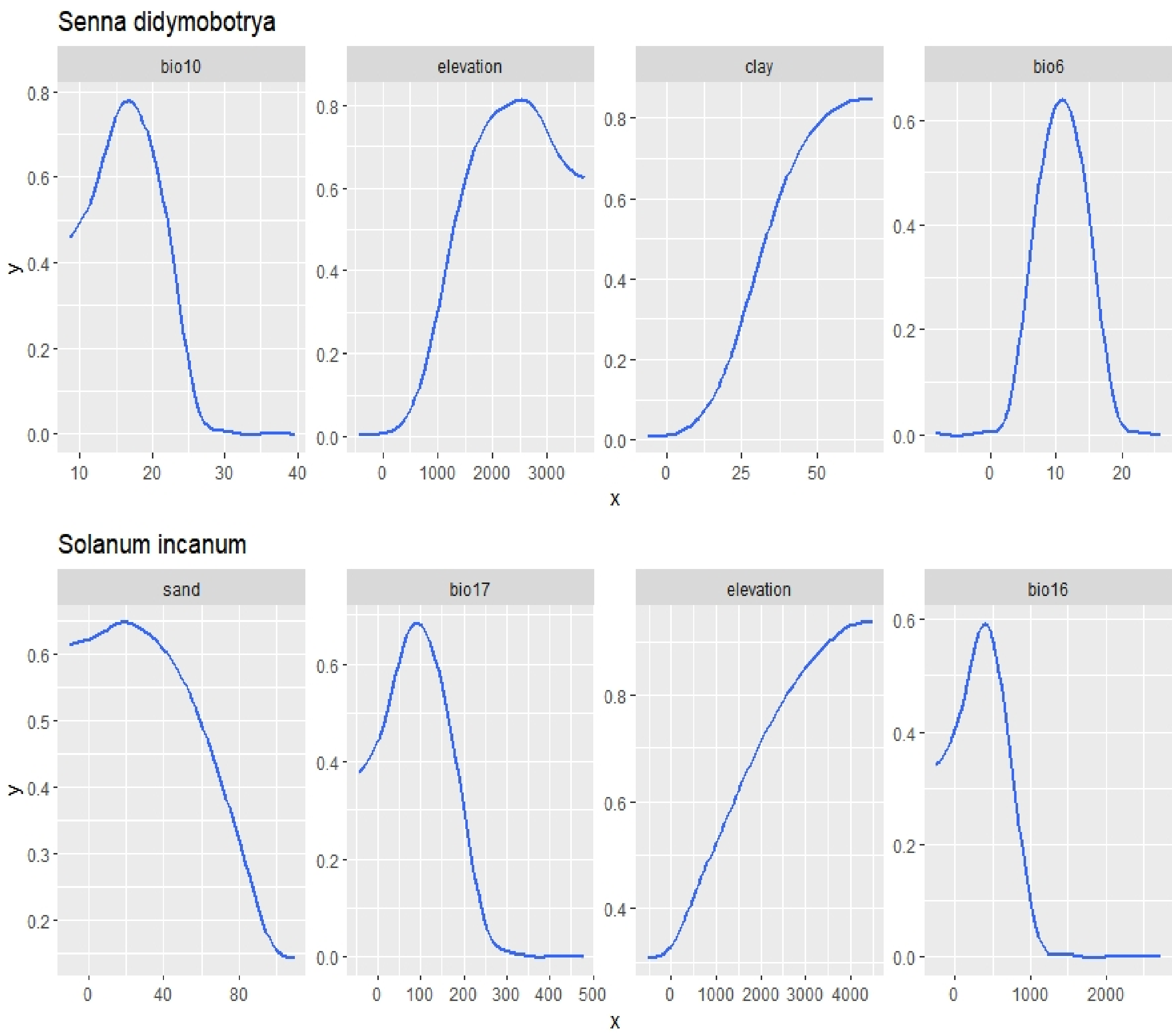

Figure 3.14.: Response curves of the four most important environmental variables for anti-malarial plant species in alphabetical order (continued).

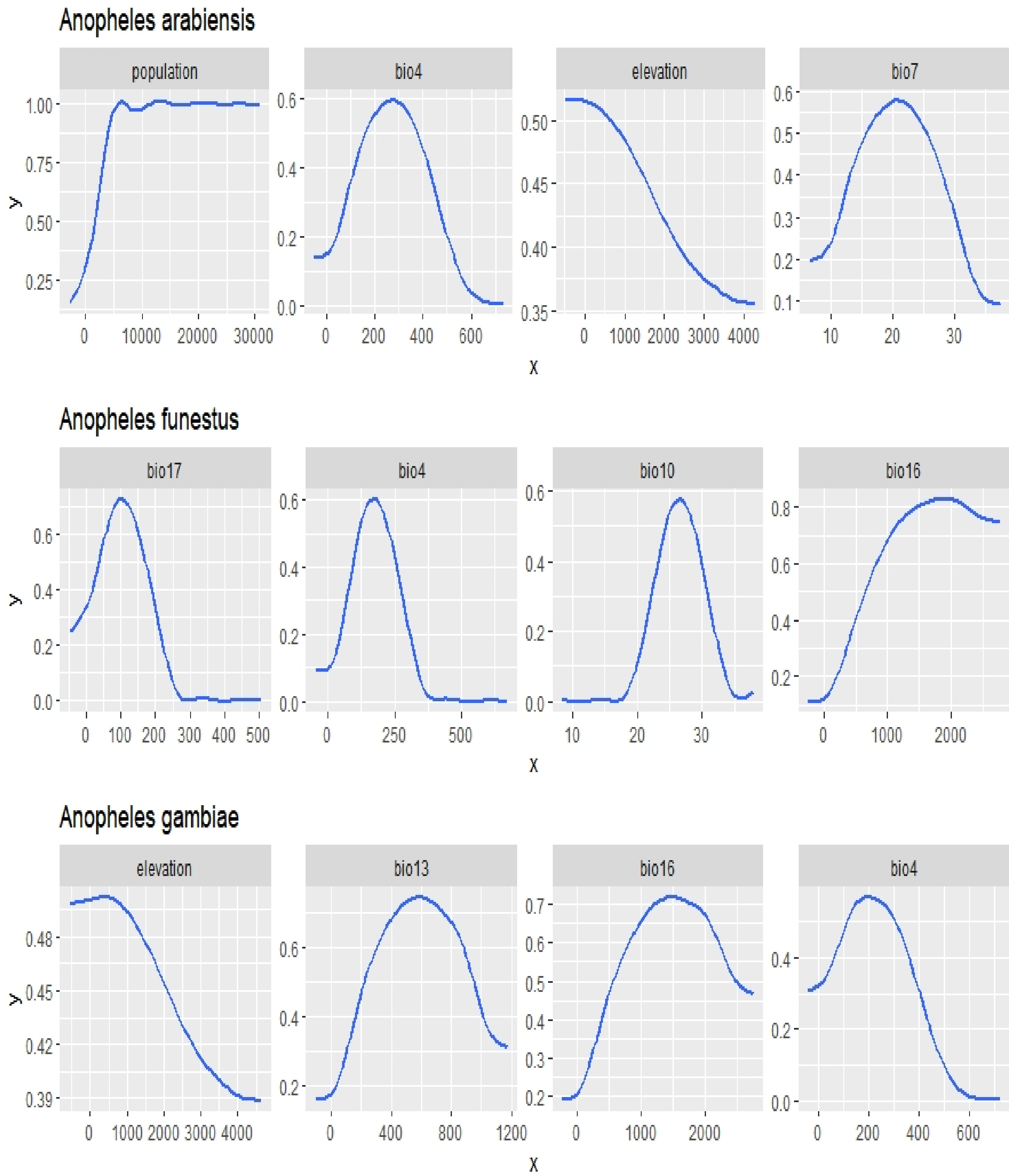

Figure 3.15.: Response curves of the four most important environmental variables for malaria vector species in alphabetical order.

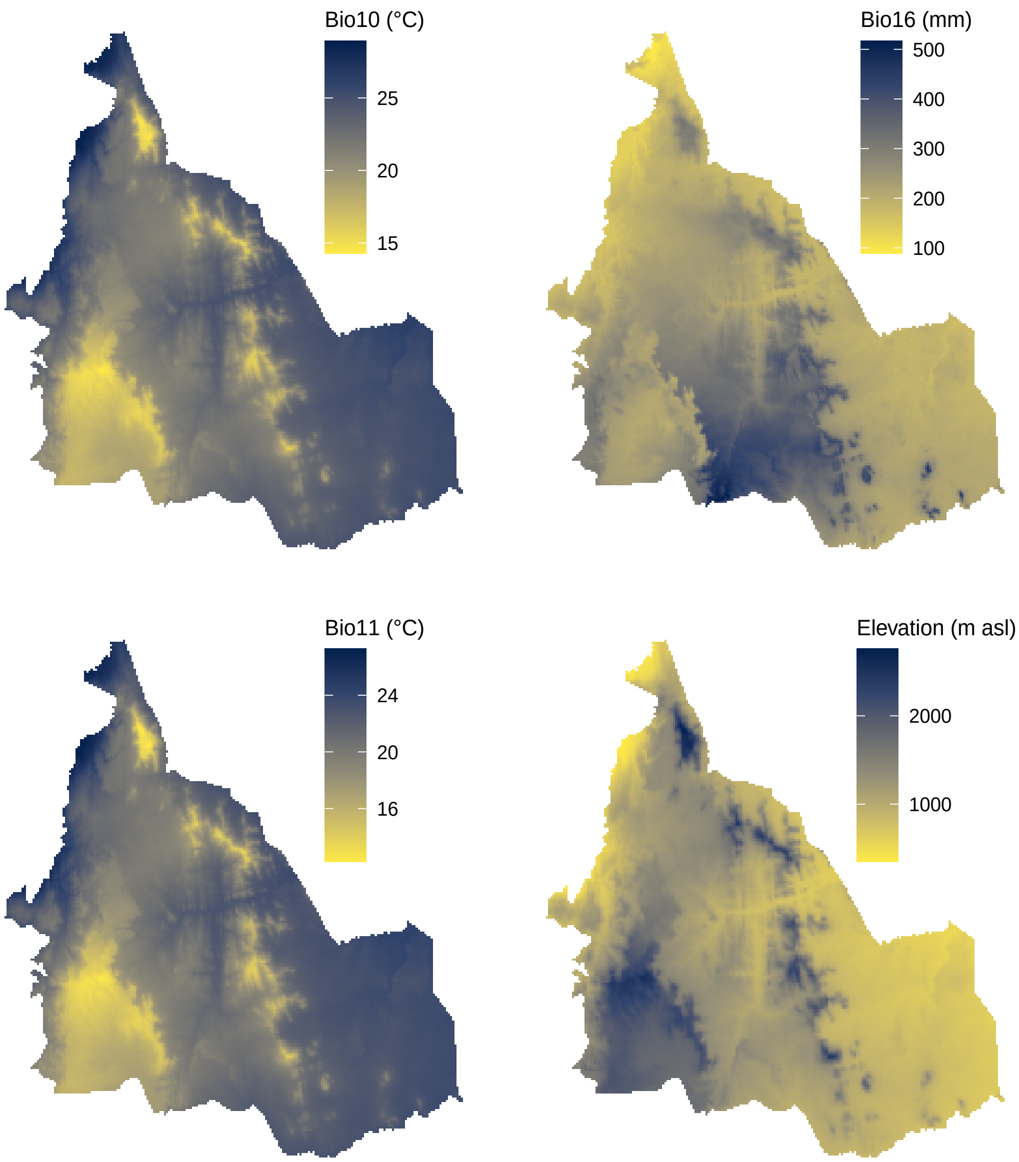

Figure 3.16.: Most important environmental variables which affected the distribution of anti-malarial plant species.

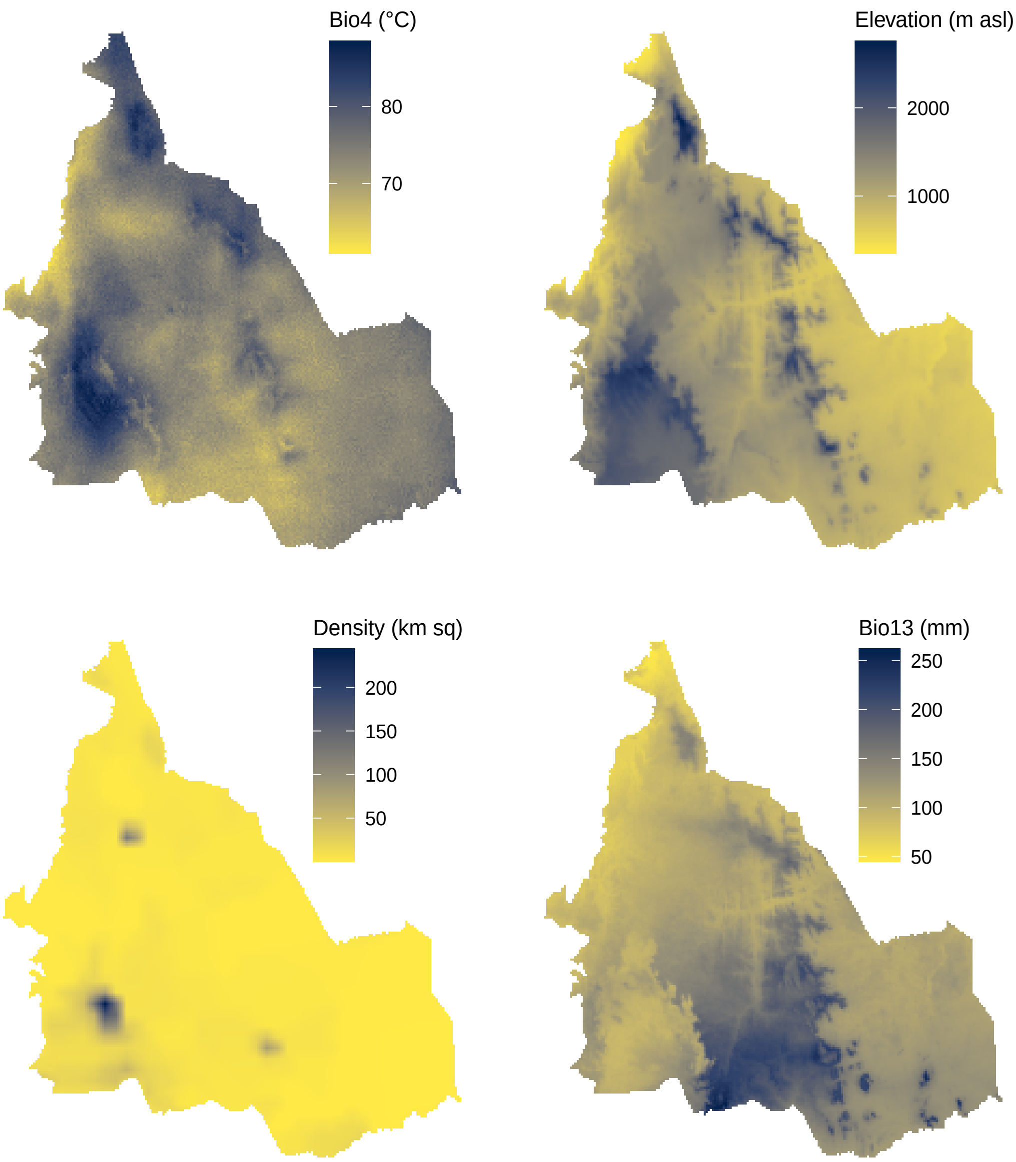

Figure 3.17.: Most important environmental variables which affected the distribution of malaria vector species.

Table 3.6: Table of t-test results under current and future climate change scenarios.

	Current		**RCP 4.5 2050s**		**RCP 4.5 2070s**		**RCP 8.5 2050s**		**RCP 8.5 2070s**	
Mean Species Richness	Inside	Outside	Inside	Outside	Inside	Outside	Inside	Outside	Inside	Outside
	12.47	8.34	7.78	10.12	7.89	10.56	8.07	10.96	3.99	8.31

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Table 3.6: Table of t-test results under current and future climate change scenarios. (Continued)

Paired t	6.58	2.14	3.21	2.76	3.72
Degrees of freedom	5495	5495	5495	5495	5495
P-value	0.012327	0.00026	0.001	0.00421	0.00036

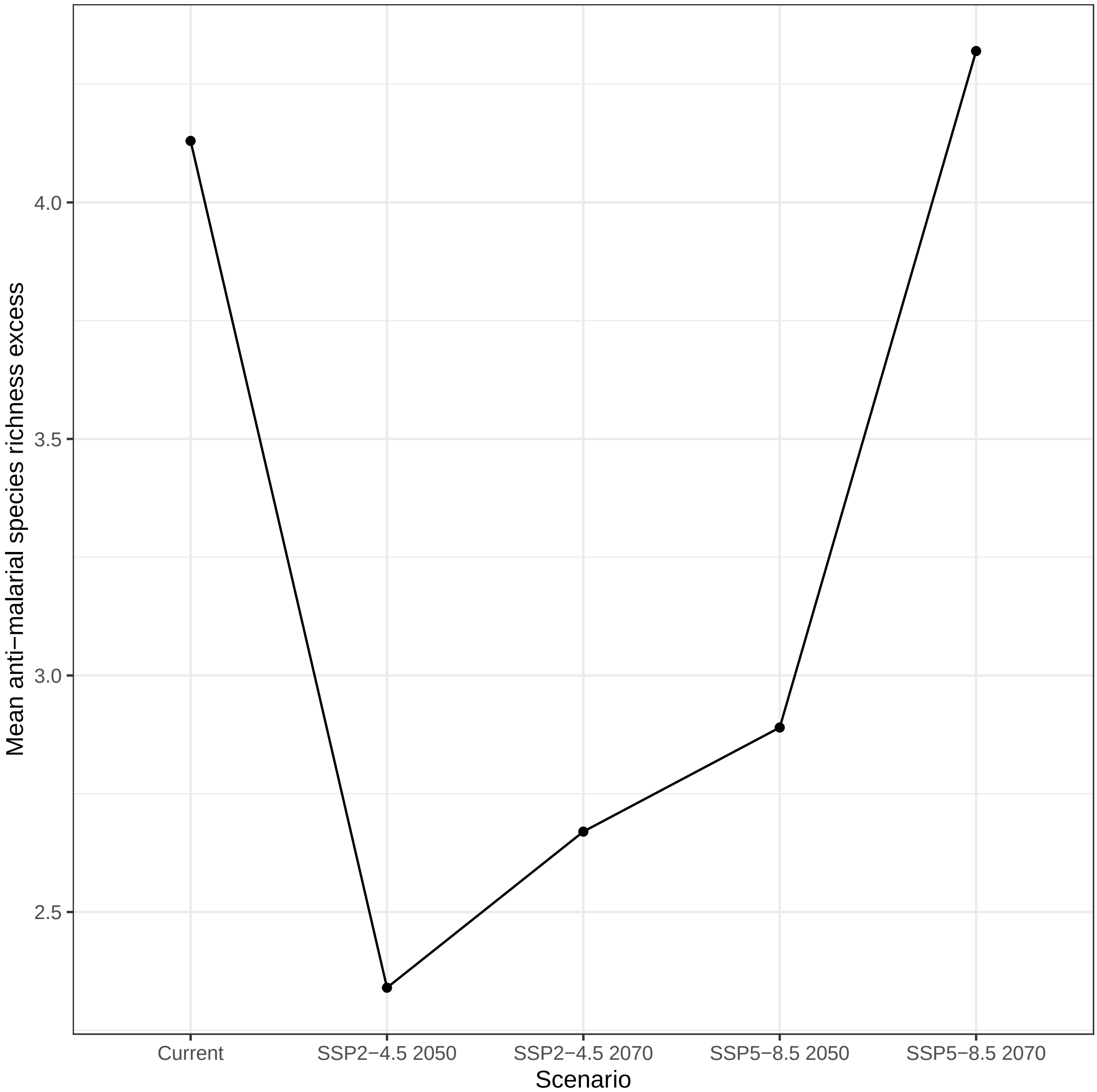

Figure 3.18.: Predicted mean anti-malarial plant species richness in excess inside protected areas relative to outside under the current scenario and in excess outside protected area relative to inside under future climate change scenarios.

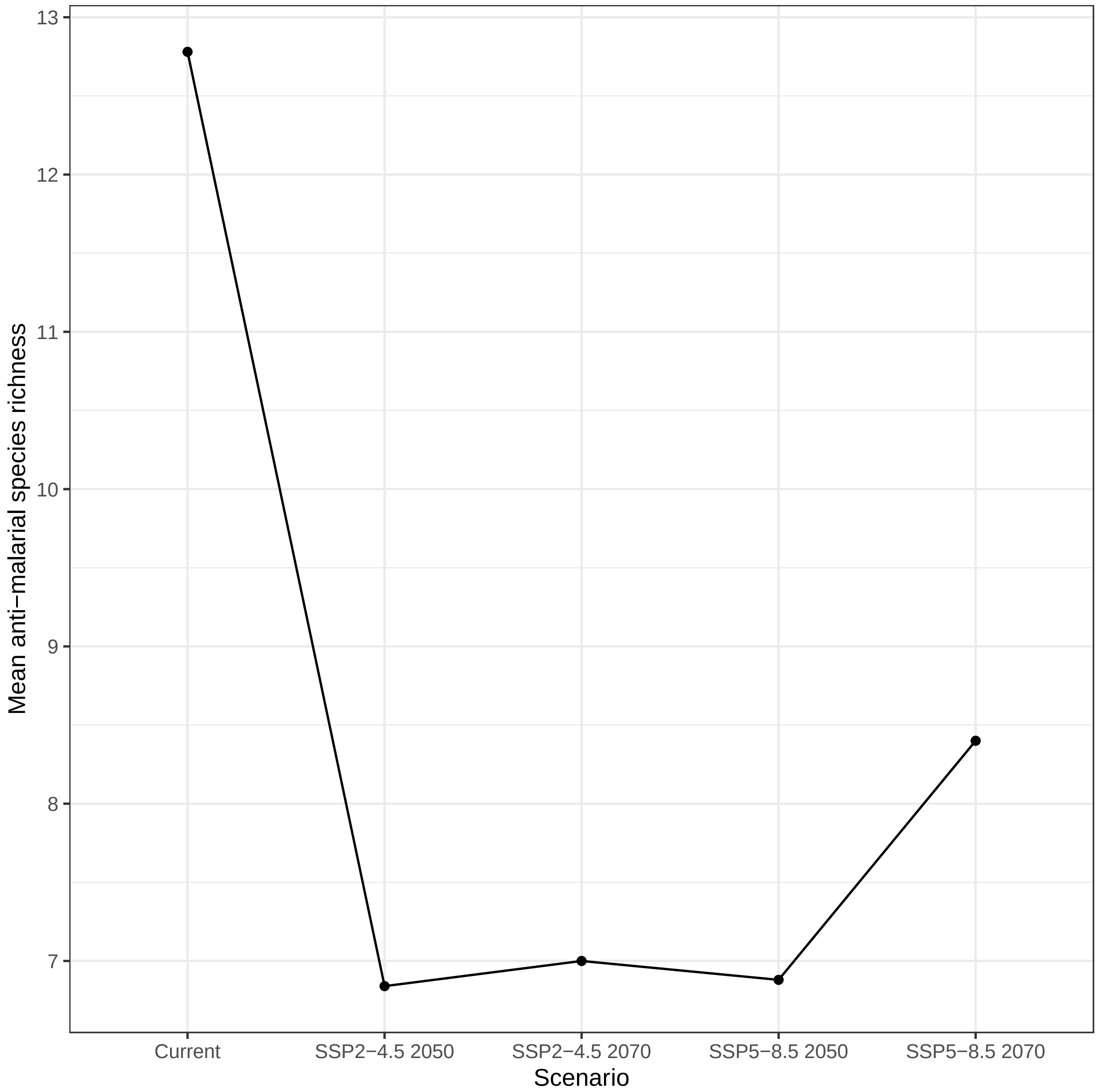

Figure 3.19.: Predicted mean anti-malarial species richness under different scenarios.

Table 3.7: List of anti-malaria plant species and their distributional area under different scenario.

Species	**Current area (Km sq)**	**SSP2-4.5 2050 (Km sq)**	**SSP2-4.5 2070 (Km sq)**	**SSP5-8.5 2050 (Km sq)**	**SSP5-8.5 2070 (Km sq)**
Acacia etbaica	21000	1390	4246	3430	17852
Acacia mellifera	21085	18239	17900	18027	17627
Acacia tortilis	7068	10389	10363	9801	9483
Acacia xanthophloea	16203	428	409	440	405
Balanites aegyptiaca	20716	18166	17850	17518	16856
Boscia angustifolia	19123	5422	5863	6080	15092
Boscia coriacea	1881	731	728	791	697
Carissa edulis	8436	3769	8443	7286	9903
Comiphora africana	5926	4345	4561	4209	4392
Cordia monoica	18582	707	640	711	10945
Croton dichogamus	18455	6490	6243	6258	5871
Croton megalocarpus	12031	12471	11956	11642	11518
Euclea divinorum	7646	12064	10536	10492	7752
Harrisonia abyssinica	4	2466	2347	2352	867
Juniperus procera	5394	1779	2081	1889	3460
Lippia javanica	5531	3302	3071	3071	2466
Myrsine africana	6387	1054	1052	1037	4496
Olea africana	20879	17174	16249	16179	14742

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Table 3.7: List of anti-malaria plant species and their distributional area under different scenario. (Continued)

Salvadora persica	17932	886	811	718	575
Senna didymobotrya	14167	3177	3036	3046	2547
Solonum incanum	21090	19714	19224	20020	19669

Table 3.8: List of anti-malarial species with their percentage change in distributional area and threat level under future climate scenarios of SSP2-4.5 2050, SSP2-4.5 2070, SSP5-8.5 2050 and SSP5-8.5 2070 respectively.

Species	% Change SSP2-4.5 2050	Threat level SSP2-4.5 2050	% Change SSP2-4.5 2070	Threat level SSP2-4.5 2070	% Change SSP5-8.5 2050	Threat level SSP5-8.5 2050	% Change SSP5-8.5 2070	Threat level SSP5-8.5 2070
Acacia etbaica	-93.00%	CR	-80.00%	CR	-84.00%	CR	-15.00%	NT
Acacia mellifera	-13.00%	NT	-15.00%	NT	-15.00%	NT	-16.00%	NT
Acacia tortilis	47.00%	LC	47.00%	LC	39.00%	LC	34.00%	LC
Acacia xanthophloea	-97.00%	CR	-97.00%	CR	-97.00%	CR	-98.00%	CR
Balanites aegyptiaca	-12.00%	NT	-14.00%	NT	-15.00%	NT	-19.00%	NT
Boscia angustifolia	-72.00%	EN	-69.00%	EN	-68.00%	EN	-21	NT
Boscia coriacea	-61.00%	EN	-61.00%	EN	-58.00%	EN	-63.00%	EN
Carissa edulis	-51.00%	EN	0.10%	LC	-14.00%	NT	17.00%	LC
Comiphora africana	-27.00%	NT	-23.00%	NT	-29.00%	NT	-26.00%	NT
Cordia monoica	-96.00%	CR	-97.00%	CR	-96.00%	CR	-41.00%	VU
Croton dichogamus	-65.00%	EN	-66.00%	EN	-66.00%	EN	-68.00%	EN
Croton megalocarpus	4.00%	LC	-0.60%	NT	-3.00%	NT	-4.00%	NT

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Table 3.8: List of anti-malarial species with their percentage change in distributional area and threat level under future climate scenarios of SSP2-4.5 2050, SSP2-4.5 2070, SSP5-8.5 2050 and SSP5-8.5 2070 respectively. (Continued)

Euclea divinorum	58.00%	LC	38.00%	LC	38.00%	LC	1.00%	LC
Harrisonia abyssinica	+61550%	LC	+58575%	LC	+58700%	LC	+21575%	LC
Juniperus procera	-67.00%	EN	-61.00%	EN	-65.00%	EN	-36.00%	VU
Lippia javanica	-40.00%	VU	-44.00%	VU	-44.00%	VU	-55.00%	EN
Myrsine africana	-83.00%	CR	-84.00%	CR	-84.00%	CR	-30.00%	NT
Olea africana	-18.00%	NT	-22.00%	NT	-23.00%	NT	-29.00%	NT
Salvadora persica	-95.00%	CR	-95.00%	CR	-96.00%	CR	-97.00%	CR
Senna didymobotrya	-78.00%	EN	-79.00%	EN	-78.00%	EN	-82.00%	CR
Solonum incanum	-7.00%	NT	-9.00%	NT	-5.00%	NT	-7.00%	NT

4. Remote Sensing-Based Mapping of Medicinal Plants Using an Ensemble One-Class Classification Algorithm in Samburu Dryland, Kenya

Dikko Jeff Gafna, Joy A. Obando, Klara Dolos, Sebastian Schmidtlein, Fabian Ewald Fassnacht

Abstract

Medicinal plants provide health benefits to humans, especially in communities where conventional drugs are unavailable. The Samburu dryland in Kenya is one example of a region where the population depends on medicinal plants for healthcare. However, conservation of these plants remains a challenge due to inadequate information regarding their distribution. Accurate mapping of medicinal plants' distribution is fundamental to informing conservation strategies for this important resource. In this study, we developed an ensemble one-class classification work-flow including Biased Support Vector machine, One Class Support Vector machine and MaxEnt and combined it with remotely sensed Sentinel-2 satellite data to model the distribution of medicinal plants in Samburu dryland, Kenya. By summing up individual model outputs, we retrieved the richness of all considered medicinal plants together as well as subsets of plants used against (i) stomach ache, (ii) wounds and (iii) diarrhoea. We furthermore tested the usefulness of ensemble binary SDM (Bin-SDM) and ensemble suitability SDM (Suit-SDM) in predicting medicinal plant species groups richness. Our findings showed that medicinal plants' distribution patterns were driven by elevation and related to a range of spectral indices including SWC, LSWI, NDVI and the Sentinel-2 band NIR8. Species used against stomach ache exhibited distribution patterns identical to most medicinal plants. In contrast, richness patterns for species used against wounds and diarrhoea were not consistent with the general medicinal plants richness pattern. Model performance varied across the medicinal plants groups, with a more accurate prediction for the species used against stomach ache. Overall, Suit-SDM produced better predictions than Bin-SDM. We conclude that richness maps derived from a combination of field inventories and remote sensing can be used to formulate conservation strategies and that the Suit-SDM approach shows potential to be adopted in predicting the richness of species of conservation concern due to their relevance as medicinal plants.

4.1. Introduction

Millions of rural households in non-industrialized nations rely on wild medicinal plant species for self-medication (Nanyingi et al., 2008). These species are also a major source of raw materials for conventional drugs (Dharani and Yenesew, 2010). Other than their medicinal value, the species also play an important role in poverty alleviation in rural areas by serving as marketable goods (Bussmann, 2006). However, populations of wild medicinal plant species are decreasing (Gafna et al., 2017), partly due to habitat loss, intensive collection and climate change (Gafna et al., 2023). This poses a threat both to the populations of wild medicinal plant species and the livelihood of the rural population who depend on them for healthcare. The threats against medicinal plants, coupled with their critical role in healthcare and in the enhancement of rural livelihood, makes it urgent for conservation planners to develop meaningful conservation programs to conserve them.

Whereas, medicinal plants continue to play a critical role in the society, fewer assessments on their distribution have been conducted in Africa (Kaky and Gilbert, 2016; Malahlela et al., 2019). For example, in Kenya, maps on the distribution of medicinal plants remain sparse. In fact, only one study by Gafna et al. (2023) modeled the distribution of anti-malarial species in the country. Such limited information regarding the distribution of medicinal plants undermines their potential and poses a challenge to their conservation.

In Kenya, Samburu dryland is appreciated for its richness in medicinal flora (Bussmann, 2006). Medicinal plants from the dryland make up 43% of the country's total medicinal flora (Dharani and Yenesew, 2010). However, recent studies suggest that most medicinal plant species in the region are vulnerable or endangered due to overgrazing, climate change and over-harvesting for commercial purposes (Bussmann, 2006; Gafna et al., 2017, 2021). Considering that over 80% of the locals in Samburu dryland rely on wild medicinal plants to meet their daily healthcare needs (Gafna et al., 2017), conservation of this important resource in the area is critical. Accurate mapping of the occurrence of these species can be a crucial starting point, in the formulation of conservation strategies in the region. Such mapping will support decision making in regards to areas where conservation efforts may be concentrated (Gafna et al., 2023). Currently, even for the species used against the most common diseases in the area like diarrhoea and wounds (Bussmann, 2006), distribution maps are still lacking.

Mapping of medicinal plants has conventionally been accomplished by modelling potential species distributions based on climatic variables like Bioclim (Kaky and Gilbert, 2016). However, climatic variables are more strongly interpolated in species rich developing nations which lie in the tropics like Kenya due to few and widely spaced weather stations. At the same time, smaller study areas may have comparatively limited variations in climatic variables like rainfall (Rao et al., 2011). Consequently, climatic variables may not always be the perfect choice for capturing finer-scale environmental differences which drive local medicinal plants occurrences. An alternative data source to directly map medicinal plants is remote sensing (RS) data collected by satellites. This satellite data is nowadays freely available and provides comprehensive measurements of the earth's spectral properties at a (very) high spatial and temporal resolution. These spectral properties are known to relate to certain optical traits of plant species, which in some cases may relate to plant biodiversity. The two Sentinel-2 (S-2) satellites provide weekly data acquisitions of the complete globe at a spatial grain of up to 10 m. Therefore, S-2 data offers the potential to incorporate seasonal-temporal information in mapping species distributions and capture fine-scale optical plant traits potentially related to biodiversity, even in inaccessible but species rich regions (Malahlela et al., 2019).

Earlier studies showed that S-2 data is well suited for mapping plant species including also medicinal plants, as its bands cover comparably narrow sections of the red-edge portion of the electromagnetic spectrum which were designed to relate to optical traits of vegetation (Malahlela et al., 2019). The broad and narrow bands of the data are used to derive various soil, water and vegetation indices. Such indices can be used to retrieve various vegetation parameters. However, the determinants of medicinal plant species distribution in a heterogeneous landscape are often too complicated to be modeled by S-2 alone (Malahlela et al., 2019). The inclusion of other environmental variables like elevation may be necessary to accurately map the species (Malahlela et al., 2019).

Classifying and mapping plant species with RS data can be accomplished with a range of approaches. The most common approach is a supervised multi-class classification in which training data is required for relevant classes occurring in the area of interest. This requirement comes into play regardless of whether the classes are of interest to the researcher (Piiroinen et al., 2018). This means that in a supervised classification, data on non-medicinal plant species is required and corresponding costly and time consuming field-campaigns are necessary (Piiroinen et al., 2018). This is a major limitation especially when the intention is to map only one or few medicinal plant species.

In such cases, One-class classifiers (OCCs), where the training data are needed only for the target class (i.e. a single medicinal plant species), could be a better alternative to the supervised multi-class classifiers (Liu et al., 2020). Specifically, one-class classification extracts a particular target class from an image using only the training data of the class of interest. Among the different applicable OCCs, biased SVM (BSVM), MaxEnt and one class SVM (OCSVM) have been frequently used (Li and Guo, 2010). Remote sensing studies have used OCCs to successfully map tree species in African savannas (Baldeck et al., 2014), invasive species in Kenya (Piiroinen et al., 2018), high nature value grasslands in Germany (Stenzel et al., 2017) and medicinal plant species in South Africa (Malahlela et al., 2019). However, the accuracy of OCCs varies depending on the selection of model parameters, type of classifier and type of target species. For instance, Mack and Waske (2017) compared the performance of OCSVM, BSVM and MaxEnt for mapping land cover and found that BSVM outperformed the other two classifiers. Baldeck et al. (2014) found that BSVM performed better than OCSVM in differentiating savanna trees. In other studies, Li and Guo (2010) and Mack and Waske (2017) evidenced that MaxEnt produced better results than OCSVM in landcover classification. The discrepancies in the accuracy of OCCs indicate that no OCC always performs well across regions, species and applications. The struggle to identify a single best

OCC has led to the suggestion that an accurate prediction may be attained using an ensemble approach (i.e. calculating the mean of classifiers), rather than relying on a single OCC (Liu et al., 2020). Ensemble models are increasingly applied in RS studies to solve multi-class classification problems (Liu et al., 2020) and have also been used to predict plant species richness (hereafter, SR) (Kaky et al., 2020).

Two different approaches have been applied to predict SR from combining output on individual species' distribution. Some scholars suggest stacking individual binary predictions to produce a SR map (hereafter: B-SDM Liu et al., 2005). The proponents of this approach argue that most conservation applications require binary maps. However, the combined errors of binary predictions are likely to be bigger than the combined errors of continuous suitabilities for occurrence (Meynard and Kaplan, 2012). An alternative to the first approach involves stacking the raw suitabilities to yield SR (Merow et al., 2013), hereafter called S-SDM. Its proponents argue that its richness predictions are less prone to accumulated errors caused by the threshold selection for binary maps and thus closer to the true SR (D'Amen et al., 2015). Whereas the two aforesaid approaches have been used in predicting plant SR (Dubuis et al., 2011), their scrutiny on medicinal plants are limited (but see Kaky and Gilbert, 2016).

In this work, we implemented an ensemble one class classifier (eOCC) work-flow to examine two research objectives: First, we aim to explore the potential of our eOCC approach combined with S-2 RS data and other RS data, to map medicinal plants in Samburu dryland, Kenya. Specifically, we focused on all medicinal plant species and those used against the most common diseases in the area: stomach ache, diarrhoea and wounds. Second, we aim to evaluate the usefulness of two methodological approaches, ensemble binary SDM (Bin-SDM) and ensemble suitability SDM (Suit-SDM), in predicting medicinal plant SR. This can inform the conservation managers on the most effective approach for predicting medicinal plant SR or other species of conservation concern.

4.2. Materials and data

4.2.1. Study area

Samburu County is located on the northern part of the rift valley, and approximately 400 km north-west of Kenya's capital, Nairobi (Fig. 4.1). The county comprises of 15 administrative wards and covers an area of 20,183 km^2 (KNBS, 2019). It has a population of 310,327 persons, with a population density of 11 persons/km^2 (KNBS, 2019). The county lies within an arid and semi-arid region. The annual precipitation of the region is 550 mm/year, and is bimodally distributed, with peaks in March-May (long rain) and July-September (short rain) (Gafna et al., 2023). The average annual temperature of most parts of the area is 22.6°C and the elevation ranges from 339 to 2795 m a.s.l (Gafna et al., 2023). The region harbors varied ecological conditions due to its variation in elevation, which contributes to its many varieties of medicinal plants (Gafna et al., 2021).

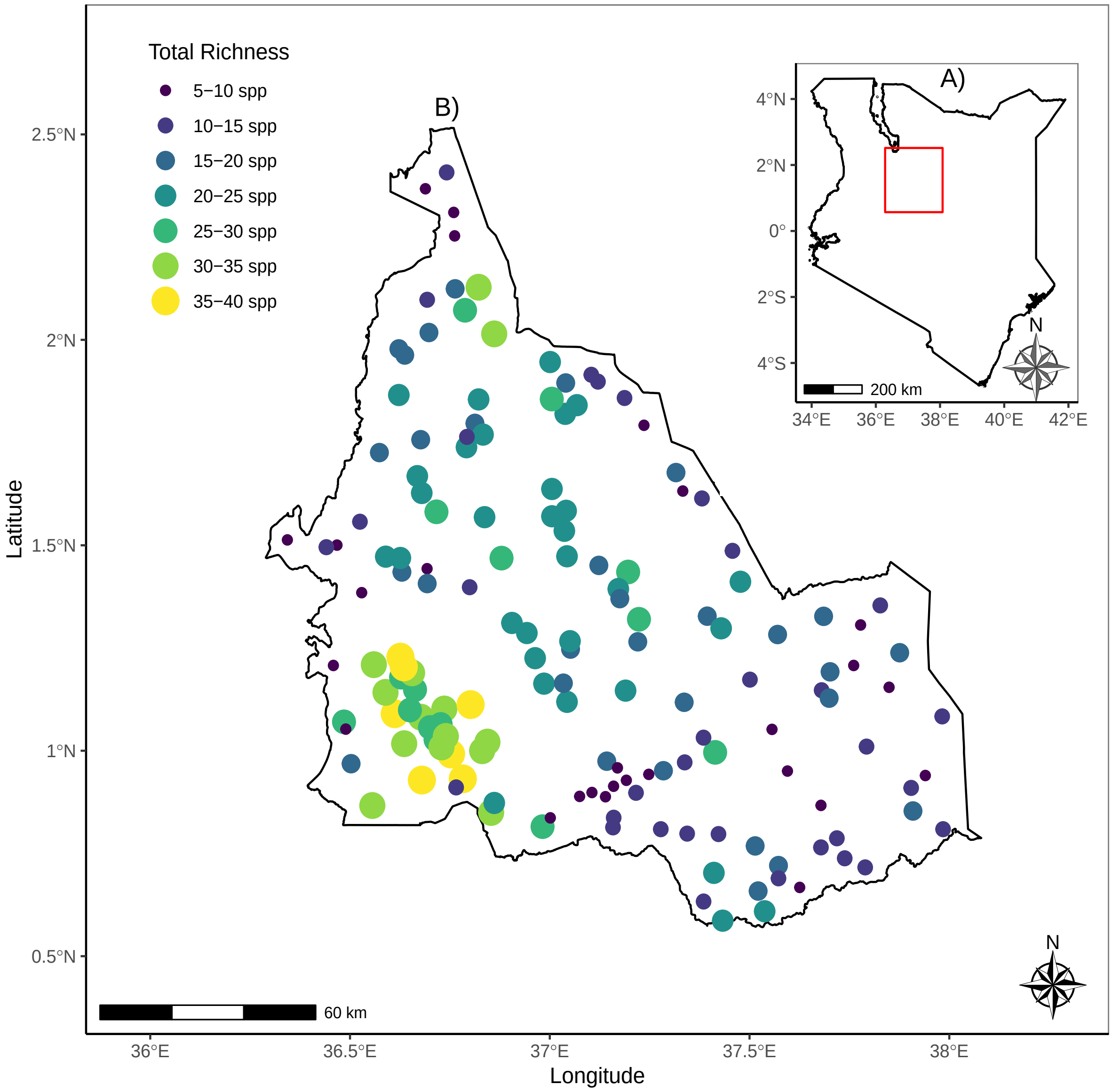

Figure 4.1.: A) Location of the study area within Kenya; B) Study area map of Samburu County and the distribution of observed medicinal plants richness (based on field survey data collected in 2016, 2017 and 2021).

4.2.2. Species data acquisition and processing

Field survey was conducted during the flowering season: March to May and July to September, 2016, 2017 and 2021. We used stratified random sampling based on land cover (Anderson et al., 1976), protected areas (KWS, 2010) and soil type (Dewitte et al., 2013) to select 190 sites, which covered most parts of Samburu. Thereafter, plots measuring 80 × 80 m were established at the sites and a species list used to record sightings of medicinal plant species. The field survey data was supplemented by occurrence records from the Global Biodiversity Information Facility (GBIF.org, 2019) and the East African Herbarium (EA).

To ensure accurate predictions, species with less than 30 records (viz. less than 30 plots where the species was present) were excluded from the analysis (Wisz et al., 2008). Collectively, we had 54 species. They were then grouped according to the diseases they treat: wounds, stomach ache, diarrhoea and all medicinal plants. For each group, we identified the dominant growth form in terms of tree, shrub and herbaceous species as described according to height by Dharani and Yenesew (2010). To reduce spatial-autocorrelation (SAC) in model residuals, we used the spThin package (Aiello-Lammens et al., 2015) to thin the occurrence records to a distance of 4 km (value > pixel of our predictors) (Zhao et al., 2021).

4.2.3. Remote sensing data

For classifying and mapping the medicinal plants, we used S-2 satellite images for the study area, with 0% cloud cover. We acquired S-2 data from Google Earth Engine platform (GEE; Gorelick et al., 2017), as image collections during the period of March to May and July to September, in 2016, 2017 and 2021 (Fig. 4.2). The platform provides top-of-atmosphere level 2A S-2 images, which are atmospherically corrected. We used all the S-2 bands by resampling the 20m/pixel and 60m/pixel bands to 10m/pixel (Malahlela et al., 2019). Based on the S-2 optical and NIR bands (i.e. blue, green, red and NIR) we calculated selected indices such as the MSAVI, NDVI, EVI and RVI (see Table 4.1 for full names and descriptions). The selection of these indices was based on straightforward rationales. For instance, NDVI, RVI, EVI and NDWI are sensitive to vegetation characteristics (Shammi and Meng, 2021). NDVI is the best indicator of the growth status of vegetation, while EVI reduces the impact of water vapor and better captures vegetation in lush regions (Shammi and Meng, 2021). Due to the very sparse to very dense vegetation with bare soil in the study area, MSAVI was preferred to compensate for the influence of high bare soil-to-plant cover ratio (Qi et al., 1994). As topological data, we used distance to villages and distance to roads calculated from OpenStreetMap data (OpenStreetMap, 2021).

Further, we used the glmc package (Zvoleff, 2020) to compute the second order Grey Level Co-Occurrence Matrix (GLCM) (Haralick, 1979) from the S-2 bands. Here, we used a moving window of 3×3 pixels because small window sizes display textural vegetation patterns which are important in successfully mapping SR (Haralick, 1979).

Likewise, we incorporated topographic metrics derived from a DEM i.e. aspect. The DEM was obtained from the Shuttle Rudder Topography Mission (STRM) (Farr et al., 2007). We also used additional RS data available in GEE: LST, aridity, GPP, evapotranspiration, LSWI, tree cover, TPI, FPAR, SWC, sand and clay content (see Table 4.2 for full names and descriptions). Finally, all the predictors were resampled to 10m, to match the spatial resolution of the S-2 imagery. Using the field occurrence data, we extracted and averaged pixel values in our variables within 80×80 m polygons to match the size of our field plots.

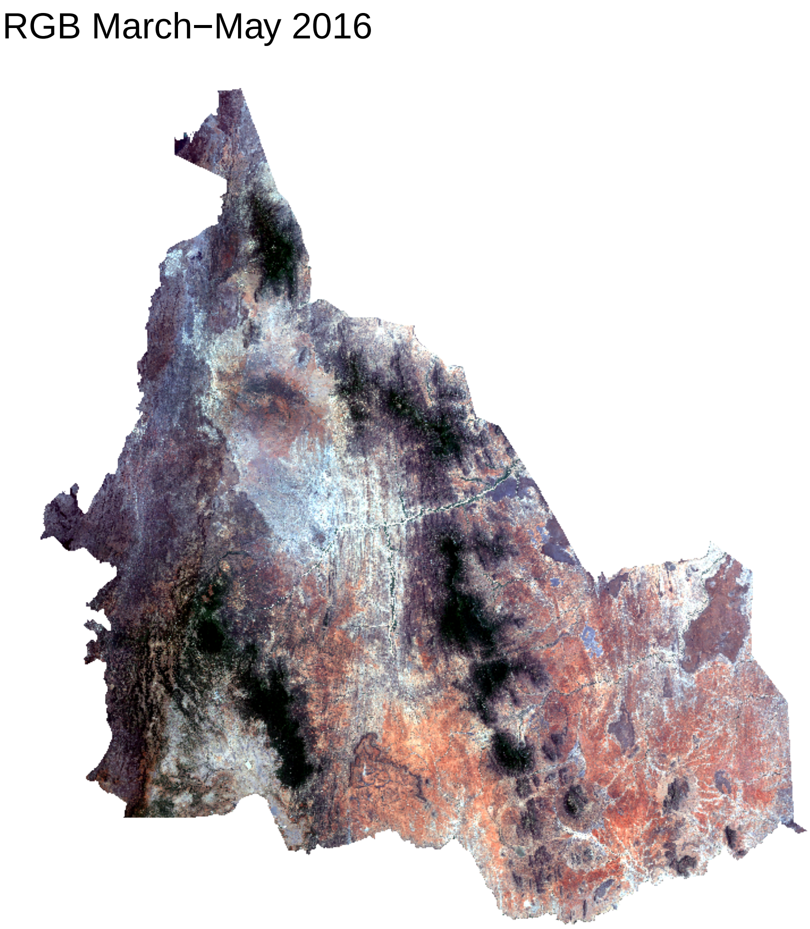

Figure 4.2.: Sentinel-2A image of Samburu County visualized using the red, green and blue wavelength bands. The image were captured between March and May 2016.

Table 4.1: List of S-2 variables and vegetation derived indices used in modelling. In the formula, red (R), blue (b), green (G), red-edge band 1 (REB1, 690-730m) and near-infrared (NIR).

Name	Formula	Description	Reference
EVI	$2.5 \times \frac{NIR-R}{NIR+6\times R-7.5\times B+1}$	Enhanced Vegetation Index	(Huete et al., 1997)
NDWI	$\frac{G-NIR}{G+NIR}$	Normalized Difference Water Index	(Gao, 1996)
NDVI	$\frac{NIR-R}{NIR+R}$	Normalized Difference Vegetation Index	(Tucker, 1979)
RVI	$\frac{R}{NIR}$	Ratio Vegetation Index	(Lemenkova, 2020)

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Table 4.1: List of S-2 variables and vegetation derived indices used in modelling. In the formula, red (R), blue (b), green (G), red-edge band 1 (REB1, 690-730m) and near-infrared (NIR). (Continued)

MSAVI	$\frac{2\times NIR+1-\sqrt{(2\times NIR+1)^2-8\times(NIR-R)}}{2}$	Modified Soil Adjusted Vegetation Index	(Zhu et al., 2014)
CLRE	$\frac{NIR}{REB1-1}$	Red-Edge Chlorophyll Index	(Gitelson et al., 1996)
GNDVI	$\frac{NIR-G}{NIR+G}$	Green Normalized Difference Vegetation Index	(Gitelson et al., 1996)

Table 4.2: List of RS variables and vegetation derived indices used in modelling. In the formula, average annual precipitation (P), Potential evapotranspiration (PET), the incident photosynthetically active radiation in a time period i.e day (PAR), fraction of PAR absorbed by vegetation canopy (FPAR), l is the light use efficiency, Total Water Mass (TWM), Dry soil mass (DSM), (FP) elevation of the cell, (FS) mean elevation of the neigboring pixels, extraterrestrial solar radiation in MJ m^{-2} d^{-1} (R), difference between mean monthly minimum and maximum temperatures in °C (TD), mean monthly air temperature in °C (TM), Hydrogen ion activity (aH), Clay thickness (CT), Sand thickness (ST), total soil thickness (TST), vegetation above 5 m (VE), output per grid cell (OPG) number of columns or rows in GLCM, row indices of the GLCM matrix (i), column indices of the GLCM matrix (j), Probability of neighboring cells having gray levels i and j P_{ij}, height in meters (HM), height at sea level (HSL).

Variable	**formula**	**Description**	**Reference**
DEM	$HM-HSL$	Digital Elevation Model	(Farr et al., 2007)
Slope	$\frac{Rise}{Run}\times 100$	Slope	(Farr et al., 2007)
Aspect	$\frac{Height}{Width}\times 100$	Aspect	(Farr et al., 2007)
Aridity	$\frac{P}{PET}$	Aridity	(UNEP, 1992)
LST	$\frac{T}{(1+\lambda(\frac{T}{14380})\ln(0.004Pv+0.986))}$, where $Pv = \left(\frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}}\right)^2$	Land Surface Temperature	(Nasseri et al., 2023)
GPP	$l\times FPAR\times PAR$	Gross Primary Product	(Prince and Goward, 1995)
EVPT	$0.0023R\sqrt{TD(TM+17.8)}$	Evapotranspiration	(UNEP, 1992)
LSWI	$\frac{NIR-SWIR}{NIR+SWIR}$	Land Surface Water Index	(Xiao et al., 2002)
Tree Cover	$\frac{VE}{OPG}\times 100$	Tree cover	(Hansen et al., 2013)
TPI	$\frac{EP}{FS}$	Topographic Position Index	(Rahmati et al., 2019)

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Table 4.2: List of RS variables and vegetation derived indices used in modelling. In the formula, average annual precipitation (P), Potential evapotranspiration (PET), the incident photosynthetically active radiation in a time period i.e day (PAR), fraction of PAR absorbed by vegetation canopy (FPAR), l is the light use efficiency, Total Water Mass (TWM), Dry soil mass (DSM), (FP) elevation of the cell, (FS) mean elevation of the neigboring pixels, extraterrestrial solar radiation in MJ m^{-2} d^{-1} (R), difference between mean monthly minimum and maximum temperatures in °C (TD), mean monthly air temperature in °C (TM), Hydrogen ion activity (aH), Clay thickness (CT), Sand thickness (ST), total soil thickness (TST), vegetation above 5 m (VE), output per grid cell (OPG) number of columns or rows in GLCM, row indices of the GLCM matrix (i), column indices of the GLCM matrix (j), Probability of neighboring cells having gray levels i and j P_{ij}, height in meters (HM), height at sea level (HSL). (Continued)

SWC	$\frac{TWM}{DSM} \times 100$	Soil Water Content	(Ma et al., 2016)
Soil pH	$\log(1/[aH])$	Soil pH	(FAO, 2021)
Clay Content	$\frac{CT}{TST} \times 100$	Clay content	(Whiting et al., 2011)
Sand Content	$\frac{ST}{TST} \times 100$	Sand content	(Whiting et al., 2011)
FPAR	$1 \times EVI$	Fraction of Photosynthetically Active Radiation	(Xiao et al., 2005)
GLCM-Mean	$\sum_{i,j=0}^{N-1} i(P_{i,j})$	Gray-Level Co-Occurrence Matrix (GLCM)- Mean	(Haralick et al., 1973)
GLCM- Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$	Gray-Level Co-Occurrence Matrix (GLCM)- Homogeneity	(Haralick et al., 1973)
GLCM-Variance	$\sum_{i,j=0}^{N-1} P_{ij}(i-u)^2$	Gray-Level Co-Occurrence Matrix (GLCM)- Variance	(Haralick et al., 1973)

4.3. Methods

4.3.1. Variable selection

Before building the OCC models, we selected the most important variables using the random forest recursive feature elimination (rf-RFE; Guyon et al., 2002). First, this wrapper approach uses all candidate variables to build a model and determines the importance of each variable. Thereafter, it ranks all the variables and iteratively removes those with the least importance in the model based on evaluation metrics (i.e. Kappa). Here, we used a repeated 10-fold-cross-validation with 5 repeats.

4.3.2. Classifiers

The OCSVM (Schölkopf et al., 2001) is a semi-supervised classification algorithm that uses only the positive data (in our case the occurrence samples of a given medicinal species) to train the classifier, irrespective of the unlabeled samples. It uses a kernel function to map the training dataset into a multi-dimensional feature space. The algorithm then iteratively estimates the hyperplane that best separates the training dataset from the origin. We randomly selected 70% of the positive samples to train the OCSVM. To attain the optimal results, the optimal combination of radial basis function (RBF) kernel parameters, upper bound training error n and inverse kernel width s, was selected by the grid search technique (Mack et al., 2014), using a repeated 10-fold-cross-validation with 5 repetitions, and a selected range of kernel parameters which yielded optimal results was chosen. Detailed information regarding the technique and the kernel parameters is available in the description of the oneClass R package (Mack et al., 2014).

BSVM (Liu et al., 2003) is a special form of binary SVM in which the training dataset contains positive and unlabeled data (Stenzel et al., 2017). The unlabeled class normally contains some samples from the positive class and is handled as weighted negative and weighted positive data. To train BSVM, we used the same positive samples as for OCSVM and 4000 unlabeled samples randomly distributed across the study area. We used the RBF kernel in the oneClass R package (Mack et al., 2014) to implement BSVM, which requires three parameters: weights of negative errors c, factor j showing the weight bias between the negative errors and positive errors, and the inverse kernel width y. The grid search technique using 5 repetitions of 10-fold-cross-validation, based on the training data was used to select the optimal combination of the kernel parameters (Liu et al., 2020). We selected the best model based on the frequently used *puF* (Liu et al., 2020). Calculations to derive the variable importance for the BSVM and OCSVM were conducted following the approach described in Kuhn (2008) as applied for instance by Liu et al. (2020).

The MaxEnt algorithm (Phillips et al., 2006) was originally developed for modeling species distribution based on environmental predictors (Dudík et al., 2007). The algorithm applies maximum entropy theory to estimate a species' distribution based on environmental variables (Phillips et al., 2006). The same training data used for BSVM was used to run the MaxEnt model. The MaxEnt parameter settings were set at default: 1) all feature classes and auto-feature selection of feature classes; 2) 500 iterations; 3) convergence threshold of 0.00001; (4) 10,000 background points; (5) replicated run type using 10 fold cross-validation with 90% training and 10% testing split ratio; and 6) regularization multiplier of 1, see the detailed explanation in Phillips et al. (2006). Default setting was chosen as it produces similar results to that of optimal parameters attained by the grid search approach (Mack and Waske, 2017) and is also in line with studies that apply MaxEnt for classification of many species (Liu et al., 2020). The R dismo package (Hijmans et al., 2022) was used to run MaxEnt models.

4.3.3. Classification process

We separately trained OCCs for each species with a consistent set of S-2 data and other RS data. First, we trained the OCCs with the S-2 reflectance information extracted from the positions of our plots. Thereafter, we applied the trained OCCs to the full S-2 scene. This procedure was repeated using other RS data.

To derive binary classification maps for a given species, we selected a threshold that yielded the best classification accuracy, based on the validation dataset (Stenzel et al., 2017). We systematically tested several thresholds before selecting the one which showed the highest overall accuracy (OA): max SSS, maximum overall accuracy and Sensitivity = Specificity. We used the SDMTools package for this step (VanDerWal et al., 2019).

4.3.4. Raw suitability maps

For each species and OCC, we also generated raw suitability maps based on S-2 data and other RS data. The suitability maps of BSVM and OCSVM were re-scaled to values between 0 and 1 using the climateStability R package (Owens and Robert, 2019) to match the values of the MaxEnt suitability map (Stenzel et al., 2017), as this ensured comparability of predictions across the OCCs.

4.3.5. Variable importance

For each group of plants, we identified the contribution of the environmental variables among the species, and across the OCCs. We ranked the variables, considering their contribution, for each species and across the OCCs. The most important variables for a group of plants were the highest ranked variables among many species, and across many OCCs (Kaky et al., 2020). We then assessed the Pearson correlation coefficient (r) between the most important variables and the respective medicinal plants groups.

4.3.6. Accuracy assessment

We used the SDMTools package (VanDerWal et al., 2019) to construct a confusion matrix of each species using the same testing data set. In the matrix, several measures of accuracy were calculated: Overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), sensitivity, specificity and Kappa statistic. Here, all the candidate thresholds were considered during the accuracy assessment (Sensitivity = Specificity, 10% omission, maximum SSS, maximum kappa and maximum OA). In the confusion matrix, true positive (TP) stands for the number of a medicinal plant species correctly detected, while true negative (TN) refers to the number correctly predicted as negative samples. Meanwhile, false negative (FN) stands for the number of positive samples incorrectly predicted as negative samples, while false positive (FP) denotes the number of negative samples incorrectly predicted as positive samples. The following equations were used to calculate the measures of accuracy:

$$Sensitivity = \frac{\sum TP}{\sum(TP + FN)} \tag{4.1}$$

$$Specificity = \frac{\sum TN}{\sum(TP + FP)} \tag{4.2}$$

$$OA = \frac{\sum TP + \sum TN}{\sum(TP + TN + FP + FN)} \tag{4.3}$$

$$TSS = Specificity + Sensitivity - 1 \tag{4.4}$$

$$kappa = \frac{(\sum TP + \sum TN) - [(\sum TP + \sum FN)(\sum TP + \sum FP) + (\sum FN + \sum TN)(\sum FP + \sum TN)]/N}{N - [(\sum TP + \sum FN)(\sum TP + \sum FP) + (\sum FN + \sum TN)(\sum FP + \sum TN)]/N} \tag{4.5}$$

4.3.7. Ensemble model

For each species, we selected the binary outputs of OCCs (with TSS values > 0.5) and summed them up using the weighted averaging method (Nourani et al., 2018), based on the TSS values (Liu et al., 2020). TSS values range from -1 to 1, where negative values or those close to zero indicate models that are not different from randomly generated models, whereas values close to 1 are considered good models (Allouche et al., 2006). The eOCC output values were within the range of 0 to 1. Thereafter, we classified output values above 0.5 as presences (Liu et al., 2020). Likewise, for each species, we selected the suitability outputs of OCCs (with TSS values > 0.5) and summed them up using the weighted averaging, based on TSS values. To this end, we produced a single suitability map with values ranging from 0 to 1.

The weighted averaging was conducted using the following equation:

$$EA_{(r)} = \sum_{i=1}^{N} v_i EA_i r \tag{4.6}$$

where v_i is the designated weight on binary or suitability output of the ith model (i.e. TSS), $EA_(r)$ is the ensemble output, $EA_(i)_r$ is the output of the ith OCC (i.e. Maxent from S-2) and N is the number of the OCCs (here, N=6).

4.3.8. Bin-SDM and Suit-SDM species richness maps

For all groups of medicinal plants, we generated the Bin-SDM SR maps by aggregating the final binary maps for each species and counting the number of species in each cell (Kaky and Gilbert, 2016). The same procedure was repeated using the final species suitability maps to generate the Suit-SDM (Merow et al., 2013).

4.3.9. Comparison between Bin-SDM and Suit-SDM

We estimated the accuracy of the Bin-SDM and Suit-SDM SR predictions. Here, the Pearson correlation coefficient (r) was used to compare the observed SR values and the number of predicted species in each sampled plot for the two modeling approaches (Dubuis et al., 2011). This comparison was done for all groups of medicinal plant species and was based on the validation datasets. We then plotted the predicted SR against the observed SR, and fitted a linear regression line to this plot. A slope is expected to be close to one and an intercept close to zero in a good predictive model (Dubuis et al., 2011).

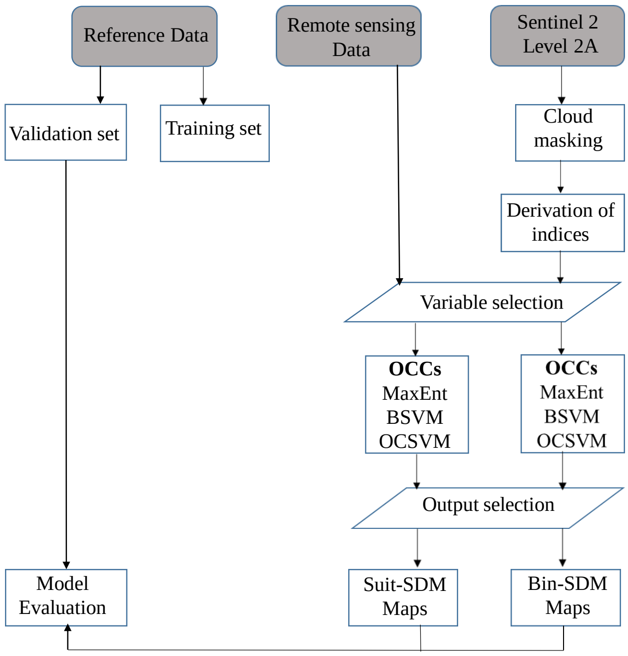

Figure 4.3.: Workflow of the ensemble One-Class Classification to map medicinal plant species based on RS data.

4.4. Results

4.4.1. Model performance and growth forms in medicinal plants groups

Predictive accuracies of all OCCs were generally good for most species with regard to OA (83.8%) and TSS (0.84), apart from three species (*Boscia angustifolia*, *Lycium europaeum* and *Kedrostis pseudogijef*; supplementary material Table 4.4, Table 4.5, Fig. 4.9 and Fig. 4.10). Species models from S-2 had a better performance than RS models based on OA and TSS metrics (supplementary material Table 4.4, Table 4.5, Fig. 4.9 and Fig. 4.10). The overall accuracies of OCCs ranged from 44.3% (BSVM) to 83.8% (OCSVM), and the TSS varied between 0.41 (OCSVM) and 0.73 (MaxEnt) for S-2 models, while for the other RS models the overall accuracies ranged between 43.4% (MaxEnt) and 79.9% (BSVM), and the TSS varied between 0.3 (OCSVM) and 0.84 (OCSVM). The ensemble SDMs for SR resulted in OA ranging from 43.6% (Bin-SDM) and 81.2% (Suit-SDM), while the TSS varied from 0.41 (Suit-SDM) and 0.76 (Bin-SDM). All medicinal plants and those used against stomach ache were dominated by tree species, while those used against wounds were dominated by herbaceous species (Fig. 4.4, supplementary material Table 4.6 to Table 4.9).

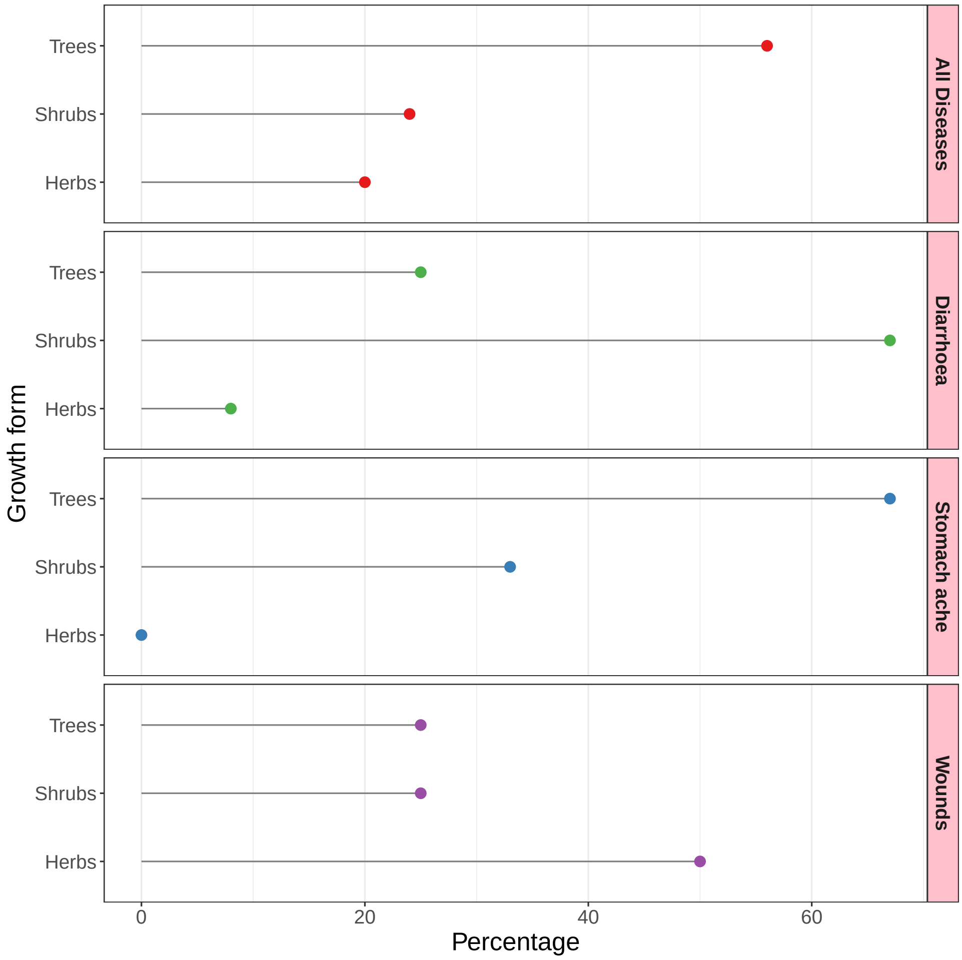

Figure 4.4.: Dot plot showing proportion of growth forms among medicinal plants groups.

4.4.2. Variables for predicting the occurrence of medicinal plants

The most important RS variable for predicting all medicinal plant SR and those used against stomach ache were elevation, soil water content and land surface water index (Fig. 4.5, supplementary material Table 4.6, Table 4.7). Among the S-2 variables, NDVI, NIR8, and SWIR 1 were the most influential in the model (Fig. 4.5, supplementary material Table 4.10), and NDVI was the most influential S-2 variable for predicting SR of plants used against stomach ache followed by NIR8 (Fig. 4.5, supplementary material Table 4.11). We observed a significant positive correlation between elevation, SWC, LSWI, NDVI and all medicinal plants, and those used against stomach ache (Table 4.3). For those species used against diarrhoea, topographic variables including elevation, slope and TPI are the strongest RS predictors. SWIR 1 and MSAVI were the S-2 variables which explained much of their distribution. For species used against wounds, tree cover, clay content and aridity were the most important RS variables (Fig. 4.5, supplementary material Table 4.9), while mean texture was important S-2 predictor. These species had a negative significant correlation with tree cover and clay content.

Table 4.3.: Correlation between significant variables and MPS groups. Significance values are denoted by asterisks: *, P < 0.05; **, P < 0.01; ***, P < 0.001.

RS Variable	Pearson's r	S-2 Variable	Pearson's r
All Medicinal Plant Species			
DEM	0.62***	NDVI	0.51***
SWC	0.38***	NIR8	0.14***
Aridity	0.42**	SWIR1	-0.14***
LSWI	0.43**	VRE2	-0.06
Stomach ache			
DEM	0.62***	NDVI	0.57***
SWC	0.27**	NIR 8	0.5***
LSWI	0.49***	VRE1	-0.29***
Diarrhoea			
DEM	-0.46***	SWIR1	0.28*
Slope	-0.25*	MSAVI	-0.46***
TPI	-0.07	SWIR2	-0.34***
Wounds			
Tree cover	-0.27***	Mean	0.18
Clay content	-0.36*	MSAVI	-0.34***
Aridity	-0.23	NDVI	-0.14

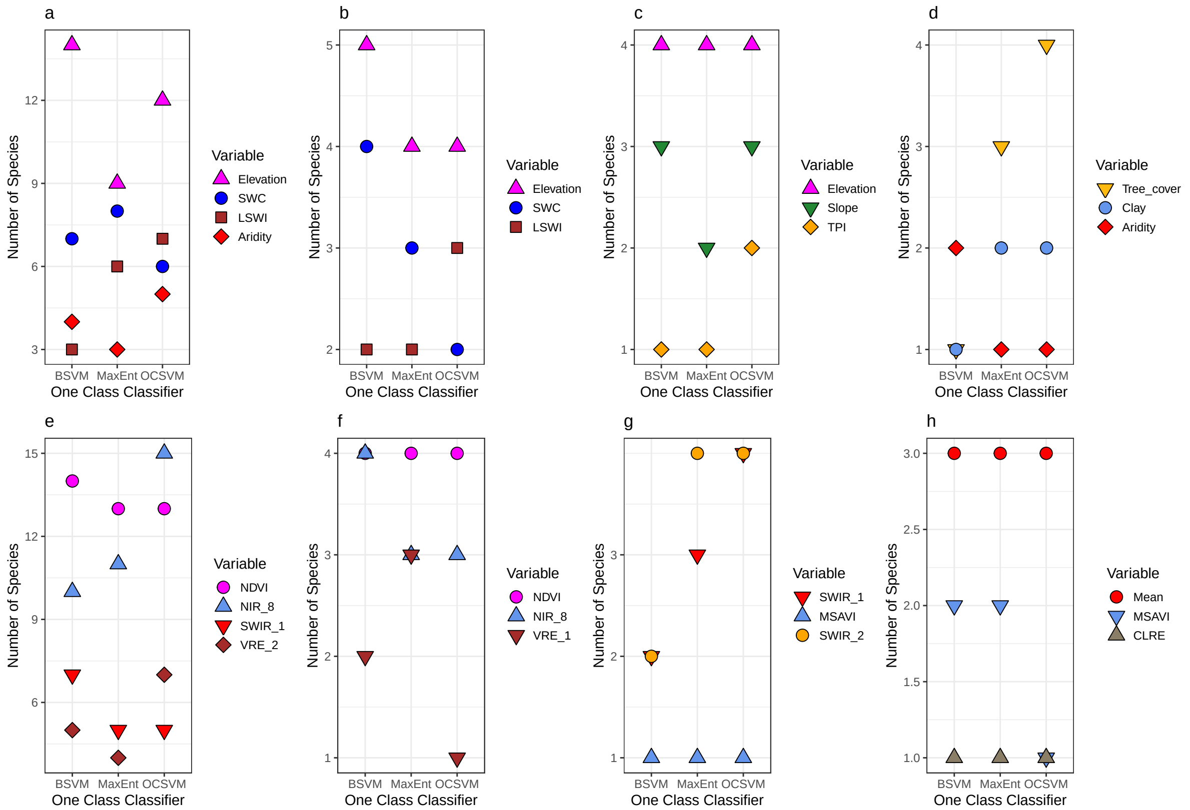

Figure 4.5.: The number of times each variable (colors and symbols) was the most important for each OCC for a) all medicinal plants; RS, b) stomach ache; RS, c) diarrhoea; RS, d) wounds; RS, e) all medicinal plants; S-2, f) stomach ache; S-2, g) diarrhoea; S-2 and h) wounds; S-2.

4.4.3. Species richness maps

Our Bin-SDM and Suit-SDM results show high richness of all medicinal plants and those used against stomach ache in the south west and pockets of the north (Fig. 4.6). These regions have high elevation, and high values for SWC, LSWI, NDVI and NIR8 (supplementary material Fig. 4.11, Fig. 4.12). Generally, Bin-SDM predicted higher richness than the Suit-SDM, especially in the south west. Unlike Bin-SDM, Suit-SDM predicted low richness of plants used against stomach ache in the north west. The southern region is predicted to have high medicinal plants richness but our observed richness there was low (Fig. 4.1, Fig. 4.6). Prediction of species used against diarrhoea by the two approaches showed high richness in areas which had moderate elevation and TPI, high SWIR 1 and SWIR 2. These areas are mostly found in the central region (Fig. 4.7, supplementary material Fig. 4.11, Fig. 4.12). Whereas Suit-SDM predicted low SR of plants used against diarrhoea in the north-west, Bin-SDM predicted moderate SR in the region. For species used against diarrhoea, parts of the south west was predicted to have high richness but our observed richness therein were low (Fig. 4.7, supplementary material Fig. 4.13). The pattern of wound-species richness predicted by the two approaches showed a west-east gradient, with higher species richness in the south-east (see Fig. 4.7). The wound-species generally showed a tendency of high richness in areas of low tree cover and low clay content. In contrast to the Suit-SDM, Bin-SDM predicted most areas of high richness of species used against wounds in the southern region. A weak spatial congruence existed between species used against diarrhoea and those used against wounds, but only in the south east.

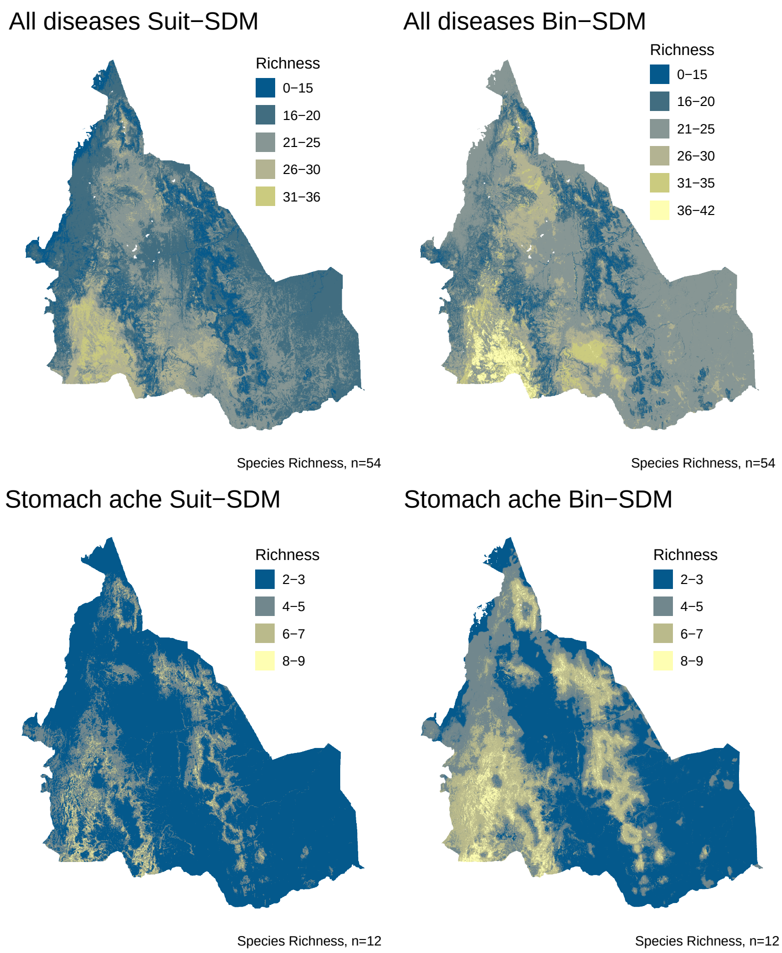

Figure 4.6.: Species richness maps of plants used against: all diseases; Suit-SDM, all diseases; Bin-SDM, stomach ache; Suit-SDM and stomach ache; Bin-SDM. White areas show areas out of the value range that were omitted by applying the convex hull mask.

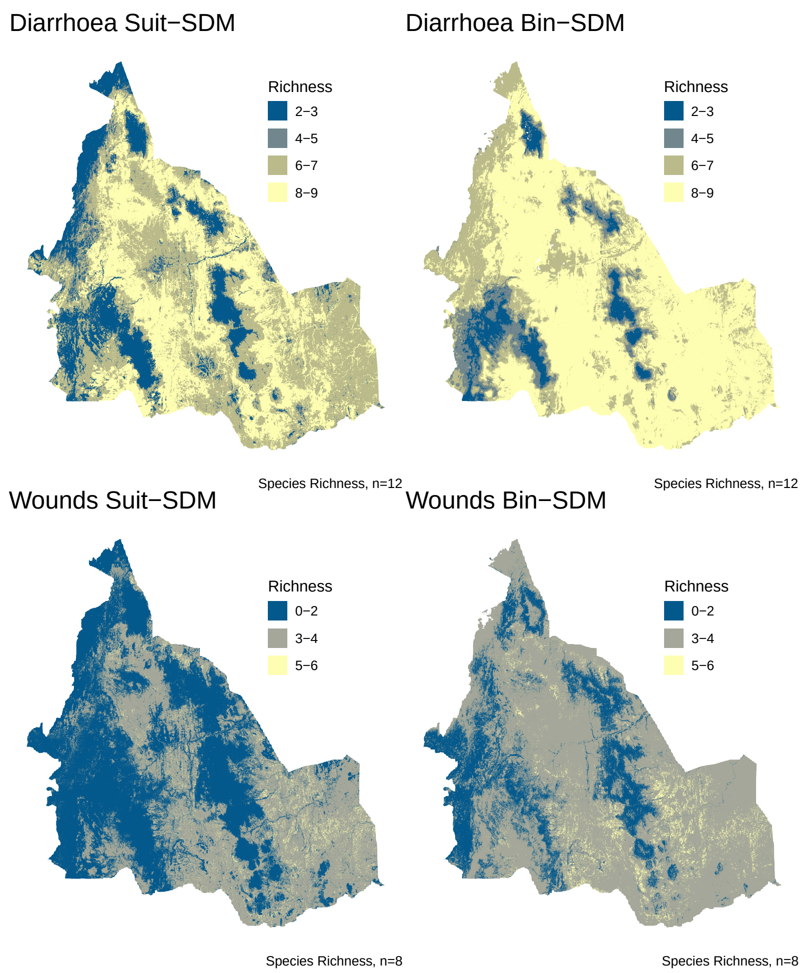

Figure 4.7.: Species richness maps of plants used against: diarrhoea; Suit-SDM, diarrhoea; Bin-SDM, wounds; Suit-SDM and wounds; Bin-SDM. White areas show areas out of the value range that were omitted by applying the convex hull mask.

4.4.4. Model Comparison

4.4.4.1. All medicinal plants

For all medicinal plants, the Suit-SDM showed underpredictions for field plots with low medicinal plant SR and overpredictions for plots of high SR (Fig. 4.8), whereas Bin-SDM generally exhibited overpredictions, which decreased towards areas of low observed SR. For the Suit-SDM the correlation between observed and predicted medicinal plant SR (Pearson's r = 0.68, nRMSE= 21.6%, n= 54 p< 0.0001) was higher than for Bin-SDM.

4.4.4.2. Stomach ache species

The correlation between the observed and predicted SR of plants used against stomach ache was the highest among all groups, especially for Suit-SDM (Pearson's r = 0.83, nRMSE=16.2%, n= 12, p<

0.0001, Fig. 4.8). For both approaches, plots with the lowest observed SR of plants used against stomach ache tended to be underpredicted, while those with the highest observed SR were mostly overpredicted.

4.4.4.3. Diarrhoea species

The predicted richness of species used against diarrhoea was moderately correlated to the richness observed by the Suit-SDM (Pearson's r = 0.66, nRMSE= 24.4%, $p < 0.001$, Fig. 4.8), as was that of Bin-SDM (Pearson's r = 0.62, nRMSE= 25.6%, n= 12, p< 0.0001). Both approaches underestimated SR of plants used against diarrhoea in plots with low observed numbers, and underestimated the richness in plots with high numbers.

4.4.4.4. Wound species

The correlation between the predicted and Suit-SDM observed SR of plants used to treat wounds was comparably low (Pearson's r = 0.59, nRMSE= 26.2%, n= 8, p< 0.0002), as was that of Bin-SDM. However, Suit-SDM outperformed Bin-SDM. Additionally, the Suit-SDM tended to overestimate plots with low observed SR of plants used to treat wounds, while those with high SR tended to be underestimated.

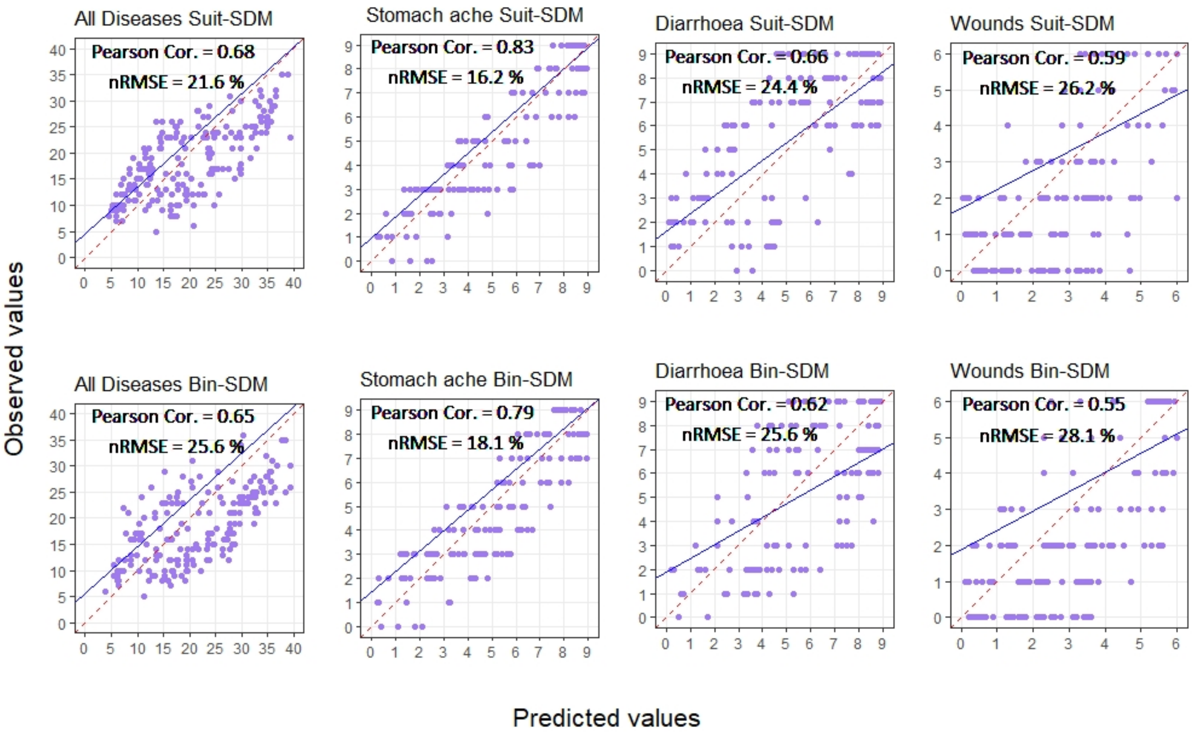

Figure 4.8.: Comparison of predicted versus observed values for medicinal plants groups using the independent test data. The red dotted line indicates a perfect relationship between predicted and observed SR, and the blue line represents the linear regression.

4.5. Discussion

In this study, the suitability of RS data for mapping medicinal plant SR in an inaccessible and data-limited area i.e. Samburu dryland is explored. The study's findings are discussed under four sections. First, we debate the ecological implications of variables considered as the most important. Second, we discuss the spatial patterns of groups of medicinal plant SR. Thirdly, we discuss the results of the two modelling approaches. Lastly, the implications of our findings for medicinal plants conservation are discussed.

4.5.1. Significant variables for the distribution of medicinal plant species

According to our results, the distribution of all medicinal plants and those used against stomach ache is related to soil water content, altitude, land surface water index, aridity and also related to NDVI and NIR8 (S-2). These results are consistent with the hypothesis that water-related variables are the primary predictors of plant SR in drylands (Liu et al., 2013; Gafna et al., 2021). Other predictors of the two groups of plants probably also partly mirror soil water availability. For example, elevation influences precipitation and hence water availability with high elevations typically receiving more precipitation (Gafna et al., 2021). Our results that elevation was a key determinant of tree-species dominant medicinal plant species and species used against stomach ache confirms the earlier findings by Ouko et al. (2020). They found that tree distribution, in the study region is mainly influenced by elevation. Additionally, areas with high NDVI values, represent areas with higher vegetation greenness, thereby indicating higher water availability, just as areas with high LSWI. NIR8 and SWIR1 were also important S-2 variables for predicting tree-dominated medicinal plants SR. The importance of NDVI and NIR8 in mapping tree species in tropical dryland forest was confirmed by Hernández-Stefanoni and Dupuy (2007).

The richness of shrub-dominated species used against diarrhoea is best explained by topographic variables. The BAK (2017) reports that topography influences local spatial heterogeneity including vertical soil nutrients distribution and water availability, which determine dryland shrub distribution. The drivers of herbaceous species dominated wound SR were tree cover and clay (Márialigeti et al., 2016). This, we believe, is explained by the impact of tree cover on light availability, which affect herbaceous species, while clay content influences water drainage which is critical for the development of herbaceous species in drylands (KSS, 2011).

4.5.2. Distribution of medicinal plants

The richness of all medicinal plants and those used against stomach ache increased in areas of high SWC, altitude, LSWI and NDVI i.e. towards the south west. This indicates that these two groups of species prefer wet areas (which is widely known for most medicinal plant species and those used against stomach ache in Samburu like *Carissa edulis* and *Olea africana* Gafna et al., 2021). Chaturvedi and Raghubanshi (2018) reported a high plant SR in areas of high SWC and LSWI in dryland communities (BAK, 2017) in Kenya. High SWC and LSWI reduce drought stress in drylands (Wang et al., 2021).

It is generally acknowledged that medicinal plant SR in Samburu increases with altitude (Gafna et al., 2023). In drylands, Gafna et al. (2023) attributed this increase to increasingly favorable environmental conditions like lower temperatures in high altitudes. The observed pattern of increasing medicinal plant SR with altitude may also be discussed in the context of accessibility of medicinal plants. Medicinal plants in low altitudes are easily exploited due to their accessibility, while those in higher altitudes are harder to reach (Gafna et al., 2021), which may explain the high richness in high altitudes. Maps of predicted SR patterns for all medicinal plants and those used against stomach ache showed the strongest spatial congruence, probably because both groups are dominated by trees, most of which respond in a similar way to the same environmental variables. For all medicinal plants and those used against stomach ache, Bin-SDM showed higher predictions in the south west, compared to the Suit-SDM. This difference may occur because the region has high SWC and LSWI, which leads to high medicinal plant richness, making it difficult to account for many biotic interactions and dispersal limitations in the region. D'Amen et al. (2015) reported that B-SDM showed overpredictions in areas where it is difficult to account for many biotic and ecological interactions, and dispersal limitations.

Shrub dominated species used against diarrhoea tend to be richer in central Samburu (Omwenga et al., 2014), which is characterized by intermediate slope and elevation. This observation may be related to the description of shrub layer, which was entirely hinged on a defined height threshold. Therefore, we speculate that, at intermediate elevation and slope, many shrub species which were unable to establish themselves at lower elevation due to unfavourable temperatures and water conditions are able to grow up to a given height. But still, they may experience challenges reaching the height of the tree layer because the environmental conditions at intermediate elevations are not as favorable as those in higher elevations.

The herb dominated species used against wounds are concentrated in areas of low tree cover and low clay content. This is probably because low tree cover in drylands allow sunlight to penetrate and reach the underneath herbs leading to better development of most herbaceous species (Guo et al., 2023) used against wounds. Additionally, low clay content enhances drainage conditions, which increases herbacious species in harsh dryland conditions (KSS, 2011).

4.5.3. Model Comparison

Pearson correlation coefficients between predicted and observed SR were significant for the four groups, suggesting that the SR maps were generally acceptable. Based on statistical evaluation, there was a clear difference between the two modelling approaches. For all groups of plants, the correlation between predicted and observed SR was higher for Suit-SDM than Bin-SDM. This is probably due to accumulating errors during the threshold selection for the binary outcomes. Our Bin-SDMs for all groups overpredicted SR, as previously found in studies that compared stacked binary and raw probability predictions (Segurado and Araújo, 2004; Calabrese et al., 2014). This overprediction is likely due to the erroneous inclusion of medicinal species which are presently not known to be found in the sites because B-SDMs do not account for restriction on the maximum number of species present in a site (Merow et al., 2013). We suggest that Suit-SDM may be the best approach in applications of conservation concern.

The Suit-SDM overestimated plots with low observed SR of plants used to treat wounds, while those with high SR were underestimated, which is more likely due to statistical instead of ecological reasons. We suspect that this is due to the low sample size of the species used against wounds, as rare species with low sample sizes are known to be overestimated by S-SDM (Calabrese et al., 2014).

Moreover, the prediction accuracy of species used against stomach ache was the highest. This is likely because of the dominance of tree species in this group, as they are known to have developed leaves which enables accurate recording of their spectral reflectance in drylands (Wang et al., 2021). In contrast, herbaceous-dominated wound-species richness had rather poor prediction. A possible reason was the scarceness of occurrence records for species used against wounds. Few herbaceous medicinal species occur in Samburu dryland because they are less tolerant to the drought conditions due to their shallow root depths, and those present are found in relatively low abundance (Nanyingi et al., 2008) which lowers their detectability (Wang et al., 2021).

4.5.4. Implications for medicinal plants conservation

Our maps can be useful for developing medicinal plants conservation strategies in Samburu. Some areas with a high predicted medicinal plant SR had low observed richness, i.e. south. The same was the case for species used against diarrhoea in the south west. Such areas should be considered for introduction and cultivation, and locals should be encouraged to exploit the medicinal species therein without damaging them. Some areas with high SR may have low observed richness because of over-exploitation and historical factors (Guisan and Thuiller, 2005). In response to the high richness areas with high observed richness, sustainable use, *in situ* conservation (i.e. establishment of protected areas), re-introduction and raising of public awareness on the need to conserve the medicinal species is advisable so as to benefit locals who use them (Gafna et al., 2023). For example, in the south west for all medicinal species and south east for those used against wounds. Regarding low richness areas, further research is needed to understand the vegetative behavior of the medicinal plants compared to the high richness areas.

Meanwhile, priority conservation areas for stomach ache species could be similar to most medicinal plant species since both groups have high richness in the same regions; as was the case for wound-species and diarrhoea-species in the south-east. In contrast, priority conservation areas for diarrhoea-species and wounds-species should be different from most medicinal plants. Together with regions of high medicinal plant SR, we suggest that conservation actions should focus on regions with overlapping high richness of species used against the common diseases, i.e. the south east of the study region. However, compared to other species groups, diarrhoea-species should receive little conservation attention because they had both high predicted and observed richness in most parts. To effectively conserve all medicinal plants groups, it would be necessary to monitor the variables considered important for their respective distributions. Additionally, further research on their economic importance, genetic diversity and seed dispersal mechanisms is required to conserve them.

4.6. Conclusion

Medicinal plants SR maps can support decision making in medicinal plants conservation, but many areas lack such maps. We developed an ensemble one class classifier (eOCC) work-flow that uses RS data to predict medicinal plants SR in Samburu dryland. In this study, we support the argument that Suit-SDM exhibits better prediction capacity of medicinal plants SR than the commonly used Bin-SDM, and should therefore be preferred. Overall, we established that altitude, SWC, LSWI, NDVI and NIR8 were the most important variables for medicinal plants prediction. The grouped approach of mapping medicinal plants SR helps to identify high richness areas for each group and makes the argument for differing management of the groups more compelling. Conservation efforts that would provide the most benefit to medicinal plant groups should be concentrated in the south west and south east. Our methods could be extended to other species of conservation concern.

Acknowledgments

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4.7. Additional Information

Table 4.4.: Modeled medicinal plants using the remote sensing variables and their evaluation metric.

	OCSVM				BSVM				MaxEnt				EB-SDM				ES-SDM			
Species	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS
Acacia etbaica	68.3	0.82	0.79	0.61	73.1	0.82	0.83	0.65	73.6	0.77	0.85	0.62	71.3	0.65	0.78	0.43	58.9	0.67	0.88	0.55
Acacia mellifera	76.1	0.76	0.87	0.63	75.4	0.79	0.84	0.63	78.2	0.74	0.67	0.41	72.9	0.83	0.85	0.63	72.8	0.84	0.89	0.73
Acacia nilotica	65.8	0.56	0.74	0.3	73.6	0.71	0.91	0.62	74.5	0.69	0.89	0.58	68.3	0.89	0.78	0.67	78.1	0.78	0.86	0.64
Acacia nubica	67.4	0.68	0.81	0.49	79.9	0.83	0.85	0.68	76.1	0.85	0.65	0.5	72.1	0.84	0.82	0.66	68.6	0.58	0.84	0.42
Acacia senegal	74.8	0.83	0.78	0.61	68.5	0.54	0.87	0.41	78.2	0.77	0.88	0.65	68.2	0.74	0.87	0.61	77.4	0.73	0.79	0.52
Acacia tortilis	71.6	0.55	0.73	0.5	66.5	0.83	0.86	0.69	73.2	0.82	0.85	0.67	56.3	0.76	0.88	0.64	58.7	0.75	0.83	0.58
Acacia xanthophloea	76.9	0.81	0.89	0.7	58.9	0.76	0.89	0.65	75.1	0.84	0.76	0.6	57.8	0.85	0.83	0.68	74.9	0.67	0.81	0.48
Acokanthera oppositifolia	66.3	0.89	0.72	0.61	71.5	0.77	0.83	0.6	68.5	0.95	0.74	0.69	65.9	0.86	0.89	0.75	72.2	0.74	0.88	0.62
Albizia gummifera	73.1	0.76	0.67	0.34	70.2	0.94	0.79	0.73	75.3	0.83	0.88	0.71	74.5	0.87	0.88	0.75	73.8	0.68	0.84	0.52
Aloe secundiflora	74.6	0.79	0.83	0.62	76.5	0.71	0.95	0.66	73.2	0.79	0.85	0.64	76.2	0.85	0.88	0.73	76.8	0.84	0.87	0.71
Balanites aegyptiaca	68.4	0.72	0.79	0.61	72.4	0.69	0.98	0.67	68.4	0.69	0.78	0.47	78.2	0.86	0.84	0.7	68.7	0.89	0.83	0.72
Balanites rotundifolia	65.1	0.73	0.68	0.41	72.9	0.53	0.87	0.4	71.7	0.78	0.84	0.62	58.4	0.85	0.89	0.74	78.3	0.85	0.86	0.71
Barleria spinisepala	73.9	0.78	0.84	0.62	74.7	0.77	0.83	0.6	69.6	0.84	0.87	0.71	66.3	0.87	0.83	0.7	75.7	0.72	0.89	0.61
Boscia angustifolia	77.8	0.87	0.82	0.69	75.4	0.75	0.86	0.61	75.4	0.81	0.86	0.67	69.7	0.83	0.85	0.68	56.3	0.78	0.68	0.46
Boscia coriacea	73.8	0.86	0.74	0.6	69.5	0.43	0.94	0.37	78.1	0.87	0.75	0.62	72.3	0.68	0.78	0.46	71.9	0.77	0.78	0.55
Cadaba farinosa	77.6	0.79	0.83	0.62	78.5	0.99	0.97	0.96	58.9	0.84	0.89	0.73	76.5	0.65	0.89	0.54	70.1	0.76	0.87	0.63
Carissa edulis	67.4	0.77	0.86	0.63	76.7	0.77	0.83	0.6	65.8	0.66	0.74	0.4	78.1	0.87	0.88	0.75	74.8	0.83	0.85	0.68
Cissus rutundifolia	69.3	0.89	0.75	0.64	71.6	0.73	0.98	0.71	67.7	0.75	0.87	0.62	73.1	0.85	0.67	0.52	72.6	0.87	0.83	0.7
Cissus quadrangularis	73.8	0.85	0.74	0.59	72.3	0.86	0.75	0.61	72.3	0.79	0.85	0.64	75.7	0.83	0.87	0.7	76.5	0.77	0.74	0.51

Table 4.4.: Modeled medicinal plants using the remote sensing variables and their evaluation metric (continued).

	OCSVM				BSVM				MaxEnt				EB-SDM				ES-SDM			
Species	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS
Commiphora africana	67.7	0.84	0.88	0.72	67.8	0.79	0.81	0.6	76.5	0.83	0.87	0.7	67.5	0.89	0.87	0.76	75.9	0.88	0.72	0.6
Cordia monoica	74.1	0.78	0.83	0.61	65.3	0.67	0.97	0.64	73.8	0.86	0.77	0.63	57.8	0.75	0.82	0.57	76.8	0.83	0.71	0.54
Croton dichogamus	71.5	0.77	0.89	0.66	77.2	0.97	0.75	0.72	74.6	0.68	0.75	0.43	71.9	0.88	0.87	0.75	78.9	0.85	0.65	0.5
Croton megalocarpus	78	0.83	0.77	0.6	68.4	0.96	0.82	0.78	66.5	0.78	0.83	0.61	65.8	0.86	0.83	0.69	75.8	0.86	0.87	0.73
Cyphostema adenocaule	76.6	0.81	0.85	0.66	67.8	0.58	0.96	0.54	75.8	0.72	0.69	0.41	76.8	0.84	0.89	0.73	72.3	0.81	0.88	0.69
Cyphostema serpens	72.4	0.83	0.89	0.72	66.6	0.56	0.86	0.42	68.3	0.67	0.87	0.54	77.2	0.76	0.83	0.59	74.6	0.82	0.75	0.57
Ekebergia angustifolia	72.8	0.83	0.79	0.62	79.4	0.77	0.83	0.6	72.7	0.86	0.89	0.75	58.9	0.85	0.87	0.72	72.5	0.75	0.69	0.44
Euclea divinorum	65.2	0.65	0.87	0.33	58.9	0.69	0.72	0.41	66.5	0.74	0.75	0.49	63.5	0.78	0.82	0.6	78.6	0.74	0.87	0.61
Euphorbia candelabrum	67.6	0.79	0.84	0.63	75.2	0.94	0.82	0.76	70.6	0.87	0.82	0.69	64.9	0.73	0.87	0.6	77.3	0.66	0.84	0.5
Euphorbia heterochroma	73.8	0.77	0.88	0.65	64.1	0.92	0.61	0.53	60.4	0.82	0.89	0.71	75.7	0.86	0.89	0.75	70.7	0.87	0.88	0.75
Flueggea virosa	69.1	0.62	0.68	0.56	63.8	0.62	0.73	0.35	75.4	0.76	0.85	0.61	59.3	0.78	0.76	0.54	75.8	0.86	0.88	0.74
Fuerstia africana	76.2	0.77	0.84	0.63	75.8	0.56	0.78	0.34	72.5	0.69	0.89	0.58	67.2	0.74	0.89	0.63	74.3	0.73	0.86	0.59
Grewia tembensis	72.6	0.67	0.92	0.6	76.3	0.84	0.87	0.71	75.3	0.83	0.81	0.64	74.3	0.87	0.88	0.75	75.6	0.75	0.87	0.62
Gutenbergia cordifolia	68.2	0.88	0.74	0.62	74.2	0.77	0.84	0.61	71.9	0.76	0.86	0.62	78.3	0.75	0.86	0.61	73.4	0.79	0.86	0.65
Ipomoea spathulata	73.5	0.77	0.84	0.61	69.7	0.78	0.85	0.63	74.7	0.64	0.79	0.43	76.3	0.78	0.88	0.66	70.1	0.71	0.87	0.58
Juniperus procera	76.5	0.85	0.77	0.62	73.4	0.85	0.78	0.63	76.4	0.72	0.87	0.59	56.7	0.79	0.87	0.66	76.8	0.76	0.79	0.55
Kedrostis pseudogijef	54.6	0.76	0.85	0.61	75.9	0.73	0.69	0.42	75.3	0.81	0.88	0.69	64.8	0.82	0.85	0.67	75.4	0.84	0.83	0.67
Lippia javanica	75.3	0.88	0.77	0.65	73.3	0.82	0.86	0.68	73.7	0.78	0.85	0.63	68.7	0.86	0.85	0.71	76.5	0.76	0.85	0.61
Lippia kituiensis	72.8	0.54	0.87	0.41	76.5	0.88	0.81	0.69	71.5	0.87	0.74	0.61	57.4	0.85	0.89	0.74	77.8	0.72	0.83	0.55
Lycium europaeum	76.5	0.88	0.58	0.8	78.2	0.78	0.84	0.62	58.7	0.84	0.86	0.7	53.6	0.87	0.88	0.75	73.5	0.74	0.78	0.52
Myrsine africana	66.3	0.68	0.78	0.64	71.5	0.88	0.73	0.61	59.3	0.85	0.79	0.64	65.1	0.84	0.85	0.69	72.5	0.75	0.86	0.61

Table 4.4.: Modeled medicinal plants using the remote sensing variables and their evaluation metric (continued).

	OCSVM				**BSVM**				**MaxEnt**				**EB-SDM**				**ES-SDM**			
Species	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS
Olea africana	68.2	0.76	0.86	0.62	75.9	0.89	0.79	0.68	65.2	0.71	0.86	0.57	66.2	0.87	0.89	0.76	69.5	0.87	0.77	0.64
Psiadia punctulata	74.2	0.85	0.69	0.78	73.1	0.68	0.89	0.57	69.5	0.73	0.88	0.61	73.8	0.86	0.85	0.71	76.5	0.88	0.85	0.73
Podocarpus falcatus	68.7	0.72	0.77	0.61	72.5	0.78	0.86	0.64	60.2	0.82	0.87	0.69	67.1	0.88	0.86	0.74	77.9	0.83	0.84	0.67
Rhamnus stado	76.8	0.88	0.96	0.84	68.9	0.78	0.85	0.63	61.6	0.84	0.73	0.57	69.3	0.87	0.86	0.73	73.5	0.85	0.83	0.68
Rhus natalensis	74.4	0.84	0.65	0.64	77.3	0.59	0.76	0.35	72.4	0.75	0.86	0.61	64.3	0.81	0.89	0.7	69.7	0.89	0.85	0.74
Salvadora persica	58.7	0.78	0.77	0.75	69.2	0.88	0.77	0.65	77.4	0.71	0.67	0.38	68.3	0.82	0.75	0.57	58.9	0.81	0.77	0.58
Scutia myrtina	74.4	0.56	0.72	0.51	75.8	0.78	0.67	0.45	74.5	0.86	0.79	0.65	62.1	0.74	0.86	0.6	74.7	0.83	0.82	0.65
Senna didymobotrya	72.5	0.74	0.87	0.61	76.1	0.66	0.79	0.45	67.1	0.73	0.87	0.6	65.2	0.86	0.84	0.7	70.5	0.86	0.83	0.69
Solanum incanum	75.4	0.83	0.86	0.69	72.8	0.75	0.89	0.64	72.6	0.81	0.88	0.69	58.3	0.88	0.75	0.63	69.8	0.85	0.87	0.72
Teclea simplicifolia	73.5	0.78	0.68	0.46	73.6	0.69	0.76	0.45	63.5	0.79	0.83	0.62	75.2	0.89	0.87	0.76	71.6	0.76	0.65	0.41
Teclea aethiopica	76.7	0.59	0.76	0.72	71.6	0.88	0.82	0.7	69.3	0.77	0.84	0.61	77.3	0.73	0.89	0.62	74.9	0.73	0.68	0.41
Zanthoxylum usambarense	77.5	0.77	0.78	0.76	75.3	0.98	0.77	0.75	68.5	0.76	0.85	0.61	78.9	0.78	0.84	0.62	69.2	0.79	0.83	0.62
Viscum tuberculatum	72.5	0.74	0.86	0.6	75.3	0.72	0.85	0.57	59.4	0.82	0.89	0.71	73.5	0.87	0.86	0.73	67.8	0.71	0.82	0.53
Ximenia caffra	71.5	0.82	0.87	0.69	74.4	0.79	0.84	0.63	73.8	0.77	0.86	0.63	67.9	0.85	0.83	0.68	74.6	0.73	0.87	0.6

Table 4.5.: Modeled medicinal plants using the Sentinel-2 variables and their evaluation metric.

	OCSVM				BSVM				MaxEnt				EB-SDM				ES-SDM			
Species	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS
Acacia etbaica	76.8	0.83	0.82	0.65	78.1	0.85	0.74	0.59	78.2	0.86	0.87	0.73	76.8	0.75	0.82	0.57	78.9	0.59	0.89	0.48
Acacia mellifera	87.1	0.78	0.84	0.5	76.4	0.82	0.88	0.7	76.7	0.79	0.86	0.65	73.3	0.89	0.77	0.66	76.7	0.77	0.84	0.61
Acacia nilotica	76.4	0.65	0.87	0.52	76.8	0.76	0.84	0.6	77.6	0.78	0.84	0.62	75.6	0.72	0.89	0.61	75.8	0.67	0.83	0.5
Acacia nubica	85.7	0.88	0.78	0.66	72.5	0.76	0.89	0.65	75.8	0.83	0.75	0.58	76.2	0.87	0.84	0.71	77.5	0.69	0.87	0.56
Acacia senegal	87.5	0.78	0.85	0.63	65.4	0.82	0.73	0.55	73.6	0.87	0.68	0.55	66.5	0.67	0.71	0.38	73.5	0.77	0.82	0.59
Acacia tortilis	79.3	0.75	0.78	0.46	75.1	0.84	0.76	0.68	76.7	0.83	0.87	0.7	76.9	0.86	0.74	0.6	68.7	0.88	0.68	0.56
Acacia xanthophloea	84.9	0.89	0.76	0.65	76.8	0.71	0.82	0.6	73.6	0.88	0.71	0.59	78.7	0.74	0.83	0.57	71.7	0.82	0.87	0.69
Acokanthera oppositifolia	82.2	0.74	0.73	0.47	77.5	0.83	0.89	0.72	76.5	0.78	0.86	0.64	74.1	0.78	0.86	0.64	70.9	0.89	0.78	0.67
Albizia gummifera	73.6	0.89	0.84	0.73	67.9	0.74	0.88	0.62	74.8	0.78	0.69	0.47	68.2	0.68	0.72	0.4	76.9	0.85	0.74	0.59
Aloe secundiflora	89.3	0.87	0.86	0.7	57.8	0.79	0.82	0.61	75.9	0.79	0.86	0.65	67.8	0.86	0.68	0.54	74.7	0.74	0.81	0.55
Balanites aegyptiaca	83.6	0.72	0.88	0.6	63.8	0.86	0.85	0.71	76.8	0.75	0.87	0.62	78.6	0.67	0.83	0.5	76.7	0.83	0.85	0.68
Balanites rotundifolia	81.2	0.79	0.86	0.65	69.5	0.73	0.82	0.55	73.4	0.82	0.87	0.69	73.5	0.74	0.86	0.6	78.5	0.88	0.78	0.66
Barleria spinisepala	76.2	0.88	0.75	0.63	76.4	0.79	0.89	0.68	76.4	0.83	0.76	0.59	77.8	0.83	0.64	0.47	73.5	0.87	0.67	0.54
Boscia angustifolia	78.6	0.79	0.89	0.68	78.6	0.85	0.73	0.58	78.7	0.82	0.84	0.66	74.8	0.85	0.72	0.57	72.6	0.89	0.78	0.67
Boscia coriacea	78.5	0.82	0.85	0.67	72.9	0.72	0.89	0.61	75.3	0.79	0.87	0.66	68.7	0.87	0.71	0.58	74.5	0.85	0.56	0.41
Cadaba farinosa	74.7	0.66	0.82	0.48	69.7	0.78	0.81	0.59	75.5	0.74	0.86	0.6	73.6	0.86	0.84	0.58	78.6	0.76	0.78	0.54
Carissa edulis	82.4	0.71	0.83	0.54	76.7	0.77	0.87	0.64	78.5	0.82	0.87	0.69	66.3	0.71	0.61	0.32	74.7	0.67	0.88	0.55
Cissus rutundifolia	95.8	0.83	0.79	0.62	78.1	0.85	0.75	0.6	75.8	0.78	0.68	0.46	69.5	0.73	0.85	0.58	77.5	0.74	0.87	0.61
Cissus quadrangularis	82.6	0.72	0.89	0.61	71.7	0.79	0.88	0.67	77.1	0.75	0.89	0.64	74.7	0.57	0.87	0.44	75.4	0.78	0.83	0.61
Commiphora africana	77.7	0.72	0.78	0.5	73.6	0.87	0.85	0.72	78.9	0.78	0.87	0.65	75.6	0.82	0.72	0.54	72.8	0.67	0.85	0.52
Cordia monoica	89.5	0.83	0.75	0.58	75.3	0.77	0.86	0.63	76.8	0.81	0.89	0.7	63.2	0.74	0.54	0.28	73.9	0.76	0.87	0.63

Table 4.5.: Modeled medicinal plants using the Sentinel-2 variables and their evaluation metric (continued).

	OCSVM				BSVM				MaxEnt				EB-SDM				ES-SDM			
Species	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS	OA (%)	Sensitivity	Specicifty	TSS
Croton dichogamus	71.3	0.74	0.89	0.63	65.9	0.76	0.87	0.63	71.9	0.83	0.87	0.7	77.9	0.86	0.78	0.64	70.5	0.58	0.89	0.47
Croton megalocarpus	87.7	0.68	0.74	0.42	73.9	0.71	0.86	0.57	74.8	0.75	0.87	0.62	72.8	0.83	0.81	0.64	73.5	0.69	0.73	0.42
Cyphostema adenocaule	84.7	0.74	0.89	0.63	68.6	0.76	0.85	0.61	69.7	0.82	0.78	0.6	71.4	0.81	0.62	0.43	69.4	0.88	0.87	0.75
Cyphostema serpens	76.1	0.83	0.86	0.69	78.5	0.77	0.84	0.61	59.5	0.85	0.66	0.51	70.5	0.86	0.77	0.63	78.4	0.66	0.81	0.47
Ekebergia angustifolia	74.6	0.79	0.81	0.6	75.3	0.83	0.71	0.54	67.9	0.72	0.89	0.61	76.9	0.78	0.62	0.4	74.7	0.85	0.87	0.72
Euclea divinorum	87.5	0.73	0.88	0.61	77.2	0.76	0.89	0.65	78.7	0.76	0.88	0.64	73.1	0.81	0.86	0.67	68.6	0.87	0.84	0.71
Euphorbia candelabrum	83.4	0.77	0.76	0.53	73.7	0.85	0.86	0.71	73.8	0.83	0.71	0.54	78.5	0.67	0.87	0.54	58.5	0.86	0.81	0.67
Euphorbia heterochroma	86.7	0.86	0.84	0.7	75.6	0.82	0.84	0.66	75.6	0.67	0.75	0.42	75.8	0.78	0.86	0.64	75.6	0.83	0.85	0.68
Flueggea virosa	75.4	0.66	0.87	0.53	66.7	0.73	0.89	0.62	72.5	0.73	0.89	0.62	72.6	0.84	0.75	0.59	73.4	0.79	0.86	0.65
Fuerstia africana	79.5	0.72	0.83	0.55	52.7	0.89	0.76	0.65	68.9	0.79	0.88	0.67	77.5	0.67	0.75	0.42	78.3	0.76	0.87	0.63
Grewia tembensis	76.8	0.69	0.89	0.58	68.4	0.76	0.82	0.58	67.8	0.69	0.83	0.52	71.7	0.86	0.81	0.67	71.9	0.83	0.85	0.68
Gutenbergia cordifolia	88.4	0.73	0.83	0.56	74.2	0.78	0.87	0.65	76.6	0.77	0.83	0.6	76.5	0.88	0.72	0.6	70.4	0.71	0.88	0.59
Ipomoea spathulata	78.9	0.89	0.72	0.61	59.8	0.82	0.76	0.58	72.9	0.84	0.87	0.71	69.7	0.67	0.75	0.42	72.3	0.66	0.82	0.48
Juniperus procera	82.5	0.76	0.89	0.65	63.9	0.74	0.87	0.61	70.3	0.76	0.83	0.59	76.9	0.81	0.87	0.68	69.3	0.87	0.88	0.75
Kedrostis pseudogijef	85.8	0.75	0.88	0.63	68.6	0.79	0.84	0.63	71.8	0.73	0.86	0.61	73.4	0.59	0.83	0.42	78.2	0.76	0.79	0.55
Lippia javanica	88.3	0.73	0.89	0.62	75.6	0.68	0.77	0.45	74.8	0.79	0.89	0.68	77.9	0.75	0.73	0.48	74.3	0.78	0.87	0.65
Lippia kituiensis	89.1	0.86	0.86	0.72	76.2	0.74	0.89	0.63	54.9	0.71	0.89	0.6	68.9	0.67	0.83	0.5	76.5	0.86	0.85	0.71
Lycium europaeum	81.6	0.79	0.83	0.62	74.3	0.83	0.85	0.68	65.7	0.75	0.86	0.61	73.7	0.82	0.72	0.54	73.4	0.84	0.83	0.67
Myrsine africana	82.4	0.84	0.87	0.71	76.8	0.78	0.85	0.63	67.8	0.75	0.89	0.64	78.5	0.83	0.76	0.59	76.7	0.87	0.81	0.68
Olea africana	85.7	0.76	0.89	0.65	73.1	0.75	0.84	0.59	76.8	0.74	0.86	0.6	74.9	0.71	0.88	0.59	77.5	0.74	0.79	0.53
Psiadia punctulata	83.5	0.84	0.76	0.6	76.8	0.81	0.88	0.69	75.3	0.82	0.76	0.58	76.5	0.68	0.78	0.46	73.2	0.78	0.77	0.55

Table 4.5.: Modeled medicinal plants using the Sentinel-2 variables and their evaluation metric (continued).

	OCSVM				**BSVM**				**MaxEnt**				**EB-SDM**				**ES-SDM**			
Species	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS	OA (%)	Sensitivity	Specicifity	TSS
Podocarpus falcatus	79.5	0.88	0.87	0.75	75.4	0.83	0.82	0.65	75.8	0.81	0.75	0.56	78.1	0.78	0.76	0.54	75.6	0.83	0.89	0.72
Rhamnus stado	87.5	0.76	0.88	0.67	59.3	0.81	0.78	0.59	66.6	0.78	0.88	0.66	74.6	0.67	0.78	0.45	78.1	0.78	0.75	0.53
Rhus natalensis	89.6	0.89	0.84	0.73	64.5	0.83	0.89	0.72	65.3	0.82	0.78	0.6	76.9	0.84	0.78	0.62	74.3	0.84	0.75	0.59
Salvadora persica	83.2	0.89	0.88	0.77	77.4	0.84	0.79	0.63	62.1	0.68	0.78	0.46	72.3	0.82	0.75	0.57	76.5	0.59	0.89	0.48
Scutia myrtina	78.5	0.87	0.76	0.63	77.5	0.76	0.76	0.73	72.7	0.74	0.86	0.6	70.6	0.87	0.86	0.73	73.4	0.88	0.69	0.57
Senna didymobotrya	89.5	0.75	0.83	0.58	74.4	0.75	0.88	0.63	65.3	0.78	0.85	0.63	58.7	0.75	0.89	0.64	72.9	0.83	0.75	0.58
Solanum incanum	83.8	0.76	0.89	0.65	71.3	0.75	0.87	0.62	58.7	0.76	0.89	0.65	64.7	0.77	0.84	0.61	73.8	0.87	0.72	0.59
Teclea simplicifolia	89.6	0.84	0.87	0.71	73.8	0.85	0.74	0.59	69.4	0.75	0.86	0.6	68.9	0.85	0.88	0.73	77.4	0.89	0.75	0.64
Teclea aethiopica	82.5	0.71	0.79	0.5	68.5	0.74	0.89	0.63	73.1	0.77	0.86	0.63	76.9	0.75	0.81	0.56	71.9	0.83	0.87	0.7
Zanthoxylum usambarense	78.6	0.72	0.87	0.59	67.8	0.86	0.78	0.64	69.3	0.65	0.76	0.41	77.8	0.89	0.83	0.72	70.4	0.76	0.83	0.59
Viscum tuberculatum	84.9	0.79	0.89	0.68	73.7	0.76	0.88	0.64	73.8	0.73	0.88	0.61	73.9	0.83	0.78	0.55	75.4	0.71	0.86	0.57
Ximenia caffra	68.4	0.82	0.85	0.67	75.8	0.79	0.81	0.6	75.2	0.84	0.59	0.43	68.9	0.87	0.76	0.63	76.8	0.89	0.67	0.56

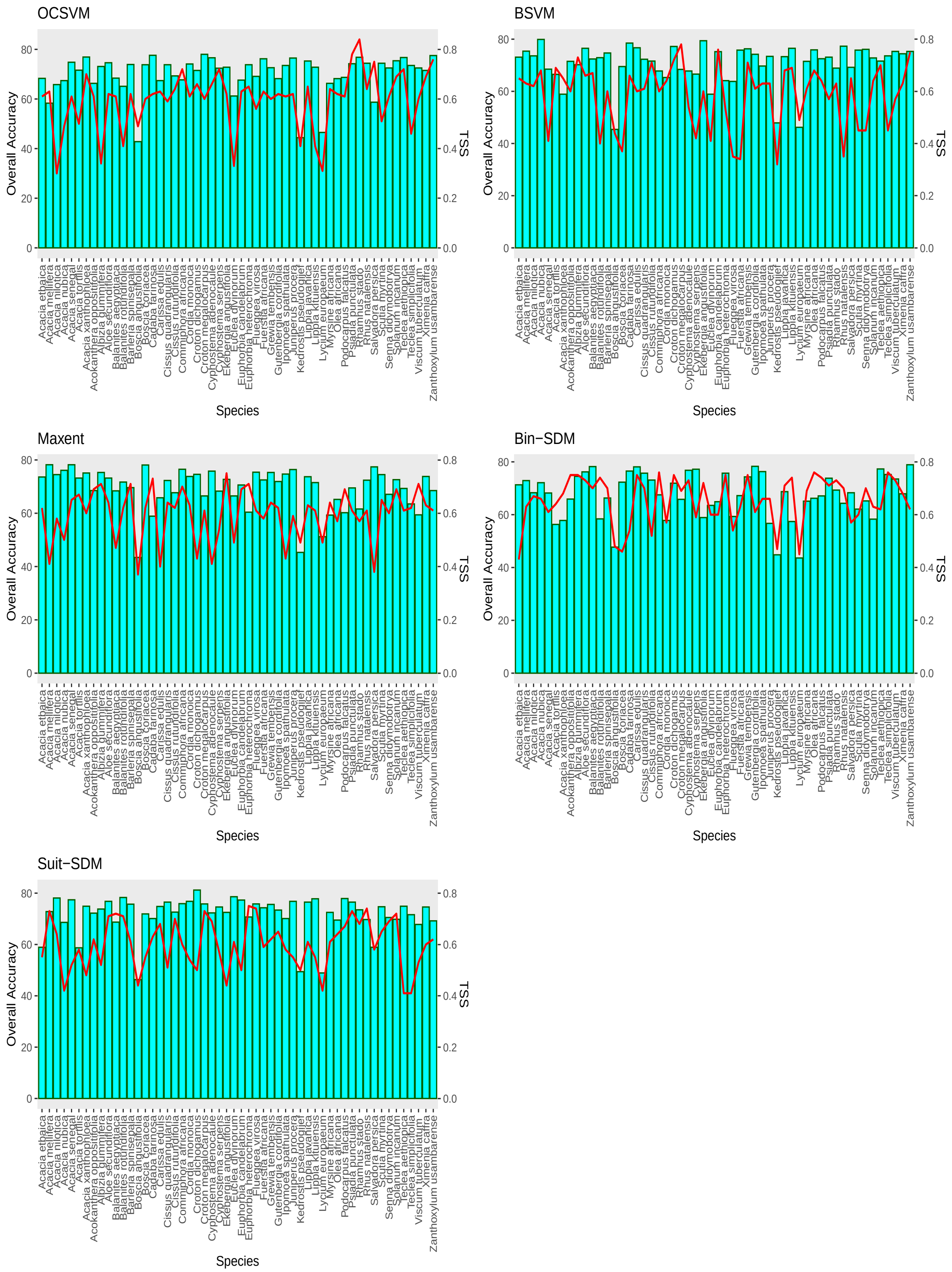

Figure 4.9.: Combined bar and line graphs showing the metrics of models fitted using remote sensing variables.

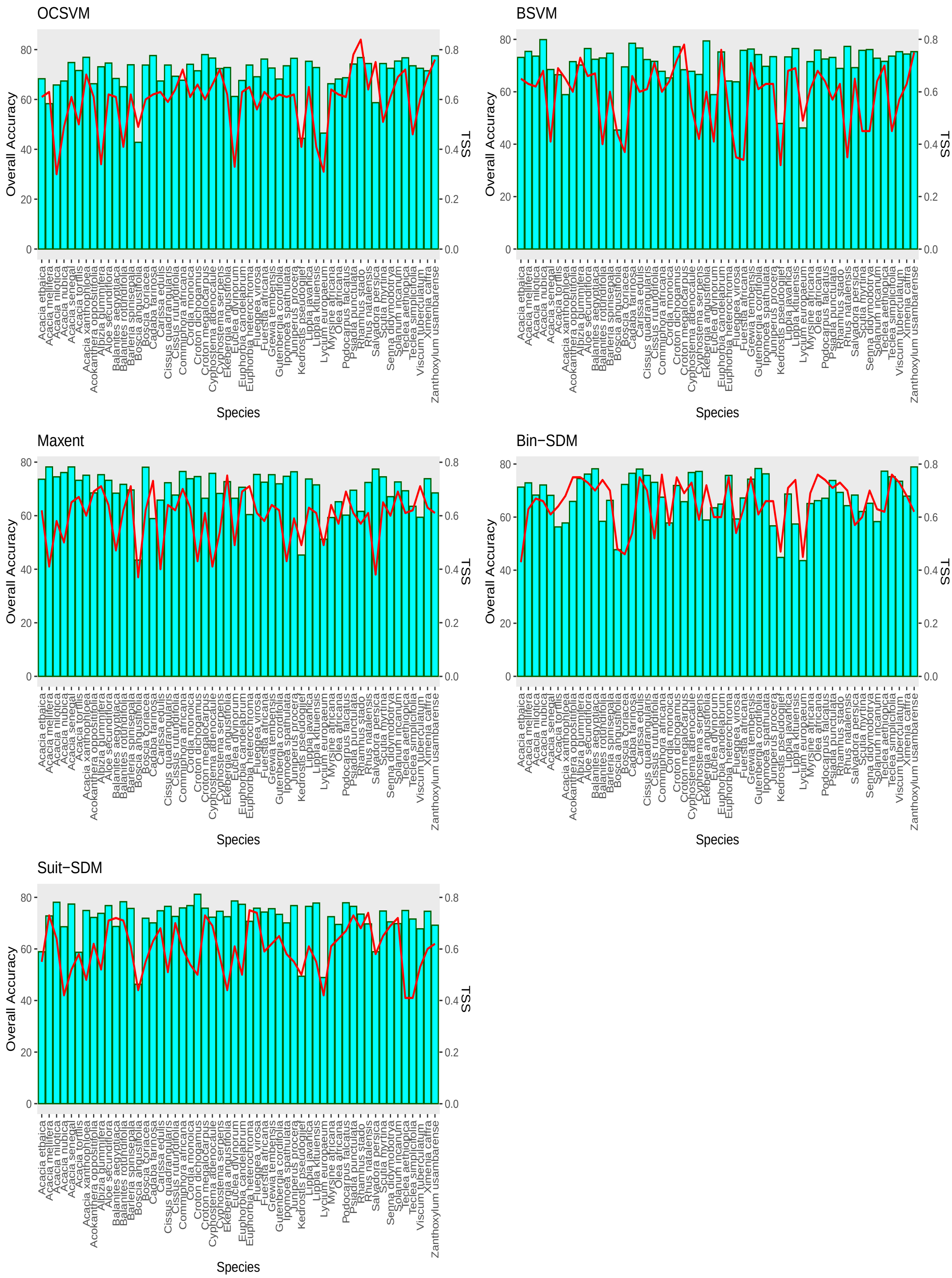

Figure 4.10.: Combined bar and line graphs showing the metrics of models fitted using Sentinel-2 variables.

Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species.

Species (Growth form)	OCSVM		BSVM		MaxEnt	
	Variable	Score	Variable	Score	Variable	Score
Acacia etbaica						
(Tree)	pH	2.3	pH	8.7	pH	4.4
	Elevation	28.6	Elevation	31.9	Elevation	22.6
	GPP	10.1	GPP	7.1	GPP	18.3
	fPAR	4.7	fPAR	0.8	fPAR	3.2
	LSWI	22.2	LSWI	20.2	LSWI	10.2
	Distance to roads	6.8	Distance to roads	8.8	Distance to roads	7.9
	SWC	25.3	SWC	22.5	SWC	33.4
Acacia mellifera						
(Tree)	SWC	4.5	SWC	26.2	SWC	19.4
	LSWI	27.1	LSWI	23.4	LSWI	25.5
	GPP	23.7	GPP	13.1	GPP	17.6
	EPT	8.8	EPT	6.8	EPT	9.1
	Distance to villages	7.4	Distance to villages	12.9	Distance to villages	11.3
	Land cover	16.4	Land cover	6.3	Land cover	4
	fPAR	8.3	fPAR	3.2	fPAR	6.8
	Aspect	3.8	Aspect	8.1	Aspect	6.3
Acacia nilotica						
(Tree)	GPP	17.2	GPP	8.7	GPP	22.7
	Elevation	26.7	Elevation	21.3	Elevation	34.9
	fPAR	5.8	fPAR	13.8	fPAR	6.4
	pH	3	pH	1.6	pH	2.3
	LSWI	32.4	LSWI	28.2	LSWI	6.6
	Clay	14.9	Clay	26.4	Clay	27.1
Acacia nubica						
(Shrub)	Aridity	31.7	Aridity	26.3	Aridity	23.3
	GPP	24.9	GPP	28.5	GPP	29.6
	Land cover	20.2	Land cover	13.7	Land cover	21.4

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	Sand	15.1	Sand	18.1	Sand	17.9
	TPI	2.2	TPI	5.7	TPI	3.8
	LST	5.9	LST	7.7	LST	4
Acacia senegal						
(Shrub)	LST	17.4	LST	10.3	LST	7.7
	TPI	25.7	TPI	27.3	TPI	27.4
	Clay	12.1	Clay	9.3	Clay	21.8
	EPT	7.7	EPT	11.2	EPT	4.3
	SWC	4.2	SWC	10.8	SWC	10.1
	LSWI	2.1	LSWI	2.9	LSWI	10.2
	Elevation	30.8	Elevation	28.2	Elevation	18.5
Acacia tortilis						
(Tree)	Elevation	24.3	Elevation	22.2	Elevation	28.1
	LST	10.4	LST	13.7	LST	23.8
	Distance to roads	3.4	Distance to roads	0.5	Distance to roads	3.7
	SWC	34.1	SWC	34.3	SWC	17.4
	Clay	17.7	Clay	17.3	Clay	13.5
	pH	3.3	pH	3.2	pH	1.2
	EPT	6.8	EPT	8.8	EPT	12.3
Acacia xanthophloea						
(Tree)	Tree cover	21.3	Tree cover	13.9	Tree cover	24.9
	TPI	14.8	TPI	22.3	TPI	21.6
	Clay	25.7	Clay	32.9	Clay	18.7
	fPAR	11.8	fPAR	7.4	fPAR	10.4
	Slope	5.3	Slope	11.6	Slope	9.2
	LSWI	12.5	LSWI	5.8	LSWI	12.8
	pH	8.6	pH	6.1	pH	2.4
Acokanthera oppositifolia						
(Tree)	Elevation	40.2	Elevation	22.9	Elevation	14.3

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	fPAR	19.4	fPAR	16.9	fPAR	11.9
	LST	5.4	LST	10.7	LST	0.6
	Clay	20.6	Clay	18.3	Clay	31.6
	SWC	13.5	SWC	28.4	SWC	33.5
	Distance to roads	0.9	Distance to roads	2.8	Distance to roads	8.1
Albizia gummifera						
(Tree)	Clay	9.3	Clay	17.1	Clay	14.6
	Distance to villages	7.2	Distance to villages	2.7	Distance to villages	18.3
	TPI	16	TPI	22.5	TPI	26.4
	Elevation	34.1	Elevation	28.3	Elevation	19.7
	LSWI	18.2	LSWI	1.8	LSWI	1
	Distance to roads	0.5	Distance to roads	13.1	Distance to roads	14.7
	Aridity	14.7	Aridity	14.5	Aridity	5.3
Aloe secundiflora						
(Herb)	Tree cover	24.3	Tree cover	19.6	Tree cover	42.3
	Elevation	18.6	Elevation	32.7	Elevation	27.8
	fPAR	11.8	fPAR	20.9	fPAR	10.6
	GPP	7.3	GPP	8.2	GPP	6.4
	Sand	23.4	Sand	17.3	Sand	2.7
	DNBR	14.6	DNBR	1.3	DNBR	10.2
Balanites aegyptiaca						
(Shrub)	LSWI	2.3	LSWI	1.7	LSWI	1.4
	fPAR	20.6	fPAR	21.1	fPAR	13.9
	Tree cover	33.1	Tree cover	36.3	Tree cover	44.8
	EPT	18.4	EPT	15.6	EPT	3.4
	Elevation	25.6	Elevation	25.3	Elevation	36.5
Balanites rotundifolia						
(Tree)	LSWI	21.4	LSWI	26.2	LSWI	23.9

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	Slope	33.8	Slope	22.8	Slope	35.7
	pH	2.3	pH	9.1	pH	2.4
	Soil carbon	7.5	Soil carbon	5.1	Soil carbon	5.5
	TPI	14.1	TPI	6.3	TPI	6.4
	Distance to villages	6.3	Distance to villages	13.3	Distance to villages	11.3
	LST	14.6	LST	17.2	LST	14.8
Barleria spinisepala						
(Shrub)	Elevation	37.4	Elevation	29.6	Elevation	27.9
	TPI	16.9	TPI	22.1	TPI	18.4
	Sand	4.3	Sand	11.8	Sand	12.5
	Distance to roads	23.1	Distance to roads	17.3	Distance to roads	23.2
	GPP	6.2	GPP	12.4	GPP	5.9
	pH	0.6	pH	0.1	pH	6.3
	Land cover	11.5	Land cover	6.7	Land cover	5.8
Boscia angustifolia						
(Shrub)	Tree cover	12.7	Tree cover	22.6	Tree cover	17.2
	SWC	28.3	SWC	34.1	SWC	27.3
	LST	11.6	LST	13.8	LST	8.6
	TPI	25.2	TPI	19.6	TPI	22.7
	Slope	7.8	Slope	2.5	Slope	6.2
	EPT	8	EPT	4.1	EPT	11.5
	Soil carbon	6.4	Soil carbon	3.3	Soil carbon	6.5
Boscia coriacea						
(Tree)	GPP	21.8	GPP	32.3	GPP	23.6
	SWC	19.3	SWC	11.8	SWC	16.7
	Distance to roads	5.8	Distance to roads	7.7	Distance to roads	2.4
	Aspect	1.4	Aspect	15.3	Aspect	6.1
	Aridity	15.4	Aridity	5.8	Aridity	22.8
	Clay	36.3	Clay	27.1	Clay	28.4

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

Cadaba farinosa						
(Tree)	Land cover	17.4	Land cover	14.6	Land cover	16.8
	Clay	26.5	Clay	27.3	Clay	26.1
	fPAR	23.9	fPAR	32.8	fPAR	28.3
	LST	15.7	LST	18.4	LST	14.9
	Aspect	2.7	Aspect	1.8	Aspect	1.3
	Distance to villages	13.8	Distance to villages	5.1	Distance to villages	12.6
Carissa edulis						
(Shrub)	Elevation	41.2	Elevation	37.2	Elevation	29.2
	GPP	14.6	GPP	20.9	GPP	18.6
	pH	3.3	pH	0.6	pH	1.4
	fPAR	13.5	fPAR	1.9	fPAR	12.3
	LSWI	3.7	LSWI	15.2	LSWI	6.1
	Distance to roads	3.9	Distance to roads	7.5	Distance to roads	9.1
	Tree cover	19.8	Tree cover	16.7	Tree cover	23.3
Cissus rutundifolia						
(Tree)	pH	0.8	pH	2.2	pH	1.6
	Soil carbon	9.3	Soil carbon	3.3	Soil carbon	0.7
	Slope	10.1	Slope	26.8	Slope	22.2
	LSWI	33.5	LSWI	25.2	LSWI	28.6
	Land cover	4.8	Land cover	11.4	Land cover	19.8
	GPP	24.7	GPP	17.4	GPP	23.7
	EPT	16.8	EPT	13.7	EPT	3.4
Cissus quadrangularis						
(Tree)	fPAR	15.2	fPAR	19.3	fPAR	3.6
	LST	11.4	LST	4.6	LST	16.2
	LSWI	1	LSWI	4.7	LSWI	0.1
	Sand	28.1	Sand	38.5	Sand	37.4
	Aridity	44.3	Aridity	32.9	Aridity	42.7

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

Commiphora africana						
(Tree)	Elevation	23.4	Elevation	28.6	Elevation	19.7
	Distance to villages	2.8	Distance to villages	7.8	Distance to villages	5.4
	EPT	19.3	EPT	23.3	EPT	21.6
	Slope	15.3	Slope	8.1	Slope	14.8
	Tree cover	0.6	Tree cover	3.3	Tree cover	1.9
	Sand	6.7	Sand	7.3	Sand	3.7
	Aridity	31.9	Aridity	21.6	Aridity	32.9
Cordia monoica						
(Shrub)	Sand	10.1	Sand	18.3	Sand	0.8
	SWC	6.3	SWC	2.6	SWC	20.4
	Elevation	25.3	Elevation	23.5	Elevation	26.8
	EPT	15.8	EPT	15.4	EPT	23.6
	Aridity	41.4	Aridity	37.9	Aridity	9.2
	Distance to villages	1.1	Distance to villages	2.3	Distance to villages	19.2
Croton dichogamus						
(Shrub)	Soil carbon	2.4	Soil carbon	10.6	Soil carbon	8.4
	Elevation	19.2	Elevation	24.1	Elevation	41.5
	fPAR	12.2	fPAR	16.7	fPAR	16.4
	SWC	32.4	SWC	36.3	SWC	22.7
	LST	28.7	LST	11.2	LST	9.2
	TPI	5.1	TPI	1.1	TPI	1.8
Croton megalocarpus						
(Tree)	EVT	8.2	EVT	14.4	EVT	9.9
	LSWI	34.9	LSWI	28.9	LSWI	18.7
	Elevation	17.2	Elevation	23.7	Elevation	23.8
	TPI	27.3	TPI	12.3	TPI	25.1
	Distance to villages	3.7	Distance to villages	15.8	Distance to villages	21.4
	Soil carbon	8.7	Soil carbon	4.9	Soil carbon	1.1

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

Cyphostema adeno-caule						
(Herb)	TPI	8.8	TPI	3.2	TPI	2.3
	Aridity	16.3	Aridity	19.2	Aridity	9.5
	Aspect	0.3	Aspect	7.9	Aspect	5.1
	Tree cover	21.4	Tree cover	12.5	Tree cover	14.9
	Distance to roads	1.9	Distance to roads	6.4	Distance to roads	11.7
	Clay	17.6	Clay	27.7	Clay	39.3
	LSWI	33.7	LSWI	23.1	LSWI	17.2
Cyphostema serpens						
(Herb)	Elevation	27.7	Elevation	20.9	Elevation	24.3
	SWC	20.9	SWC	17.7	SWC	26.9
	EPT	3.2	EPT	2.2	EPT	6.6
	Land cover	14.3	Land cover	16.4	Land cover	14.1
	fPAR	22.5	fPAR	26.5	fPAR	12.9
	Aridity	2.5	Aridity	13.8	Aridity	8.4
	pH	8.9	pH	2.5	pH	6.8
Ekebergia angustifo-lia						
(Tree)	Elevation	23.5	Elevation	28.8	Elevation	25.7
	SWC	3.7	SWC	12.6	SWC	17.4
	LSWI	36.1	LSWI	23.9	LSWI	34.5
	Clay	17.7	Clay	19.5	Clay	3.3
	Soil carbon	0.9	Soil carbon	1.8	Soil carbon	4.6
	Aridity	5.5	Aridity	11.1	Aridity	9.9
	Land cover	12.6	Land cover	2.3	Land cover	4.6
Euclea divinorum						
(Tree)	LST	6.3	LST	11.3	LST	15.9
	Sand	4.1	Sand	7.7	Sand	2.5
	Aridity	26.2	Aridity	32.6	Aridity	25.1
	TPI	24.7	TPI	2	TPI	13.7

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	Elevation	21.5	Elevation	25.4	Elevation	4.2
	EPT	9.8	EPT	14.7	EPT	27.3
	Distance to villages	7.4	Distance to villages	6.3	Distance to villages	11.3
Euphorbia heterochroma						
(Herb)	Aspect	1.3	Aspect	9.6	Aspect	0.4
	Clay	33.7	Clay	21.1	Clay	17.4
	Tree cover	36.9	Tree cover	41.2	Tree cover	46.5
	TPI	15.3	TPI	26.3	TPI	32.3
	Soil carbon	12.8	Soil carbon	1.8	Soil carbon	3.4
Euphorbia Candelabrum						
(Tree)	Aspect	1.3	Aspect	9.6	Aspect	0.4
	EPT	33.7	EPT	41.2	EPT	46.5
	LSWI	36.9	LSWI	21.1	LSWI	17.4
	TPI	15.3	TPI	26.3	TPI	32.3
	Soil carbon	12.8	Soil carbon	1.8	Soil carbon	3.4
Flueggea virosa						
(Tree)	Elevation	29.1	Elevation	22.4	Elevation	36.5
	Clay	23.6	Clay	27.7	Clay	24.8
	Distance to villages	6.6	Distance to villages	4.9	Distance to villages	13.6
	EPT	1.7	EPT	4.1	EPT	4.8
	Soil carbon	2.2	Soil carbon	2.3	Soil carbon	2.8
	Land cover	19.8	Land cover	12.9	Land cover	10.2
	TPI	11.4	TPI	15.8	TPI	4.1
	LSWI	5.6	LSWI	9.9	LSWI	3.2
Fuerstia africana						
(Tree)	SWC	35.2	SWC	26.1	SWC	27.2
	pH	0.8	pH	6	pH	12.7
	Distance to roads	3.4	Distance to roads	10.9	Distance to roads	2.8

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	LST	24.6	LST	4.7	LST	13.3
	fPAR	22.8	fPAR	28.8	fPAR	26.5
	TPI	10.3	TPI	15.3	TPI	10.9
	Aridity	2.9	Aridity	8.2	Aridity	6.6
Grewia tembensis						
(Shrub)	Elevation	26.3	Elevation	23.8	Elevation	23.9
	Clay	24.9	Clay	26.4	Clay	26.1
	LSWI	35.8	LSWI	42.7	LSWI	38.2
	Land cover	7.1	Land cover	1.9	Land cover	4.7
	TPI	5.9	TPI	5.2	TPI	7.1
Gutenbergia cordifolia						
(Tree)	SWC	41.3	SWC	33.8	SWC	26.1
	EPT	22.7	EPT	16.4	EPT	30.8
	GPP	4.1	GPP	5	GPP	11.9
	TPI	0.8	TPI	3.5	TPI	15.4
	Land cover	15.8	Land cover	24.1	Land cover	3.1
	Distance to roads	2	Distance to roads	5.4	Distance to roads	8.3
	EPT	13.3	EPT	11.8	EPT	4.4
Ipomoea spathulata						
(Shrub)	Elevation	37.8	Elevation	27.4	Elevation	24.2
	Tree cover	11.4	Tree cover	17.4	Tree cover	15.4
	Slope	33.1	Slope	30.2	Slope	38.1
	EPT	4.2	EPT	5.3	EPT	0.5
	Soil carbon	4.2	Soil carbon	11.6	Soil carbon	19.7
	LSWI	9.3	LSWI	8.1	LSWI	2.1
Juniperus procera						
(Tree)	Elevation	27.6	Elevation	37.2	Elevation	21.7
	SWC	23.9	SWC	25.6	SWC	23.8
	Sand	8.8	Sand	13.6	Sand	13.6
	LST	15.2	LST	8.2	LST	10.2

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	GPP	11.1	GPP	10.3	GPP	16.3
	EPT	9.4	EPT	1.9	EPT	13.1
	pH	4	pH	3.2	pH	1.3
Kedrostis pseudogijef						
(Tree)	GPP	6.1	GPP	11.3	GPP	16.4
	Slope	17.1	Slope	4.8	Slope	19.4
	SWC	16.3	SWC	23.2	SWC	11.3
	Distance to roads	2.2	Distance to roads	8.6	Distance to roads	2.3
	LSWI	23.9	LSWI	23.7	LSWI	26.9
	Aridity	34.7	Aridity	28.4	Aridity	23.7
Lippia javanica						
(Herb)	Elevation	27.2	Elevation	35.5	Elevation	27.1
	pH	0.3	pH	3.7	pH	0.6
	LSWI	24.6	LSWI	23.4	LSWI	18.4
	GPP	17.4	GPP	26.9	GPP	25.8
	EPT	23.4	EPT	6.7	EPT	22.3
	Soil carbon	7.1	Soil carbon	3.8	Soil carbon	5.8
Lippia kituiensis						
(Herb)						
	EPT	22.1	EPT	19.7	EPT	14.1
	LSWI	13.5	LSWI	7.7	LSWI	2.1
	Land cover	17.7	Land cover	24.8	Land cover	26.8
	Aridity	34.9	Aridity	31.8	Aridity	10.5
	fPAR	1.3	fPAR	12.5	fPAR	17.9
	GPP	9.6	GPP	1.1	GPP	3.3
	Clay	0.9	Clay	2.4	Clay	25.3
Lycium europaeum						
(Tree)	LSWI	37.6	LSWI	25.9	LSWI	33.6
	EPT	9.2	EPT	6.8	EPT	1.1
	Slope	23.1	Slope	28.1	Slope	20.1

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	pH	12.2	pH	23.5	pH	17.3
	Distance to villages	16.7	Distance to villages	8.3	Distance to villages	22.7
	Sand	1.2	Sand	7.4	Sand	5.2
Myrsine africana						
(Tree)	SWC	12	SWC	10.4	SWC	4.3
	Elevation	15.3	Elevation	18.3	Elevation	23.8
	GPP	7.7	GPP	8.1	GPP	24.9
	Clay	4.9	Clay	24.7	Clay	38.6
	TPI	24.6	TPI	20.9	TPI	1.3
	LSWI	35.5	LSWI	17.6	LSWI	7.1
Olea africana						
(Tree)	Slope	29.2	Slope	15.3	Slope	24.1
	GPP	24.7	GPP	23.8	GPP	13.9
	Distance to roads	12.4	Distance to roads	8.4	Distance to roads	3.7
	TPI	20.5	TPI	41.4	TPI	37.2
	Tree cover	10.2	Tree cover	7.8	Tree cover	18.6
	Clay	3	Clay	3.3	Clay	2.5
Psiadia punctulata						
(Herb)	SWC	23.7	SWC	12.9	SWC	19.9
	Soil carbon	15.3	Soil carbon	18.3	Soil carbon	4.3
	EPT	22.9	EPT	31.8	EPT	26.2
	Aspect	2.4	Aspect	3.4	Aspect	3.8
	LST	30.8	LST	22.1	LST	28.5
	Land cover	4.9	Land cover	11.5	Land cover	17.3
Podocarpus falcatus						
(Tree)	TPI	7.9	TPI	5.3	TPI	13.4
	LSWI	38.1	LSWI	27.5	LSWI	24.6
	fPAR	22.6	fPAR	24.1	fPAR	34.7
	Sand	17.4	Sand	23.3	Sand	19.2

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	Soil carbon	0.1	Soil carbon	1.2	Soil carbon	5.8
	Tree cover	13.9	Tree cover	18.6	Tree cover	2.3
Rhamnus stado						
(Herb)	GPP	24.1	GPP	29.4	GPP	25.8
	SWC	32.8	SWC	26.6	SWC	30.2
	TPI	20.7	TPI	14.9	TPI	18.7
	Clay	19.4	Clay	8.2	Clay	3.1
	Distance to villages	0.7	Distance to villages	7.6	Distance to villages	5.8
	Tree cover	2.3	Tree cover	13.8	Tree cover	16.4
Rhus natalensis						
(Shrub)	Elevation	32.2	Elevation	13.2	Elevation	27.9
	GPP	20.7	GPP	36.1	GPP	22.3
	LSWI	18.4	LSWI	13.7	LSWI	0.3
	Clay	6.2	Clay	7.8	Clay	19.6
	SWC	7.8	SWC	3.8	SWC	4.5
	EPT	14.7	EPT	25.4	EPT	25.4
Salvadora persica						
(Shrub)	Distance to villages	3.9	Distance to villages	2.5	Distance to villages	4.6
	Elevation	22.3	Elevation	23.5	Elevation	43.5
	SWC	19.2	SWC	36.6	SWC	28.9
	LST	17.4	LST	20.1	LST	14.6
	Aridity	37.2	Aridity	17.3	Aridity	8.4
Scutia myrtina						
(Tree)	fPAR	13.2	fPAR	23.7	fPAR	18.2
	GPP	15.8	GPP	17.9	GPP	26.3
	Clay	41.4	Clay	29.4	Clay	22.7
	Aridity	5.7	Aridity	13.4	Aridity	3.1
	LSWI	14.8	LSWI	14.1	LSWI	15.9
	pH	9.1	pH	1.5	pH	13.8

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

Senna didymobotrya						
(Herb)	Elevation	34.8	Elevation	28.3	Elevation	24.6
	EPT	18.1	EPT	23.1	EPT	3.1
	GPP	9.9	GPP	13.7	GPP	18.3
	TPI	2.4	TPI	1.6	TPI	6.4
	LSWI	2	LSWI	3.3	LSWI	12.7
	Land cover	7.5	Land cover	10.1	Land cover	7.6
	Clay	25.3	Clay	19.9	Clay	27.3
Solanum incanum						
(Herb)	SWC	20.2	SWC	18.7	SWC	11.4
	Aridity	8.3	Aridity	31.1	Aridity	21.4
	Tree cover	31.3	Tree cover	16.2	Tree cover	25.9
	Clay	27.8	Clay	28.5	Clay	14.2
	pH	0.6	pH	0.7	pH	8.3
	Soil carbon	3.4	Soil carbon	3.6	Soil carbon	5.1
	fPAR	8.4	fPAR	1.2	fPAR	13.7
Teclea simplicifolia						
(Tree)	TPI	36.6	TPI	32.5	TPI	11.6
	Elevation	21.8	Elevation	17.8	Elevation	39.2
	LST	14.7	LST	14.8	LST	8.4
	fPAR	18.7	fPAR	19.4	fPAR	32.7
	Distance to roads	0.7	Distance to roads	4.9	Distance to roads	3.8
	Clay	7.5	Clay	10.6	Clay	4.3
Teclea aethiopica						
(Tree)	TPI	6.9	TPI	2.4	TPI	13.9
	Distance to villages	11.6	Distance to villages	14.7	Distance to villages	23.6
	Aridity	21.4	Aridity	25.5	Aridity	10.4
	LSWI	1	LSWI	3.8	LSWI	1.1

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Table 4.6: Variable importance of remote sensing variables used in modelling all medicinal plant species. (Continued)

	TPI	20.7	TPI	22.6	TPI	8.3
	Aspect	7.9	Aspect	7.2	Aspect	13.5
	SWC	30.5	SWC	23.8	SWC	29.2
Zanthoxylum usambarense						
(Tree)	LSWI	21.8	LSWI	10	LSWI	13.6
	Soil carbon	0.9	Soil carbon	2.6	Soil carbon	1.2
	Tree cover	15.2	Tree cover	17.4	Tree cover	14.7
	GPP	16.1	GPP	12.1	GPP	24.1
	fPAR	18.3	fPAR	26.8	fPAR	17.8
	Aridity	27.4	Aridity	31.1	Aridity	28.6
Viscum tuberculatum						
(Shrub)	Sand	9.7	Sand	11.7	Sand	5.3
	Soil carbon	21.5	Soil carbon	1.9	Soil carbon	1.6
	LSWI	7.3	LSWI	1.6	LSWI	14.7
	EPT	13.4	EPT	19.2	EPT	23.1
	TPI	16.9	TPI	26.6	TPI	1.3
	Distance to roads	4	Distance to roads	13.1	Distance to roads	21.3
	Slope	27.2	Slope	25.9	Slope	32.7
Ximenia caffra						
(Tree)	Elevation	21.4	Elevation	18.3	Elevation	38.4
	GPP	18.4	GPP	20.7	GPP	18.8
	SWC	27.5	SWC	23.5	SWC	12.6
	Tree cover	20.2	Tree cover	18.1	Tree cover	23.6
	Clay	11.3	Clay	16.2	Clay	5.3
	LSWI	1.2	LSWI	3.2	LSWI	1.3

Table 4.7: Variable importance of remote sensing variables used in modelling species used against stomach ache.

Species (Growth form)	**OCSVM**		**BSVM**		**MaxEnt**	
	Variable	**Score**	**Variable**	**Score**	**Variable**	**Score**

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Table 4.7: Variable importance of remote sensing variables used in modelling species used against stomach ache. (Continued)

Acacia etbaica						
(Tree)	pH	2.3	pH	8.7	pH	4.4
	Elevation	28.6	Elevation	31.9	Elevation	22.6
	GPP	10.1	GPP	7.1	GPP	18.3
	fPAR	4.7	fPAR	0.8	fPAR	3.2
	LSWI	22.2	LSWI	20.2	LSWI	10.2
	Distance to roads	6.8	Distance to roads	8.8	Distance to roads	7.9
	SWC	25.3	SWC	22.5	SWC	33.4
Acacia nilotica						
(Tree)	GPP	17.2	GPP	8.7	GPP	22.7
	Elevation	26.7	Elevation	21.3	Elevation	34.9
	fPAR	5.8	fPAR	13.8	fPAR	6.4
	pH	3	pH	1.6	pH	2.3
	LSWI	32.4	LSWI	28.2	LSWI	6.6
	Clay	14.9	Clay	26.4	Clay	27.1
Acacia senegal						
(Shrub)	LST	17.4	LST	10.3	LST	7.7
	TPI	25.7	TPI	27.3	TPI	27.4
	Clay	12.1	Clay	9.3	Clay	21.8
	EPT	7.7	EPT	11.2	EPT	4.3
	SWC	4.2	SWC	10.8	SWC	10.1
	LSWI	2.1	LSWI	2.9	LSWI	10.2
	Elevation	30.8	Elevation	28.2	Elevation	18.5
Acacia tortilis						
(Tree)	Elevation	24.3	Elevation	22.2	Elevation	28.1
	LST	10.4	LST	13.7	LST	23.8
	Distance to roads	3.4	Distance to roads	0.5	Distance to roads	3.7
	SWC	34.1	SWC	34.3	SWC	17.4
	Clay	17.7	Clay	17.3	Clay	13.5
	pH	3.3	pH	3.2	pH	1.2
	EPT	6.8	EPT	8.8	EPT	12.3

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Table 4.7: Variable importance of remote sensing variables used in modelling species used against stomach ache. (Continued)

Acokanthera oppositifolia						
(Tree)	Elevation	40.2	Elevation	22.9	Elevation	14.3
	fPAR	19.4	fPAR	16.9	fPAR	11.9
	LST	5.4	LST	10.7	LST	0.6
	Clay	20.6	Clay	18.3	Clay	31.6
	SWC	13.5	SWC	28.4	SWC	33.5
	Distance to roads	0.9	Distance to roads	2.8	Distance to roads	8.1
Commiphora africana						
(Tree)	Elevation	23.4	Elevation	28.6	Elevation	19.7
	Distance to villages	2.8	Distance to villages	7.8	Distance to villages	5.4
	EPT	19.3	EPT	23.3	EPT	21.6
	Slope	15.3	Slope	8.1	Slope	14.8
	Tree cover	0.6	Tree cover	3.3	Tree cover	1.9
	Sand	6.7	Sand	7.3	Sand	3.7
	Aridity	31.9	Aridity	21.6	Aridity	32.9
Croton dichogamus						
(Shrub)	Soil carbon	2.4	Soil carbon	10.6	Soil carbon	8.4
	Elevation	19.2	Elevation	24.1	Elevation	41.5
	fPAR	12.2	fPAR	16.7	fPAR	16.4
	SWC	32.4	SWC	36.3	SWC	22.7
	LST	28.7	LST	11.2	LST	9.2
	TPI	5.1	TPI	1.1	TPI	1.8
Croton megalocarpus						
(Tree)	EVT	8.2	EVT	14.4	EVT	9.9
	LSWI	34.9	LSWI	28.9	LSWI	18.7
	Elevation	17.2	Elevation	23.7	Elevation	23.8
	TPI	27.3	TPI	12.3	TPI	25.1

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Table 4.7: Variable importance of remote sensing variables used in modelling species used against stomach ache. (Continued)

	Distance to villages	3.7	Distance to villages	15.8	Distance to villages	21.4
	Soil carbon	8.7	Soil carbon	4.9	Soil carbon	1.1
Juniperus procera						
(Tree)	Elevation	27.6	Elevation	37.2	Elevation	21.7
	SWC	23.9	SWC	25.6	SWC	23.8
	Sand	8.8	Sand	13.6	Sand	13.6
	LST	15.2	LST	8.2	LST	10.2
	GPP	11.1	GPP	10.3	GPP	16.3
	EPT	9.4	EPT	1.9	EPT	13.1
	pH	4	pH	3.2	pH	1.3
Rhus natalensis						
(Shrub)	Elevation	32.2	Elevation	13.2	Elevation	22.3
	GPP	20.7	GPP	36.1	GPP	0.3
	LSWI	18.4	LSWI	13.7	LSWI	27.9
	Clay	6.2	Clay	7.8	Clay	19.6
	SWC	7.8	SWC	3.8	SWC	4.5
	EPT	14.7	EPT	25.4	EPT	25.4
Salvadora persica						
(Shrub)	Distance to villages	3.9	Distance to villages	2.5	Distance to villages	4.6
	Elevation	22.3	Elevation	23.5	Elevation	43.5
	SWC	19.2	SWC	36.6	SWC	28.9
	LST	17.4	LST	20.1	LST	14.6
	Aridity	37.2	Aridity	17.3	Aridity	8.4
Ximenia caffra						
(Tree)	Elevation	21.4	Elevation	18.3	Elevation	38.4
	GPP	18.4	GPP	20.7	GPP	18.8
	SWC	27.5	SWC	23.5	SWC	12.6
	Tree cover	20.2	Tree cover	18.1	Tree cover	23.6
	Clay	11.3	Clay	16.2	Clay	5.3
	LSWI	1.2	LSWI	3.2	LSWI	1.3

Table 4.8: Variable importance of remote sensing variables used in modelling species used against diarrhoea.

Species (Growth form)	OCSVM		BSVM		MaxEnt	
	Variable	Score	Variable	Score	Variable	Score
Acacia etbaica						
(Tree)	pH	2.3	pH	8.7	pH	4.4
	Elevation	28.6	Elevation	31.9	Elevation	22.6
	GPP	10.1	GPP	7.1	GPP	18.3
	fPAR	4.7	fPAR	0.8	fPAR	3.2
	LSWI	22.2	LSWI	20.2	LSWI	10.2
	Distance to roads	6.8	Distance to roads	8.8	Distance to roads	7.9
	SWC	25.3	SWC	22.5	SWC	33.4
Acacia senegal						
(Shrub)	LST	17.4	LST	10.3	LST	7.7
	TPI	25.7	TPI	27.3	TPI	27.4
	Clay	12.1	Clay	9.3	Clay	21.8
	EPT	7.7	EPT	11.2	EPT	4.3
	SWC	4.2	SWC	10.8	SWC	10.1
	LSWI	2.1	LSWI	2.9	LSWI	10.2
	Elevation	30.8	Elevation	28.2	Elevation	18.5
Carissa edulis						
(Shrub)	Elevation	41.2	Elevation	37.2	Elevation	29.2
	GPP	14.6	GPP	20.9	GPP	18.6
	pH	3.3	pH	0.6	pH	1.4
	fPAR	13.5	fPAR	1.9	fPAR	12.3
	LSWI	3.7	LSWI	15.2	LSWI	6.1
	Distance to roads	3.9	Distance to roads	7.5	Distance to roads	9.1
	Tree cover	19.8	Tree cover	16.7	Tree cover	23.3
Commiphora africana						
(Tree)	Elevation	23.4	Elevation	28.6	Elevation	19.7
	Distance to villages	2.8	Distance to villages	7.8	Distance to villages	5.4

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Table 4.8: Variable importance of remote sensing variables used in modelling species used against diarrhoea. (Continued)

	EPT	19.3	EPT	23.3	EPT	21.6
	Slope	15.3	Slope	8.1	Slope	14.8
	Tree cover	0.6	Tree cover	3.3	Tree cover	1.9
	Sand	6.7	Sand	7.3	Sand	3.7
	Aridity	31.9	Aridity	21.6	Aridity	32.9
Cordia monoica						
(Shrub)	Sand	10.1	Sand	18.3	Sand	0.8
	SWC	6.3	SWC	2.6	SWC	20.4
	Elevation	25.3	Elevation	23.5	Elevation	26.8
	EPT	15.8	EPT	15.4	EPT	23.6
	Aridity	41.4	Aridity	37.9	Aridity	9.2
	Distance to villages	1.1	Distance to villages	2.3	Distance to villages	19.2
Ipomoea spathulata						
(Shrub)	Elevation	37.8	Elevation	27.4	Elevation	24.2
	Tree cover	11.4	Tree cover	17.4	Tree cover	15.4
	Slope	33.1	Slope	30.2	Slope	38.1
	EPT	4.2	EPT	5.3	EPT	0.5
	Soil carbon	4.2	Soil carbon	11.6	Soil carbon	19.7
	LSWI	9.3	LSWI	8.1	LSWI	2.1
Olea africana						
(Tree)	Slope	29.2	Slope	15.3	Slope	24.1
	GPP	24.7	GPP	23.8	GPP	13.9
	Distance to roads	12.4	Distance to roads	8.4	Distance to roads	3.7
	TPI	20.5	TPI	41.4	TPI	37.2
	Tree cover	10.2	Tree cover	7.8	Tree cover	18.6
	Clay	3	Clay	3.3	Clay	2.5
Rhus natalensis						
(Shrub)	Elevation	32.2	Elevation	13.2	Elevation	27.9
	GPP	20.7	GPP	36.1	GPP	22.3

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Table 4.8: Variable importance of remote sensing variables used in modelling species used against diarrhoea. (Continued)

	LSWI	18.4	LSWI	13.7	LSWI	0.3
	Clay	6.2	Clay	7.8	Clay	19.6
	SWC	7.8	SWC	3.8	SWC	4.5
	EPT	14.7	EPT	25.4	EPT	25.4
Solanum incanum						
(Herb)	SWC	20.2	SWC	18.7	SWC	11.4
	Aridity	8.3	Aridity	31.1	Aridity	21.4
	Tree cover	31.3	Tree cover	16.2	Tree cover	25.9
	Clay	27.8	Clay	28.5	Clay	14.2
	pH	0.6	pH	0.7	pH	8.3
	Soil carbon	3.4	Soil carbon	3.6	Soil carbon	5.1
	fPAR	8.4	fPAR	1.2	fPAR	13.7
Salvadora persica						
(Shrub)	Distance to villages	3.9	Distance to villages	2.5	Distance to villages	4.6
	Elevation	22.3	Elevation	23.5	Elevation	43.5
	SWC	19.2	SWC	36.6	SWC	28.9
	LST	17.4	LST	20.1	LST	14.6
	Aridity	37.2	Aridity	17.3	Aridity	8.4
Teclea simplicifolia						
(Shrub)	TPI	36.6	TPI	32.5	TPI	11.6
	Elevation	21.8	Elevation	17.8	Elevation	39.2
	LST	14.7	LST	14.8	LST	8.4
	fPAR	18.7	fPAR	19.4	fPAR	32.7
	Distance to roads	0.7	Distance to roads	4.9	Distance to roads	3.8
	Clay	7.5	Clay	10.6	Clay	4.3
Viscum tuberculatum						
(Shrub)	Sand	9.7	Sand	11.7	Sand	5.3
	Soil carbon	21.5	Soil carbon	1.9	Soil carbon	1.6

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Table 4.8: Variable importance of remote sensing variables used in modelling species used against diarrhoea. (Continued)

	LSWI	7.3	LSWI	1.6	LSWI	14.7
	EPT	13.4	EPT	19.2	EPT	23.1
	TPI	16.9	TPI	26.6	TPI	1.3
	Distance to roads	4	Distance to roads	13.1	Distance to roads	21.3
	Slope	27.2	Slope	25.9	Slope	32.7

Table 4.9: Variable importance of remote sensing variables used in modelling species used against wounds.

Species (Growth form)	OCSVM		BSVM		MaxEnt	
	Variable	**Score**	**Variable**	**Score**	**Variable**	**Score**
Aloe secundiflora						
(Herb)	Tree cover	24.3	Tree cover	19.6	Tree cover	42.3
	Elevation	18.6	Elevation	32.7	Elevation	27.8
	fPAR	11.8	fPAR	20.9	fPAR	10.6
	GPP	7.3	GPP	8.2	GPP	6.4
	Sand	23.4	Sand	17.3	Sand	2.7
	DNBR	14.6	DNBR	1.3	DNBR	10.2
Balanites aegyptiaca						
(shrub)	LSWI	2.3	LSWI	1.7	LSWI	1.4
	fPAR	20.6	fPAR	21.1	fPAR	13.9
	Tree cover	33.1	Tree cover	36.3	Tree cover	44.8
	EPT	18.4	EPT	15.6	EPT	3.4
	Elevation	25.6	Elevation	25.3	Elevation	36.5
Commiphora africana						
(Tree)	Elevation	23.4	Elevation	28.6	Elevation	19.7
	Distance to villages	2.8	Distance to villages	7.8	Distance to villages	5.4
	EPT	19.3	EPT	23.3	EPT	21.6
	Slope	15.3	Slope	8.1	Slope	14.8
	Tree cover	0.6	Tree cover	3.3	Tree cover	1.9
	Sand	6.7	Sand	7.3	Sand	3.7

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Table 4.9: Variable importance of remote sensing variables used in modelling species used against wounds. (Continued)

	Aridity	31.9	Aridity	21.6	Aridity	32.9
Cissus quadrangularis						
(Herb)	fPAR	15.2	fPAR	19.3	fPAR	3.6
	LST	11.4	LST	4.6	LST	16.2
	LSWI	1	LSWI	4.7	LSWI	0.1
	Clay	44.3	Clay	38.5	Clay	37.4
	Aridity	28.1	Aridity	32.9	Aridity	42.7
Cordia monoica						
(shrub)	Sand	10.1	Sand	18.3	Sand	0.8
	SWC	6.3	SWC	2.6	SWC	20.4
	Elevation	25.3	Elevation	23.5	Elevation	26.8
	EPT	15.8	EPT	15.4	EPT	23.6
	Aridity	41.4	Aridity	37.9	Aridity	9.2
	Distance to villages	1.1	Distance to villages	2.3	Distance to villages	19.2
Myrsine africana						
(Tree)	SWC	12	SWC	10.4	SWC	4.3
	Elevation	15.3	Elevation	18.3	Elevation	23.8
	GPP	7.7	GPP	8.1	GPP	24.9
	Clay	4.9	Clay	24.7	Clay	38.6
	TPI	24.6	TPI	20.9	TPI	1.3
	LSWI	35.5	LSWI	17.6	LSWI	7.1
Euphorbia heterochroma						
(Herb)	Aspect	1.3	Aspect	9.6	Aspect	0.4
	Clay	33.7	Clay	21.1	Clay	17.4
	Tree cover	36.9	Tree cover	41.2	Tree cover	46.5
	TPI	15.3	TPI	26.3	TPI	32.3
	Soil carbon	12.8	Soil carbon	1.8	Soil carbon	3.4
Solanum incanum						

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Table 4.9: Variable importance of remote sensing variables used in modelling species used against wounds. (Continued)

(Herb)	SWC	20.2	SWC	18.7	SWC	11.4
	Aridity	8.3	Aridity	31.1	Aridity	21.4
	Tree cover	31.3	Tree cover	16.2	Tree cover	25.9
	Clay	27.8	Clay	28.5	Clay	14.2
	pH	0.6	pH	0.7	pH	8.3
	Soil carbon	3.4	Soil carbon	3.6	Soil carbon	5.1
	fPAR	8.4	fPAR	1.2	fPAR	13.7

Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species.

Species	**OCSVM**		**BSVM**		**MaxEnt**	
	Variable	**Score**	**Variable**	**Score**	**Variable**	**Score**
Acacia etbaica						
	MSAVI	24.6	MSAVI	28.5	MSAVI	29.6
	NDVI	21.3	NDVI	21.3	NDVI	9.7
	SWIR 2 (B12)	32.8	SWIR 2 (B12)	11.7	SWIR 2 (B12)	23.5
	VRE 1	4.8	VRE 1	16.3	VRE 1	13.3
	Red	9	Red	13.2	Red	10.7
	CLRE	2.1	CLRE	4.6	CLRE	8.4
	SWIR 1 (B11)	5.4	SWIR 1 (B11)	4.4	SWIR 1 (B11)	4.8
Acacia mellifera						
	Blue	12.4	Blue	7.4	Blue	17.5
	CLRE	7.7	CLRE	11.2	CLRE	4.1
	NIR8	26.9	NIR8	31.3	NIR8	27.4
	NDVI	25.7	NDVI	25.9	NDVI	25.9
	Homogeneity	3.9	Homogeneity	6.7	Homogeneity	5.6
	VRE 1	19.3	VRE 1	7.9	VRE 1	6.2
	SWIR 2 (B12)	4.1	SWIR 2 (B12)	9.6	SWIR 2 (B12)	13.3
Acacia nilotica						

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	NIR8	17.3	NIR8	6.8	NIR8	21.7
	NDVI	26.7	NDVI	19.9	NDVI	28.4
	SWIR 1 (B11)	4.5	SWIR 1 (B11)	7.4	SWIR 1 (B11)	16.6
	MSAVI	23.7	MSAVI	15.7	MSAVI	10.2
	Blue	7.4	Blue	1.5	Blue	5.3
	Red	5.8	Red	16.2	Red	4.8
	VRE 1	14.6	VRE 1	32.5	VRE 1	13
Acacia nubica						
	SWIR 1 (B11)	11.2	SWIR 1 (B11)	26.4	SWIR 1 (B11)	25.9
	Red	18.3	Red	19.6	Red	12.4
	CLRE	0.7	CLRE	1.8	CLRE	5.3
	Green	5.2	Green	15.5	Green	16.1
	VRE 2	36.1	VRE 2	23.9	VRE 2	28.3
	NDWI	13.8	NDWI	3.1	NDWI	4.8
	EVI	14.7	EVI	9.7	EVI	7.2
Acacia senegal						
	VRE 2	8.6	VRE 2	11.4	VRE 2	8.5
	Blue	2.5	Blue	8.4	Blue	5.1
	NDVI	23.4	NDVI	13.8	NDVI	15.4
	SWIR 1 (B11)	41.2	SWIR 1 (B11)	28.7	SWIR 1 (B11)	38.3
	NIR8	9.3	NIR8	9.6	NIR8	3.7
	VRE 1	7.7	VRE 1	26.1	VRE 1	22.7
	NDWI	7.3	NDWI	2	NDWI	6.3
Acacia tortilis						
	SWIR 1 (B11)	16.4	SWIR 1 (B11)	16.9	SWIR 1 (B11)	21.6
	VRE 2	3.5	VRE 2	4.8	VRE 2	5.4
	NDVI	39.2	NDVI	26.3	NDVI	34.7
	MSAVI	8.8	MSAVI	19.3	MSAVI	19.9
	NIR8	24.7	NIR8	28.4	NIR8	18.1

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	Homogeneity	7.4	Homogeneity	4.3	Homogeneity	0.3
Acacia xanthophloea						
	NDVI	23.9	NDVI	28.3	NDVI	27.2
	Red	15.1	Red	9.1	Red	12.8
	VRE 2	36.2	VRE 2	22.7	VRE 2	6.2
	SWIR 2 (B12)	0.9	SWIR 2 (B12)	14.2	SWIR 2 (B12)	19.2
	NIR 8	10.3	NIR 8	17.2	NIR 8	25.9
	CLRE	13.6	CLRE	8.5	CLRE	8.7
Acokanthera oppositifolia						
	SWIR 1 (B11)	17.6	SWIR 1 (B11)	22.7	SWIR 1 (B11)	27.8
	NIR8	21.3	NIR8	35.6	NIR8	12.4
	VRE 1	30.2	VRE 1	7.7	VRE 1	30.6
	EVI	15.4	EVI	14.5	EVI	5.2
	Red	6.5	Red	10.1	Red	6.8
	MSAVI	3.2	MSAVI	2.6	MSAVI	8.9
	NDWI	5.8	NDWI	6.8	NDWI	8.3
Albizia gummifera						
	NDVI	24.7	NDVI	27	NDVI	22.3
	Red	20.1	Red	14.3	Red	5.6
	NIR8	33.3	NIR8	25.9	NIR8	16.2
	SWIR 1 (B11)	16.2	SWIR 1 (B11)	12.4	SWIR 1 (B11)	26.1
	Homogeneity	2.5	Homogeneity	6.6	Homogeneity	23.7
	Blue	3.2	Blue	13.8	Blue	6.1
Aloe secundiflora						
	SWIR (B12)	2.5	SWIR (B12)	2.2	SWIR (B12)	5.8
	Mean	27.2	Mean	25.6	Mean	9.3
	NDVI	8.8	NDVI	12.2	NDVI	3.9

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	Red	19.6	Red	9.5	Red	2.4
	CLRE	12.8	CLRE	16.8	CLRE	25.7
	MSAVI	21.9	MSAVI	20.1	MSAVI	37.6
	NDWI	7.2	NDWI	13.6	NDWI	15.3
Balanites aegyptiaca						
	MSAVI	23.4	MSAVI	35.1	MSAVI	25.7
	CLRE	4.9	CLRE	10.2	CLRE	10.3
	Red	12.9	Red	8.9	Red	3.8
	Mean	39.7	Mean	22.2	Mean	32.1
	VRE 2	10.2	VRE 2	8.6	VRE 2	16.2
	EVI	7.9	EVI	11.8	EVI	9.4
	Blue	1	Blue	3.2	Blue	2.5
Balanites rotundifolia						
	VRE 3	20.9	VRE 3	23.1	VRE 3	35.7
	SWIR 1 (B11)	13.1	SWIR 1 (B11)	11.4	SWIR 1 (B11)	24.2
	Red	9.4	Red	7.3	Red	4.4
	NDVI	25.5	NDVI	28.6	NDVI	19.9
	Homogeneity	2.6	Homogeneity	3.3	Homogeneity	1.1
	MSAVI	13.3	MSAVI	16.2	MSAVI	11.6
	NIR8	15.2	NIR8	10.1	NIR8	3.1
Barleria spinisepala						
	NDVI	14.7	NDVI	21.1	NDVI	25.5
	VRE 2	21.6	VRE 2	28.4	VRE 2	14.1
	NIR8	29.4	NIR8	23.5	NIR8	34.6
	Red	8.1	Red	12.3	Red	5.3
	NDWI	21.6	NDWI	12.9	NDWI	11.3
	Blue	4.6	Blue	1.8	Blue	9.2
Boscia angustifolia						
	NIR8	26.2	NIR8	25.8	NIR8	37.1
	VRE 1	7.3	VRE 1	17.4	VRE 1	10.3

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	Red	12.4	Red	2.7	Red	7.1
	MSAVI	1.3	MSAVI	14.9	MSAVI	21.6
	SWIR 1 (B11)	23.7	SWIR 1 (B11)	31.6	SWIR 1 (B11)	12.8
	CLRE	14.6	CLRE	3.3	CLRE	7.8
	Homogeneity	14.5	Homogeneity	4.3	Homogeneity	3.3
Boscia coriacea						
	VRE 3	23.1	VRE 3	23.1	VRE 3	34.2
	NIR 8	26.2	NIR 8	38.3	NIR 8	22.1
	Red	7.7	Red	6.7	Red	14.9
	NDWI	16.9	NDWI	9.6	NDWI	17.4
	Green	1.3	Green	14.9	Green	4.1
	MSAVI	24.8	MSAVI	7.4	MSAVI	7.3
Cadaba farinosa						
	NIR8	4.2	NIR8	9.3	NIR8	39.2
	VRE 2	27.5	VRE 2	24.3	VRE 2	8.5
	VRE 3	19.3	VRE 3	26.1	VRE 3	17.2
	Red	18.6	Red	10.6	Red	2.7
	NDVI	7.5	NDVI	15.4	NDVI	6.3
	SWIR 1 (B11)	9.9	SWIR 1 (B11)	11.5	SWIR 1 (B11)	14.9
	Mean	13	Mean	2.8	Mean	11.2
Carissa edulis						
	VRE 3	6.4	VRE 3	1.5	VRE 3	5.2
	SWIR 1 (B11)	36.9	SWIR 1 (B11)	39.1	SWIR 1 (B11)	23.9
	Red	24.2	Red	17.7	Red	27.3
	NDVI	6.4	NDVI	12.8	NDVI	17.2
	Blue	7.5	Blue	11.1	Blue	6.2
	NIR 8	12.7	NIR 8	14.2	NIR 8	12.1
	CLRE	5.9	CLRE	3.6	CLRE	8.1

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

Cissus rutundifolia						
	NDVI	33.5	NDVI	23.9	NDVI	32.4
	Red	6.1	Red	2.7	Red	7.7
	NDWI	21.6	NDWI	27.4	NDWI	25.1
	MSAVI	13.7	MSAVI	19.6	MSAVI	2.3
	NIR8	18.2	NIR8	5.3	NIR8	18.3
	VRE2	4.7	VRE2	14.8	VRE2	10.2
	Blue	2.2	Blue	6.3	Blue	4
Cissus quadrangularis						
	CLRE	27.4	CLRE	34.3	CLRE	41.2
	Red	19.9	Red	18.5	Red	16.3
	NDVI	8.3	NDVI	19.7	NDVI	23.8
	Mean	18.7	Mean	17.5	Mean	10.9
	SWIR (B12)	16.1	SWIR (B12)	7.7	SWIR (B12)	1.4
	Green	9.6	Green	2.3	Green	6.4
Commiphora africana						
	SWIR 1 (B11)	31.6	SWIR 1 (B11)	21.7	SWIR 1 (B11)	22.8
	NIR8	18.1	NIR8	33.6	NIR8	35.6
	VRE 3	22.4	VRE 3	7.7	VRE 3	12.4
	EVI	16.8	EVI	17.5	EVI	8.2
	Red	7.5	Red	12.1	Red	6.2
	MSAVI	2.2	MSAVI	3.6	MSAVI	7.3
	NDWI	1.4	NDWI	3.8	NDWI	7.5
Cordia monoica						
	Mean	23.9	Mean	29.8	Mean	33.4
	MSAVI	28.1	MSAVI	25.7	MSAVI	7.7
	Red	8.8	Red	6.3	Red	14.5
	VRE 2	16.7	VRE 2	12.7	VRE 2	13.9
	NIR8	10.6	NIR8	8.3	NIR8	18.6
	SWIR (B12)	10.6	SWIR (B12)	16.4	SWIR (B12)	11.3
	Homogeneity	1.3	Homogeneity	0.8	Homogeneity	0.6

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

Croton dichogamus						
	MSAVI	12.6	MSAVI	10.4	MSAVI	8.7
	NIR8	33.8	NIR8	23.7	NIR8	37.2
	Red	14.2	Red	7.2	Red	12.7
	NDVI	21.3	NDVI	45.6	NDVI	21.5
	SWIR 2 (B12)	17.9	SWIR 2 (B12)	6.8	SWIR 2 (B12)	6.4
	NDWI	0.2	NDWI	6.3	NDWI	13.5
Croton megalocarpus						
	Mean	7.8	Mean	6.3	Mean	1.5
	NDVI	28.4	NDVI	36.2	NDVI	34.9
	Blue	2.9	Blue	2.8	Blue	4.7
	SWIR 2 (B12)	23.6	SWIR 2 (B12)	15.1	SWIR 2 (B12)	11.6
	MSAVI	5.3	MSAVI	11.7	MSAVI	22.1
	Red	17.7	Red	17.6	Red	21.3
	NDWI	14.3	NDWI	10.3	NDWI	3.9
Cyphostema adenocaule						
	Red	16.5	Red	19.2	Red	23.9
	NIR8	29.4	NIR8	33.7	NIR8	27.5
	VRE 3	8.4	VRE 3	8.8	VRE 3	6.2
	SWIR 1 (B11)	24.7	SWIR 1 (B11)	16.9	SWIR 1 (B11)	21.1
	NDVI	6.2	NDVI	0.4	NDVI	4.4
	CLRE	12.5	CLRE	11.6	CLRE	14.6
	RVI	2.3	RVI	9.4	RVI	2.3
Cyphostema serpens						
	NDWI	12.8	NDWI	4.1	NDWI	1.2
	Red	8.4	Red	3.7	Red	18.2
	VRE 1	17.9	VRE 1	16.2	VRE 1	6.4
	NDVI	22.3	NDVI	27.3	NDVI	17.7

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	SWIR 2 (B12)	10.2	SWIR 2 (B12)	24.7	SWIR 2 (B12)	21.6
	NIR 8	26.1	NIR 8	14.6	NIR 8	32.8
	Homogeneity	2.3	Homogeneity	9.4	Homogeneity	2.1
Ekebergia angustifolia						
	RVI	29.5	RVI	21.9	RVI	27.5
	MSAVI	17.7	MSAVI	11.3	MSAVI	4.2
	CLRE	12.7	CLRE	23.4	CLRE	18.5
	Red	9.6	Red	13.8	Red	14.4
	VRE 2	22.3	VRE 2	24.7	VRE 2	21.9
	SWIR 1 (B11)	5.8	SWIR 1 (B11)	1.8	SWIR 1 (B11)	9.4
	Mean	2.4	Mean	3.1	Mean	4.1
Euclea divinorum						
	VRE 3	12.5	VRE 3	26.1	VRE 3	23.1
	Blue	7.1	Blue	13.9	Blue	4.2
	NIR8	37.2	NIR8	24.7	NIR8	36.9
	Red	5	Red	6.1	Red	7.2
	SWIR 2 (B12)	13.8	SWIR 2 (B12)	17.3	SWIR 2 (B12)	15.4
	VRE 1	13.9	VRE 1	5.7	VRE 1	1.4
	MSAVI	10.5	MSAVI	6.2	MSAVI	11.8
Euphorbia candelabrum						
	NIR 8	7.5	NIR 8	12.1	NIR 8	13.7
	VRE 2	10.1	VRE 2	5.7	VRE 2	6.1
	MSAVI	3.5	MSAVI	12.3	MSAVI	18.8
	SWIR 1 (B11)	23.7	SWIR 1 (B11)	33.6	SWIR 1 (B11)	23.9
	CLRE	9.3	CLRE	8.5	CLRE	3.8
	NDVI	42.1	NDVI	19.3	NDVI	26.5
	Mean	3.8	Mean	8.5	Mean	7.2

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

Euphorbia heterochroma						
	SWIR (B11)	13.6	SWIR (B11)	14.1	SWIR (B11)	26.4
	NDWI	26.2	NDWI	20.2	NDWI	18.4
	MSAVI	38.3	MSAVI	27.4	MSAVI	32.2
	Green	2.5	Green	6.5	Green	7.4
	Red	10.8	Red	14.5	Red	13.8
	Homogeneity	8.6	Homogeneity	17.3	Homogeneity	1.8
Flueggea virosa						
	VRE 2	35.7	VRE 2	25.8	VRE 2	27.2
	Red	13.9	Red	9.5	Red	12.3
	NIR8	22.8	NIR8	27.3	NIR8	19.4
	Blue	3.2	Blue	3.6	Blue	2.9
	VRE 1	10.2	VRE 1	14.9	VRE 1	13.8
	MSAVI	6.7	MSAVI	5.3	MSAVI	6.3
	SWIR (B11)	4.1	SWIR (B11)	7.1	SWIR (B11)	7.9
	RVI	3.4	RVI	6.5	RVI	10.2
Fuerstia africana						
	Homogeneity	13.7	Homogeneity	11.7	Homogeneity	17.4
	MSAVI	21.3	MSAVI	27.5	MSAVI	21.6
	Red	9.1	Red	5.1	Red	6.9
	NDVI	12.4	NDVI	13.5	NDVI	10.6
	SWIR 1 (B11)	8.7	SWIR 1 (B11)	23.9	SWIR 1 (B11)	15.2
	VRE2	34.8	VRE2	18.3	VRE2	28.3
Grewia tembensis						
	MSAVI	14.1	MSAVI	22.7	MSAVI	35.9
	VRE 2	39.2	VRE 2	29.5	VRE 2	17.4
	NDWI	4.7	NDWI	2.4	NDWI	7.8
	SWIR 2 (B12)	18.9	SWIR 2 (B12)	17.3	SWIR 2 (B12)	23.3
	Green	5.9	Green	14.4	Green	9.3

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	VRE 2	17.2	VRE 2	13.7	VRE 2	6.3
Gutenbergia cordifolia						
	NDVI	37.2	NDVI	27.5	NDVI	27.9
	MSAVI	23.1	MSAVI	19.6	MSAVI	23.1
	Green	10.8	Green	23.8	Green	2.9
	CLRE	3.2	CLRE	5.4	CLRE	10.5
	SWIR 2 (B12)	5.9	SWIR 2 (B12)	7	SWIR 2 (B12)	15.6
	VRE 2	8.4	VRE 2	9.4	VRE 2	7.2
	VRE 1	11.4	VRE 1	7.3	VRE 1	12.8
Ipomoea spathulata						
	Green	8.5	Green	10.2	Green	10.6
	SWIR 2 (B12)	33.6	SWIR 2 (B12)	28.4	SWIR 2 (B12)	14.5
	NIR8	23.8	NIR8	25.1	NIR8	15.3
	SWIR 1 (B11)	8.1	SWIR 1 (B11)	2.7	SWIR 1 (B11)	30.2
	VRE 1	15.9	VRE 1	14.6	VRE 1	21.2
	Mean	4.9	Mean	5.1	Mean	3.8
	NDVI	5.2	NDVI	13.9	NDVI	4.4
Juniperus procera						
	NIR8	29.7	NIR8	32.4	NIR8	16.6
	SWIR 2 (B12)	17.4	SWIR 2 (B12)	14.3	SWIR 2 (B12)	14.3
	RVI	2.1	RVI	6.1	RVI	12.8
	NDWI	10.8	NDWI	5	NDWI	9.2
	VRE 1	22.5	VRE 1	23.8	VRE 1	29.7
	Homogeneity	2.2	Homogeneity	9.9	Homogeneity	4.9
	Blue	15.3	Blue	8.5	Blue	12.5
Kedrostis pseudogijef						
	NIR8	37.3	NIR8	24.2	NIR8	26.5
	VRE2	22.4	VRE2	26.9	VRE2	24.8

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	Green	15.9	Green	19.9	Green	25.1
	VRE 3	20.1	VRE 3	14.5	VRE 3	5.4
	NDVI	2.8	NDVI	6.2	NDVI	10.2
	RVI	1.5	RVI	8.3	RVI	8
Lippia javanica						
	MSAVI	9.6	MSAVI	15.5	MSAVI	23.1
	SWIR 1 (B11)	20.7	SWIR 1 (B11)	24.2	SWIR 1 (B11)	20.7
	CLRE	6.1	CLRE	4.2	CLRE	0.9
	NIR8	25.3	NIR8	11.3	NIR8	13.9
	SWIR 2 (B12)	17.6	SWIR 2 (B12)	20.1	SWIR 2 (B12)	27.4
	Blue	4.4	Blue	8.9	Blue	3.2
	VRE 1	11.3	VRE 1	7.4	VRE 1	1.3
	NDWI	5	NDWI	8.4	NDWI	9.5
Lippia kituiensis						
	NDVI	28.4	NDVI	16.6	NDVI	38.5
	MSAVI	14.3	MSAVI	23.1	MSAVI	18.3
	NIR8	6.1	NIR8	32.7	NIR8	6.4
	VRE 2	19.6	VRE 2	2.1	VRE 2	24.9
	SWIR 2 (B12)	17	SWIR 2 (B12)	12.3	SWIR 2 (B12)	7.2
	Homogeneity	14.6	Homogeneity	13.2	Homogeneity	4.7
Lycium europaeum						
	CLRE	10.5	CLRE	17.5	CLRE	14.7
	SWIR 1 (B11)	37.2	SWIR 1 (B11)	26.8	SWIR 1 (B11)	27.3
	Mean	3.6	Mean	7.7	Mean	8.9
	RVI	24.2	RVI	25.2	RVI	22.5
	NDWI	13.5	NDWI	20.6	NDWI	16.2
	NDVI	11	NDVI	2.2	NDVI	10.4
Myrsine africana						

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	Red	11.9	Red	14.7	Red	7.3
	NIR8	5	NIR8	23.6	NIR8	9.1
	VRE 2	11.4	VRE 2	20.2	VRE 2	22.7
	NDVI	36.7	NDVI	2.3	NDVI	43.8
	SWIR (B12)	32.3	SWIR (B12)	31.3	SWIR (B12)	10.5
	Mean	2.7	Mean	7.9	Mean	6.6
Olea africana						
	Red	11.6	Red	17.3	Red	12.9
	SWIR 2 (B12)	27.5	SWIR 2 (B12)	23.1	SWIR 2 (B12)	35.2
	NIR8	24.9	NIR8	26.4	NIR8	13.6
	NDWI	6.4	NDWI	10.2	NDWI	11.8
	RVI	7.6	RVI	7.3	RVI	8.5
	VRE 2	14.8	VRE 2	15.3	VRE 2	14.8
	MSAVI	7.2	MSAVI	0.4	MSAVI	3.2
Psiadia punctulata						
	NIR8	36.2	NIR8	29.5	NIR8	27.3
	Blue	0.5	Blue	9.3	Blue	12.9
	VRE 3	23.7	VRE 3	26.1	VRE 3	23.6
	NDVI	19.8	NDVI	13.8	NDVI	20.2
	MSAVI	5.3	MSAVI	9.9	MSAVI	4.4
	SWIR 1 (B11)	14.5	SWIR 1 (B11)	11.4	SWIR 1 (B11)	11.6
Podocarpus falcatus						
	CLRE	6.1	CLRE	13.9	CLRE	12.5
	MSAVI	13.2	MSAVI	21.4	MSAVI	19.9
	NDVI	28.4	NDVI	25.8	NDVI	24.7
	SWIR 2 (B12)	22.7	SWIR 2 (B12)	19.6	SWIR 2 (B12)	1.6
	VRE 2	3.4	VRE 2	0.5	VRE 2	23.9
	NIR 8	7.7	NIR 8	3.1	NIR 8	3.8
	Homogeneity	4.9	Homogeneity	8.2	Homogeneity	6.5

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	VRE 1	13.6	VRE 1	7.5	VRE 1	7.1
Rhamnus stado						
	Entropy	2.2	Entropy	7.9	Entropy	10.2
	NIR8	34.6	NIR8	12.7	NIR8	24.2
	MSAVI	23.1	MSAVI	29.2	MSAVI	23.1
	SWIR 2 (B12)	8	SWIR 2 (B12)	12.7	SWIR 2 (B12)	19.7
	VRE 1	21.8	VRE 1	11.1	VRE 1	5.5
	NDVI	10.3	NDVI	26.4	NDVI	17.3
Rhus natalensis						
	SWIR 2 (B12)	11.8	SWIR 2 (B12)	17.4	SWIR 2 (B12)	19.6
	NIR8	33.8	NIR8	12.7	NIR8	17.2
	VRE 1	8.2	VRE 1	27.6	VRE 1	25.5
	NDVI	22.4	NDVI	24.9	NDVI	7.4
	NDWI	18.6	NDWI	16.3	NDWI	23.8
	Blue	5.2	Blue	1.1	Blue	6.5
Salvadora persica						
	RVI	4.9	RVI	17.3	RVI	18.9
	Homogeneity	6.3	Homogeneity	3.5	Homogeneity	13.7
	NIR8	16.4	NIR8	27.2	NIR8	29.6
	Blue	11.7	Blue	21.8	Blue	6
	SWIR 1 (B11)	42.1	SWIR 1 (B11)	24.9	SWIR 1 (B11)	24.1
	CLRE	18.6	CLRE	5.3	CLRE	7.7
Scutia myrtina						
	Homogeneity	6.6	Homogeneity	11.6	Homogeneity	16.2
	MSAVI	8	MSAVI	4	MSAVI	9.7
	Red	20	Red	23.1	Red	12.9
	NDVI	27.4	NDVI	23.8	NDVI	25.8
	VRE 2	21.2	VRE 2	25.5	VRE 2	22.5

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	SWIR 2 (B12)	14.2	SWIR 2 (B12)	9.2	SWIR 2 (B12)	5.5
	Blue	2.6	Blue	2.8	Blue	7.4
Senna didymobotrya						
	Red	19.3	Red	19.6	Red	21.1
	VRE 2	17.5	VRE 2	23.8	VRE 2	25.4
	NDVI	23.1	NDVI	26.4	NDVI	11.3
	NDWI	5.7	NDWI	3.7	NDWI	6.1
	SWIR 2 (B12)	8.8	SWIR 2 (B12)	10.1	SWIR 2 (B12)	10.9
	VRE 3	12.5	VRE 3	8.9	VRE 3	16.2
	Green	13.1	Green	7.5	Green	8.2
Solanum incanum						
	Mean	24.8	Mean	42.1	Mean	43.5
	Blue	18.3	Blue	15.3	Blue	15.6
	CLRE	4.6	CLRE	0.9	CLRE	3.7
	NIR8	24.2	NIR8	9.6	NIR8	14.8
	Red	1.6	Red	14.4	Red	1.1
	VRE 1	26.5	VRE 1	17.7	VRE 1	21.3
Teclea simplicifolia						
	SWIR 2 (B12)	34.7	SWIR 2 (B12)	13.3	SWIR 2 (B12)	26.9
	Blue	4.6	Blue	6.2	Blue	8.8
	VRE 2	5.1	VRE 2	9.1	VRE 2	6.1
	NDWI	23.1	NDWI	26.4	NDWI	1.6
	NDVI	18.9	NDVI	30.2	NDVI	23.7
	Red	6.4	Red	8.5	Red	21.4
	CLRE	7.2	CLRE	6.3	CLRE	11.5
Teclea aethiopica						
	NIR8	22.5	NIR8	27.3	NIR8	29.1
	NDVI	16.6	NDVI	25.1	NDVI	26.8

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Table 4.10: Variable importance of Sentinel-2 variables used in modelling all medicinal plant species. (Continued)

	SWIR 1 (B11)	10.4	SWIR 1 (B11)	6.8	SWIR 1 (B11)	5.4
	VRE 2	33.7	VRE 2	10.6	VRE 2	17.5
	Blue	3.9	Blue	6.9	Blue	2.1
	CLRE	1.6	CLRE	15.9	CLRE	12.2
	RVI	11.3	RVI	8.4	RVI	6.9
Zanthoxylum usambarense						
	MSAVI	4.8	MSAVI	10.3	MSAVI	8.2
	SWIR 2 (B12)	19.2	SWIR 2 (B12)	18.1	SWIR 2 (B12)	26.4
	VRE 1	22.6	VRE 1	25.9	VRE 1	6.7
	NIR 8	35.3	NIR 8	5.2	NIR 8	17.7
	Green	6.7	Green	12.8	Green	9.9
	NDVI	11.4	NDVI	27.7	NDVI	34.1
Viscum tuberculatum						
	Blue	8.2	Blue	11.6	Blue	7.2
	SWIR 1 (B11)	29.3	SWIR 1 (B11)	23.5	SWIR 1 (B11)	28.8
	VRE 3	22.7	VRE 3	24.7	VRE 3	21.1
	RVI	15.5	RVI	8.4	RVI	13.6
	NIR 8	11.4	NIR 8	21.1	NIR 8	25.3
	VRE 1	12.9	VRE 1	10.7	VRE 1	4

Table 4.11: Variable importance of Sentinel-2 variables used in modelling species used against stomach ache.

Species	OCSVM		BSVM		MaxEnt	
	Variable	**Score**	**Variable**	**Score**	**Variable**	**Score**
Acacia etbaica						
	MSAVI	24.6	MSAVI	28.5	MSAVI	29.6
	NDVI	21.3	NDVI	21.3	NDVI	9.7
	SWIR 2 (B12)	32.8	SWIR 2 (B12)	11.7	SWIR 2 (B12)	23.5
	VRE 1	4.8	VRE 1	16.3	VRE 1	13.3

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Table 4.11: Variable importance of Sentinel-2 variables used in modelling species used against stomach ache. (Continued)

	Red	9	Red	13.2	Red	10.7
	CLRE	2.1	CLRE	4.6	CLRE	8.4
	SWIR 1 (B11)	5.4	SWIR 1 (B11)	4.4	SWIR 1 (B11)	4.8
Acacia nilotica						
	NIR8	17.3	NIR8	6.8	NIR8	21.7
	NDVI	26.7	NDVI	19.9	NDVI	28.4
	SWIR 1 (B11)	4.5	SWIR 1 (B11)	7.4	SWIR 1 (B11)	16.6
	MSAVI	23.7	MSAVI	15.7	MSAVI	10.2
	Blue	7.4	Blue	1.5	Blue	5.3
	Red	5.8	Red	16.2	Red	4.8
	VRE 1	14.6	VRE 1	32.5	VRE 1	13
Acacia senegal						
	VRE 2	8.6	VRE 2	11.4	VRE 2	8.5
	Blue	2.5	Blue	8.4	Blue	5.1
	NDVI	23.4	NDVI	13.8	NDVI	15.4
	SWIR 1 (B11)	41.2	SWIR 1 (B11)	28.7	SWIR 1 (B11)	38.3
	NIR8	9.3	NIR8	9.6	NIR8	3.7
	VRE 1	7.7	VRE 1	26.1	VRE 1	22.7
	NDWI	7.3	NDWI	2	NDWI	6.3
Acacia tortilis						
	SWIR 1 (B11)	16.4	SWIR 1 (B11)	16.9	SWIR 1 (B11)	21.6
	VRE 2	3.5	VRE 2	4.8	VRE 2	5.4
	NDVI	39.2	NDVI	26.3	NDVI	34.7
	MSAVI	8.8	MSAVI	19.3	MSAVI	19.9
	NIR8	24.7	NIR8	28.4	NIR8	18.1
	Homogeneity	7.4	Homogeneity	4.3	Homogeneity	0.3
Acokanthera oppositifolia						

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Table 4.11: Variable importance of Sentinel-2 variables used in modelling species used against stomach ache. (Continued)

	SWIR 1 (B11)	17.6	SWIR 1 (B11)	22.7	SWIR 1 (B11)	27.8
	NIR8	21.3	NIR8	35.6	NIR8	12.4
	VRE 1	30.2	VRE 1	7.7	VRE 1	30.6
	EVI	15.4	EVI	14.5	EVI	5.2
	Red	6.5	Red	10.1	Red	6.8
	MSAVI	3.2	MSAVI	2.6	MSAVI	8.9
	NDWI	5.8	NDWI	6.8	NDWI	8.3
Commiphora africana						
	SWIR 1 (B11)	31.6	SWIR 1 (B11)	21.7	SWIR 1 (B11)	22.8
	NIR8	18.1	NIR8	33.6	NIR8	35.6
	VRE 3	22.4	VRE 3	7.7	VRE 3	12.4
	EVI	16.8	EVI	17.5	EVI	8.2
	Red	7.5	Red	12.1	Red	6.2
	MSAVI	2.2	MSAVI	3.6	MSAVI	7.3
	NDWI	1.4	NDWI	3.8	NDWI	7.5
Croton dichogamus						
	MSAVI	12.6	MSAVI	10.4	MSAVI	8.7
	NIR8	33.8	NIR8	23.7	NIR8	37.2
	Red	14.2	Red	7.2	Red	12.7
	NDVI	21.3	NDVI	45.6	NDVI	21.5
	SWIR 2 (B12)	17.9	SWIR 2 (B12)	6.8	SWIR 2 (B12)	6.4
	NDWI	0.2	NDWI	6.3	NDWI	13.5
Croton megalocarpus						
	Mean	7.8	Mean	6.3	Mean	1.5
	NDVI	28.4	NDVI	36.2	NDVI	34.9
	Blue	2.9	Blue	2.8	Blue	4.7
	SWIR 2 (B12)	23.6	SWIR 2 (B12)	15.1	SWIR 2 (B12)	11.6
	MSAVI	5.3	MSAVI	11.7	MSAVI	22.1
	Red	17.7	Red	17.6	Red	21.3

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Table 4.11: Variable importance of Sentinel-2 variables used in modelling species used against stomach ache. (Continued)

	NDWI	14.3	NDWI	10.3	NDWI	3.9
Juniperus procera						
	NIR8	29.7	NIR8	32.4	NIR8	16.6
	SWIR 2 (B12)	17.4	SWIR 2 (B12)	14.3	SWIR 2 (B12)	14.3
	RVI	2.1	RVI	6.1	RVI	12.8
	NDWI	10.8	NDWI	5	NDWI	9.2
	VRE 1	22.5	VRE 1	23.8	VRE 1	29.7
	Homogeneity	2.2	Homogeneity	9.9	Homogeneity	4.9
	Blue	15.3	Blue	8.5	Blue	12.5
Rhus natalensis						
	SWIR 2 (B12)	11.8	SWIR 2 (B12)	17.4	SWIR 2 (B12)	19.6
	NIR8	33.8	NIR8	12.7	NIR8	17.2
	VRE 1	8.2	VRE 1	27.6	VRE 1	25.5
	NDVI	22.4	NDVI	24.9	NDVI	7.4
	NDWI	18.6	NDWI	16.3	NDWI	23.8
	Blue	5.2	Blue	1.1	Blue	6.5
Salvadora persica						
	RVI	4.9	RVI	17.3	RVI	18.9
	Homogeneity	6.3	Homogeneity	3.5	Homogeneity	13.7
	NIR8	16.4	NIR8	27.2	NIR8	29.6
	Blue	11.7	Blue	21.8	Blue	6
	SWIR 1 (B11)	42.1	SWIR 1 (B11)	24.9	SWIR 1 (B11)	24.1
	CLRE	18.6	CLRE	5.3	CLRE	7.7
Ximenia caffra						
	NDVI	26.2	NDVI	34.4	NDVI	34.7
	Red	16.5	Red	17.9	Red	17.9
	NIR8	24.7	NIR8	22.1	NIR8	25.2
	VRE 2	18.9	VRE 2	17.3	VRE 2	11.2
	CLRE	8.3	CLRE	1.9	CLRE	6.5

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Table 4.11: Variable importance of Sentinel-2 variables used in modelling species used against stomach ache. (Continued)

	Blue	5.4	Blue	6.4	Blue	4.5

Table 4.12: Variable importance of Sentinel-2 variables used in modelling species used against diarrhoea.

Species	**OCSVM**		**BSVM**		**Maxent**	
	Variable	**Score**	**Variable**	**Score**	**Variable**	**Score**
Acacia etbaica						
	MSAVI	24.6	MSAVI	28.5	MSAVI	29.6
	NDVI	21.3	NDVI	21.3	NDVI	9.7
	SWIR 2 (B12)	32.8	SWIR 2 (B12)	11.7	SWIR 2 (B12)	23.5
	VRE 1	4.8	VRE 1	16.3	VRE 1	13.3
	Red	9	Red	13.2	Red	10.7
	CLRE	2.1	CLRE	4.6	CLRE	8.4
	SWIR 1 (B11)	5.4	SWIR 1 (B11)	4.4	SWIR 1 (B11)	4.8
Acacia senegal						
	VRE 2	8.6	VRE 2	11.4	VRE 2	8.5
	Blue	2.5	Blue	8.4	Blue	5.1
	NDVI	23.4	NDVI	13.8	NDVI	15.4
	SWIR 1 (B11)	41.2	SWIR 1 (B11)	28.7	SWIR 1 (B11)	38.3
	NIR8	9.3	NIR8	9.6	NIR8	3.7
	VRE 1	7.7	VRE 1	26.1	VRE 1	22.7
	NDWI	7.3	NDWI	2	NDWI	6.3
Carissa edulis						
	VRE 3	6.4	VRE 3	1.5	VRE 3	5.2
	SWIR 1 (B11)	36.9	SWIR 1 (B11)	39.1	SWIR 1 (B11)	23.9
	Red	24.2	Red	17.7	Red	27.3
	NDVI	6.4	NDVI	12.8	NDVI	17.2
	Blue	7.5	Blue	11.1	Blue	6.2
	NIR 8	12.7	NIR 8	14.2	NIR 8	12.1
	CLRE	5.9	CLRE	3.6	CLRE	8.1
Commiphora africana						
	SWIR 1 (B11)	31.6	SWIR 1 (B11)	21.7	SWIR 1 (B11)	22.8

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Table 4.12: Variable importance of Sentinel-2 variables used in modelling species used against diarrhoea. (Continued)

	NIR8	18.1	NIR8	33.6	NIR8	35.6
	VRE 3	22.4	VRE 3	7.7	VRE 3	12.4
	EVI	16.8	EVI	17.5	EVI	8.2
	Red	7.5	Red	12.1	Red	6.2
	MSAVI	2.2	MSAVI	3.6	MSAVI	7.3
	NDWI	1.4	NDWI	3.8	NDWI	7.5
Cordia monoica						
	Mean	23.9	Mean	29.8	Mean	33.4
	MSAVI	28.1	MSAVI	25.7	MSAVI	7.7
	Red	8.8	Red	6.3	Red	14.5
	VRE 2	16.7	VRE 2	12.7	VRE 2	13.9
	NIR8	10.6	NIR8	8.3	NIR8	18.6
	SWIR (B12)	10.6	SWIR (B12)	16.4	SWIR (B12)	11.3
	Homogeneity	1.3	Homogeneity	0.8	Homogeneity	0.6
Ipomoea spathulata						
	Green	8.5	Green	10.2	Green	10.6
	SWIR 2 (B12)	33.6	SWIR 2 (B12)	28.4	SWIR 2 (B12)	14.5
	NIR8	23.8	NIR8	25.1	NIR8	15.3
	SWIR 1 (B11)	8.1	SWIR 1 (B11)	2.7	SWIR 1 (B11)	30.2
	VRE 1	15.9	VRE 1	14.6	VRE 1	21.2
	Mean	4.9	Mean	5.1	Mean	3.8
	NDVI	5.2	NDVI	13.9	NDVI	4.4
Olea africana						
	Red	11.6	Red	17.3	Red	12.9
	SWIR 2 (B12)	27.5	SWIR 2 (B12)	23.1	SWIR 2 (B12)	35.2
	NIR8	24.9	NIR8	26.4	NIR8	13.6
	NDWI	6.4	NDWI	10.2	NDWI	11.8
	RVI	7.6	RVI	7.3	RVI	8.5
	VRE 2	14.8	VRE 2	15.3	VRE 2	14.8
	MSAVI	7.2	MSAVI	0.4	MSAVI	3.2
Rhus natalensis						

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Table 4.12: Variable importance of Sentinel-2 variables used in modelling species used against diarrhoea. (Continued)

	SWIR 2 (B12)	11.8	SWIR 2 (B12)	17.4	SWIR 2 (B12)	25.5
	NIR8	18.6	NIR8	16.3	NIR8	17.2
	VRE 2	8.2	VRE 2	12.7	VRE 2	19.6
	NDVI	22.4	NDVI	24.9	NDVI	7.4
	VRE 1	33.8	VRE 1	27.6	VRE 1	23.8
	Blue	5.2	Blue	1.1	Blue	6.5
Solanum incanum						
	Mean	24.8	Mean	42.1	Mean	43.5
	Blue	18.3	Blue	15.3	Blue	15.6
	CLRE	4.6	CLRE	0.9	CLRE	3.7
	NIR8	24.2	NIR8	9.6	NIR8	14.8
	Red	1.6	Red	14.4	Red	1.1
	VRE 1	26.5	VRE 1	17.7	VRE 1	21.3
Salvadora persica						
	RVI	4.9	RVI	17.3	RVI	18.9
	Homogeneity	6.3	Homogeneity	3.5	Homogeneity	13.7
	NIR8	16.4	NIR8	27.2	NIR8	29.6
	Blue	11.7	Blue	21.8	Blue	6
	SWIR 1 (B11)	42.1	SWIR 1 (B11)	24.9	SWIR 1 (B11)	24.1
	CLRE	18.6	CLRE	5.3	CLRE	7.7
Teclea simplicifolia						
	SWIR 2 (B12)	34.7	SWIR 2 (B12)	13.3	SWIR 2 (B12)	26.9
	Blue	4.6	Blue	6.2	Blue	8.8
	VRE 2	5.1	VRE 2	9.1	VRE 2	6.1
	NDWI	23.1	NDWI	30.2	NDWI	1.6
	NDVI	18.9	NDVI	26.4	NDVI	23.7
	Red	6.4	Red	8.5	Red	21.4
	CLRE	7.2	CLRE	6.3	CLRE	11.5
Viscum tuberculatum						
	Blue	8.2	Blue	11.6	Blue	7.2
	SWIR 1 (B11)	29.3	SWIR 1 (B11)	23.5	SWIR 1 (B11)	28.8

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Table 4.12: Variable importance of Sentinel-2 variables used in modelling species used against diarrhoea. (Continued)

	SWIR 2 (B12)	22.7	SWIR 2 (B12)	24.7	SWIR 2 (B12)	21.1
	RVI	15.5	RVI	8.4	RVI	13.6
	NIR 8	11.4	NIR 8	21.1	NIR 8	25.3
	VRE 1	12.9	VRE 1	10.7	VRE 1	4

Table 4.13: Variable importance of Sentinel-2 variables used in modelling species used against wounds.

	OCSVM		BSVM		MaxEnt	
Species	**Variable**	**Score (%)**	**Variable**	**Score (%)**	**Variable**	**Score (%)**
Aloe secundiflora						
	SWIR (B12)	2.5	SWIR (B12)	2.2	SWIR (B12)	5.8
	Mean	27.2	Mean	25.6	Mean	9.3
	NDVI	8.8	NDVI	12.2	NDVI	3.9
	Red	19.6	Red	9.5	Red	2.4
	CLRE	12.8	CLRE	16.8	CLRE	25.7
	MSAVI	21.9	MSAVI	20.1	MSAVI	37.6
	NDWI	7.2	NDWI	13.6	NDWI	15.3
Balanites aegyptiaca						
	MSAVI	23.4	MSAVI	35.1	MSAVI	25.7
	CLRE	4.9	CLRE	10.2	CLRE	10.3
	Red	12.9	Red	8.9	Red	3.8
	Mean	39.7	Mean	22.2	Mean	32.1
	VRE 2	10.2	VRE 2	8.6	VRE 2	16.2
	EVI	7.9	EVI	11.8	EVI	9.4
	Blue	1	Blue	3.2	Blue	2.5
Commiphora africana						
	SWIR 1 (B11)	31.6	SWIR 1 (B11)	21.7	SWIR 1 (B11)	22.8
	NIR8	18.1	NIR8	33.6	NIR8	35.6
	VRE 3	22.4	VRE 3	7.7	VRE 3	12.4
	EVI	16.8	EVI	17.5	EVI	8.2

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Table 4.13: Variable importance of Sentinel-2 variables used in modelling species used against wounds. (Continued)

	Red	7.5	Red	12.1	Red	6.2
	MSAVI	2.2	MSAVI	3.6	MSAVI	7.3
	NDWI	1.4	NDWI	3.8	NDWI	7.5
Cissus quadrangularis						
	CLRE	27.4	CLRE	34.3	CLRE	41.2
	Red	19.9	Red	18.5	Red	16.3
	NDVI	8.3	NDVI	19.7	NDVI	23.8
	Mean	18.7	Mean	17.5	Mean	10.9
	SWIR (B12)	16.1	SWIR (B12)	7.7	SWIR (B12)	1.4
	Green	9.6	Green	2.3	Green	6.4
Cordia monoica						
	Mean	23.9	Mean	29.8	Mean	33.4
	MSAVI	28.1	MSAVI	25.7	MSAVI	7.7
	Red	8.8	Red	6.3	Red	14.5
	VRE 2	16.7	VRE 2	12.7	VRE 2	13.9
	NIR8	10.6	NIR8	8.3	NIR8	18.6
	SWIR (B12)	10.6	SWIR (B12)	16.4	SWIR (B12)	11.3
	Homogeneity	1.3	Homogeneity	0.8	Homogeneity	0.6
Myrsine africana						
	Red	11.9	Red	14.7	Red	7.3
	NIR8	5	NIR8	23.6	NIR8	9.1
	VRE 2	11.4	VRE 2	20.2	VRE 2	22.7
	NDVI	36.7	NDVI	2.3	NDVI	43.8
	SWIR (B12)	32.3	SWIR (B12)	31.3	SWIR (B12)	10.5
	Mean	2.7	Mean	7.9	Mean	6.6
Euphorbia heterochroma						

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Table 4.13: Variable importance of Sentinel-2 variables used in modelling species used against wounds. (Continued)

	SWIR (B11)	13.6	SWIR (B11)	14.1	SWIR (B11)	26.4
	NDWI	26.2	NDWI	20.2	NDWI	18.4
	MSAVI	38.3	MSAVI	27.4	MSAVI	32.2
	Green	2.5	Green	6.5	Green	7.4
	Red	10.8	Red	14.5	Red	13.8
	Homogeneity	8.6	Homogeneity	17.3	Homogeneity	1.8
Solanum incanum						
	Mean	24.8	Mean	42.1	Mean	43.5
	Blue	18.3	Blue	15.3	Blue	15.6
	CLRE	4.6	CLRE	0.9	CLRE	3.7
	NIR8	24.2	NIR8	9.6	NIR8	14.8
	Red	1.6	Red	14.4	Red	1.1
	VRE 1	26.5	VRE 1	17.7	VRE 1	21.3

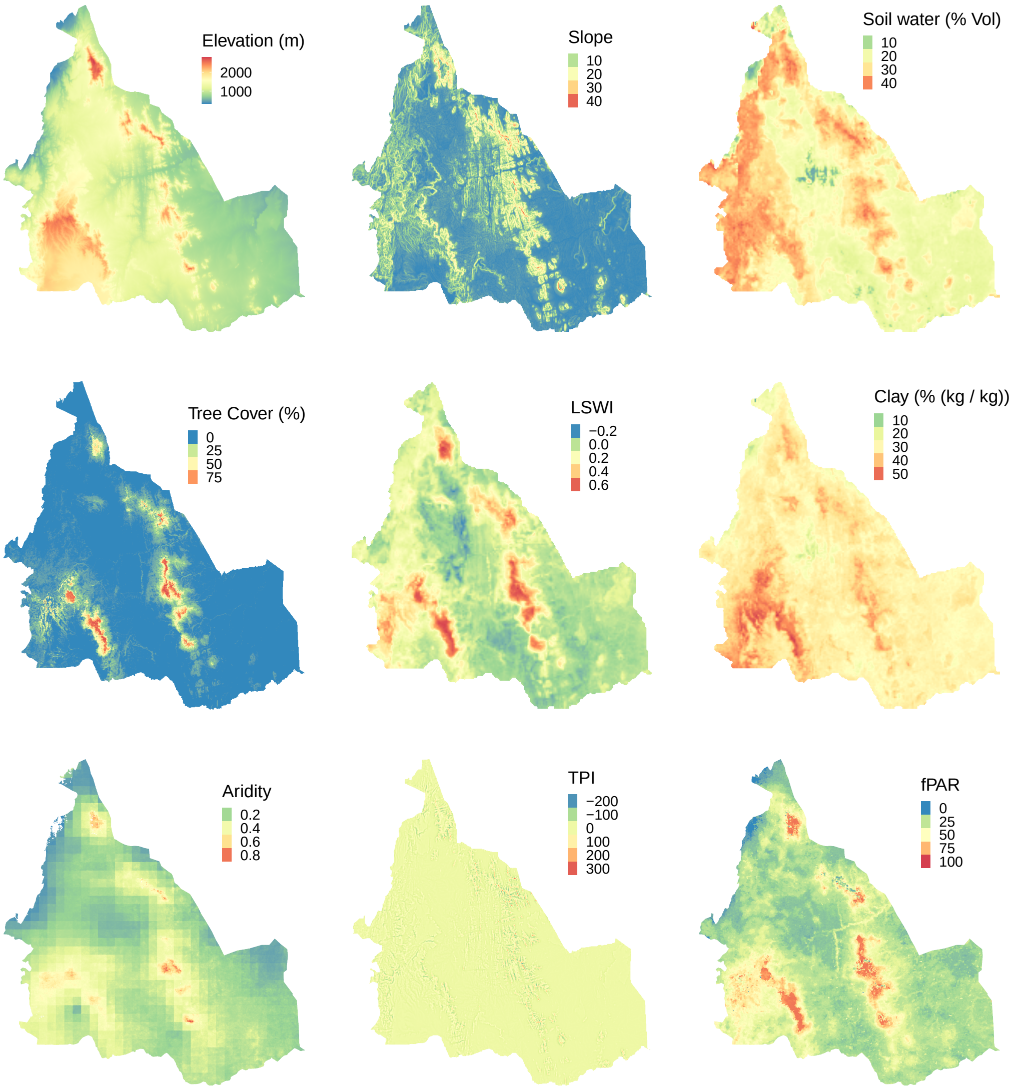

Figure 4.11.: Maps of important remote sensing variables used in modelling.

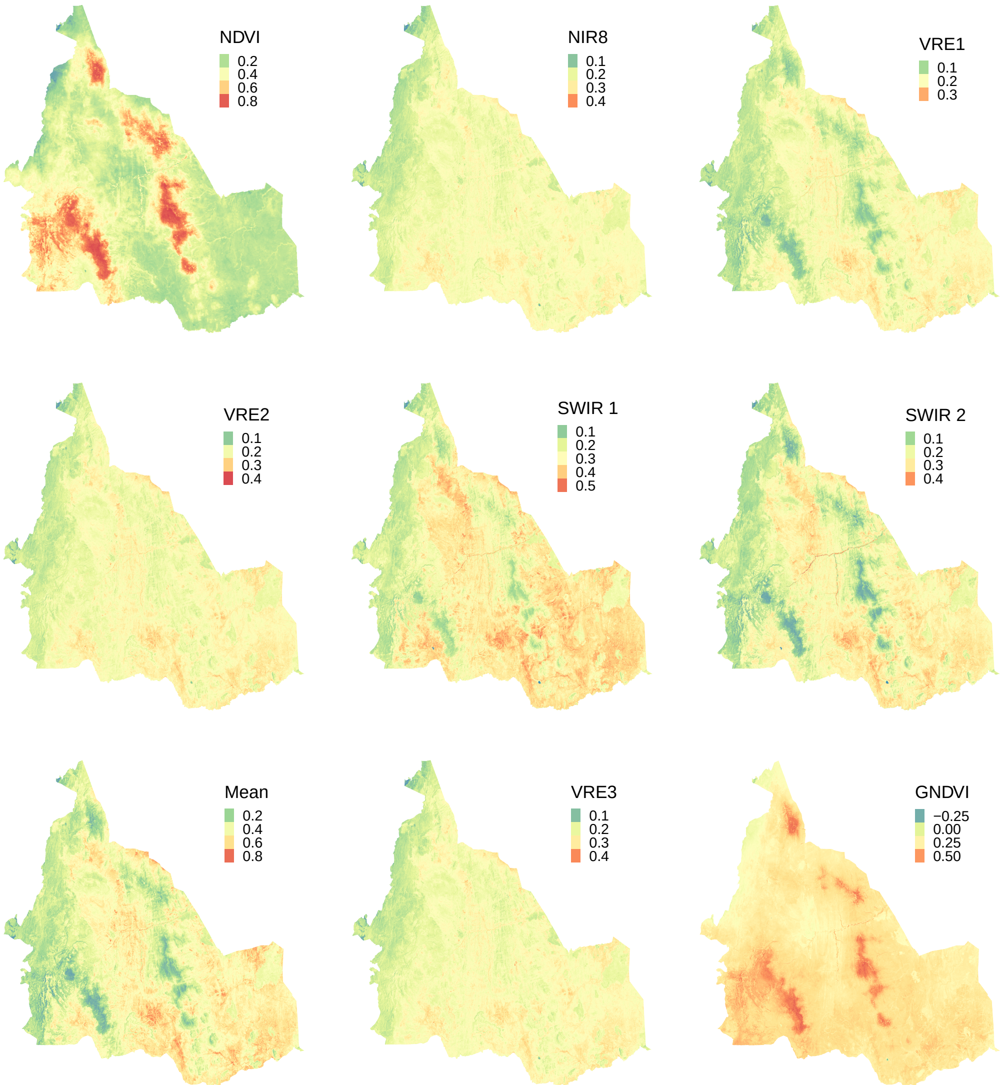

Figure 4.12.: Maps of important Sentinel-2 variables used in modelling.

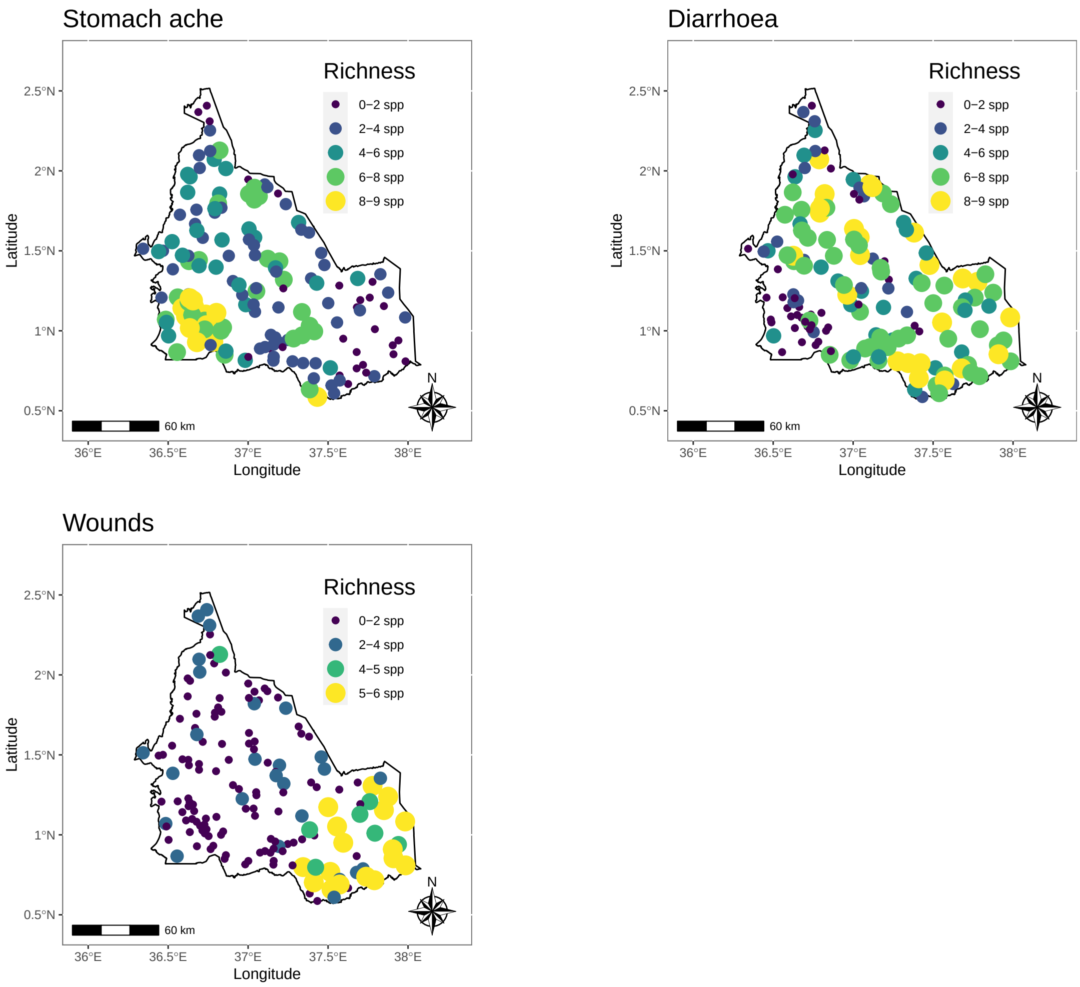

Figure 4.13.: Maps showing observed species richness among the medicinal plant groups.

5. Synthesis and Outlook

5.1. Synthesis

Medicinal plants are of great importance to millions of people worldwide, especially in rural communities. They continue to be used in the maintenance of people's health and serve as a source of income for many people involved in their collection and trade. However, assessments on the distribution and supply of medicinal plant species in terms of species that grow together, and those used against various diseases, especially the common diseases are so far limited. Such assessments are needed because they could provide knowledge to support the fight against common diseases, evaluate the value of certain areas for conservation measures as well as efficient collection trips. Towards this end, this thesis is breaking new ground by investigating the distribution and supply of medicinal plant species in terms groups of species that grow together, and those used against various diseases, especially the common diseases, and bringing forward recommendations regarding their conservation, as well as evaluate their implications for conservation. In this respect, three main research gaps were identified, and they will be extensively discussed in this section.

How do medicinal plant assemblages differ in terms of medicinal service supply by wild medicinal plants?

Conservation strategies that are geared towards conserving both the medicinal plant species and assemblages are likely to yield more promising results that those that only focus on medicinal plant species (Dharani and Yenesew, 2010). Therefore, the first paper compared the supply of medicinal service by wild plants among MPA. Such comparisons can reveal the differences in supply diversity and supply security among different MPA. This paper represents the first study conducted to understand the supply of medicinal service by wild plant species among different MPA. It was shown that the patterns of medicinal plant co-occurrences depicted in the distribution of MPA (forest, savanna, wooded grassland and bushed grassland) were driven by variation in drought, slope, grazing pressure and sand content in soils; which implies that the differentiation of medicinal plants into the different groups was driven by those variables. However, the study showed that grazing intensity and fire history had no impact on medicinal plants co-occurrences. These results are surprising as other studies reported that grazing intensity (Adnan et al., 2015) influenced medicinal plants co-occurrences. The study further assessed the threat level of the medicinal plant species, and categorized the species into various threat levels. This assessment confirms the result of other studies: most medicinal plant species in Samburu are threatened and needed urgent conservation measures (Gafna et al., 2017). *Rhus natalensis* and *Olea africana* were among the species listed as endangered. It can therefore be concluded that the current medicinal plant species conservation measures are not effective and needed to be adjusted or strengthened. Therefore, the Kenya Biodiversity Research Institute, non-governmental organizations concerned with species conservation and conservationists should increase conservation actions such as protection of threatened medicinal plant species and educating the public on the importance of medicinal plants conservation, especially for those species that are threatened or endangered. The threat level of each medicinal plant species (as shown in our study) should be considered when formulating medicinal plants conservation strategies to maximize the conservation effectiveness.

The analysis of medicinal service supply security is difficult in instances where many medicinal plant species are involved. To tackle this challenge, the N+1 redundancy concept was adopted in our analysis. The results of this paper demonstrated that MPA differ in terms of supply diversity and supply security, with the forest having the highest supply diversity (plant species used to treat 67 illnesses), while the savanna MPA had the highest supply redundancy. It is therefore important to recognize that availability of many medicinal plants in an assemblage does not automatically guarantee high medicinal supply security. These results are striking as most previous scientific research equated availability of medicinal plant species in an area or a habitat to medicinal supply security (Chalo et al., 2016; Kamau et al., 2016). The differences in supply diversity and security were also depicted in the location of the assemblages in areas with different environmental conditions. The study suggested that the differences in supply security and diversity should be considered in the formulation of conservation strategies for MPA, as this will ensure that the assemblage with the highest supply security (in our case the savanna) receives the highest conservation priority. Previous studies demonstrated that the number of medicinal plants species used against diseases tended to differ among habitats (Dharani and Yenesew, 2010; Chalo et al., 2016). However, a large part of these studies primarily conducted questionnaire surveys to determine the number of diseases treated by the medicinal plants in these habitats. Such qualitative surveys may not clearly show the supply diversity and security, since the plants may have been mentioned by the respondents as present in the study area, but they may not actually exist in the wild due to extinction. Still in regard to supply security, the paper identified the key medicinal plant species responsible for the high supply security in each MPA, and underlined the importance of conserving such species in the assemblages, especially in the savanna which had the highest supply security. This is important because conservationists can now focus the limited conservation resources on these key medicinal plant species, to ensure sustenance of medicinal service supply. With regard to groups of species used against different diseases, the paper showed the redundancy level each group of species used against a given disease, and in each assemblage. Thus, to conserve a group of medicinal plant species used against a given disease, conservation actions towards this group of species could be directed to the assemblage which had the highest redundancy of that given species group. Owing to the significance of drought in medicinal plants co-occurrences and its negative correlation with supply security and diversity, it is likely that climate change will only reduce the supply security and diversity. Therefore, the conservation of endangered and vulnerable key medicinal plant species should be conducted to alleviate the negative effects of climate change on supply security and diversity. This paper will start the conversation regarding the adoption of conservation strategies that target both medicinal plant species and assemblages.

Does climate change impact on the availability of anti-malarial plants?

Among the many diseases which affect the locals in Samburu, malaria has been ranked as the deadliest and most common (Kimuyu et al., 2017). Therefore, in the second paper, the impact of climate change on the availability of anti-malarial plant species and malaria vectors was predicted. In contrast to other studies that assessed malaria vulnerability by only mapping the distribution of malaria vectors (Kulkarni et al., 2010; Kimuyu et al., 2017), this paper developed a novel approach based on overlaying the distribution map of malaria vectors on top of anti-malarial plant species richness map. The paper further compared the current and future overlaps between the distributional pattern of anti-malarial plant species and malaria vectors, so as to assess the current and future malaria vulnerability. The findings of this study revealed that the effects of climate change will be detrimental, since most areas will witness huge losses in anti-malarial species suitable habitat while only a few gained or remained stable. This results agree with the findings of Cahyaningsih et al. (2021) and highlights the need of revising the current anti-malarial plants conservation strategies in future. Different anti-malarial plant species conservation strategies were recommended for the areas that will gain (i.e. *in-situ* conservation) or loss (i.e. *ex-situ*) suitable habitat. The paper revealed a decrease in the future mean anti-malarial plant species richness in comparison to the current scenario (Silva et al., 2022), while an increase in the suitable habitat for malaria vectors was predicted (Kulkarni et al., 2010; Kimuyu et al., 2017). This results contradict those by Kaky and Gilbert (2017) in Egypt which showed an increase in the mean medicinal plant species richness due to climate change. This could have been due to difference in ecological niche location Samburu and Egypt, as well as use of other climatic variables and future climate scenarios. The subsequent increase in malaria vectors suitable habitat will only mean an increase in the use of anti-malarial plants. Consequently, there is need to focus on future conservation of anti-malarial plants (Tshabalala et al., 2022). Additionally, the study demonstrated that the future overlap between malaria vectors suitable habitat and low anti-malarial plant species richness areas (high vulnerability malaria areas) will increase. These results are worrying as most of the population will be vulnerable to malaria in future, which calls for up-scaling and re-adjustments of measures to conserve anti-malarial plant species and control malaria in future, especially in the high vulnerability areas identified in the study. Strikingly, the study showed that even the current anti-malarial plants conservation and malaria control measures were not well designed and needed urgent re-adjustments to take into account the current malaria vulnerability in Samburu.

The study also tested the effectiveness of protected areas in Samburu to conserve anti-malarial plant species, under the current scenario and in the face of climate change. The results were promising under the current scenarios, but under future climate change, it was evident that the protected areas will not be able to conserve the anti-malarial plant species. Therefore, the local authorities should take this into consideration when designing new protected areas in the region. As suggested in the paper, new protected areas should be located in the future suitable habitat for anti-malarial plants. The study also assessed the threat level for each species under future climate change scenarios, and the priority conservation species were classified as those that will be critically endangered under the four future climate change i.e. *Acacia xanthophloea* and *Salvadora persica*. Urgent conservation actions were suggested for these anti-malarial plant species in future, as this would guarantee future supply of anti-malarial plants.

Can remote sensing data combined with an ensemble one class classification workflow be used to map medicinal plant species?

Considering that other than malaria, the locals in Samburu are affected by other common diseases (Bussmann, 2006), it was also important to assess the distribution of plant species used to treat common diseases in the area. The third paper therefore tested, for the first time, the suitability of remote sensing satellite data together with an ensemble one class classification workflow to map the distribution of medicinal plant species, and those species used to treat common diseases: 1) Wounds 2) Diarrhoea and 3) Stomach ache. The conventional method of mapping medicinal plants distribution entails mapping their potential distribution using climatic variables such as Bioclim (Cahyaningsih et al., 2021). However, the sole use of climatic data in mapping medicinal plant species is often challenging and may yield less accurate results (Malahlela et al., 2019). The novel approach used in our study differs from other studies where medicinal plants were mapping using climatic data (Tshabalala et al., 2022), or a single classifiers (Kaky and Gilbert, 2016). This was important because previous studies already demonstrated that remote sensing data together with field inventories (Ferrier, 2002), as well as ensemble modelling (Liu et al., 2020) yield more accurate results. Our findings evidenced that an ensemble one class classifier together with remote sensing data is suitable for mapping medicinal plant species, and those species used against common diseases like wounds, diarrhoea and stomach ache. With this approach it is possible to accurately identify the high richness areas, which are of conservation concern. This is important because conservation actions can then be directed to such areas (Dharani and Yenesew, 2010). Here, species used against stomach ache showed an identical distribution pattern to most medicinal plant species, whereas the distribution patterns of species used to treat wounds and diarrhoea differed from majority of medicinal plants. This difference in spatial patterns of groups of species used against different diseases could be due to the variation in growth forms which dominated the groups. Therefore, the resulting difference in the distribution maps of various species groups used against different diseases underscores the need of adopting different conservation strategies for the groups of medicinal plants. Based on these distributional patterns, the study identified the overlapping high richness areas of medicinal plants and those used against stomach ache, as well as of species used against wounds and diarrhoea as priority conservation areas.

Meanwhile, the study showed that soil water content, elevation, land surface water index and NDVI were the most influential variables for predicting the richness of plants used against stomach ache and all medicinal plant species. This similarity in the most influential variables between the two groups of medicinal plants was due to the possibility that both groups were dominated by the same growth form-tree species, which respond in a similar way to the environmental conditions. The findings of this paper showed that especially species used against stomach ache were classified with the highest accuracy, due to the dominance of tree species within this group. Trees have well developed leaves that facilitate precise measurement of their spectral reflectance in arid regions (Wang et al., 2021). Prediction accuracy of the wounds-species was poor due to the low sample size of species in this group, suggesting that the accuracy of this group may be improved by increasing the sample size of the species within the group and inclusion of additional remote sensing variables which are known to influence the distribution of the species in the group. The findings of paper 3 further underline the potential of Suit-SDM as the best modelling approach for predicting medicinal plant species richness or the richness of other species of conservation value. As shown in the paper, prediction accuracy of this modelling approach were better than the Bin-SDM, and hence Suit-SDM approach should be adopted by conservation ecologists.

In summary, this dissertation adopted two main approaches to assess the distribution and supply of medicinal plant species and bring forward the conservation issues around them, as well as evaluate their implications for conservation.

1. The first approach combined three techniques (classification, ordination and the N+1 redundancy concept) to understand the distribution and supply of medicinal plant species among different MPA (paper 1). Here, classification technique can show the patterns of medicinal plant species co-occurrences, while the ordination technique helps to understand the drivers of the variations in patterns of medicinal plant co-occurrences. On the other hand, the redundancy concept helps to understand the medicinal plants supply diversity and security among MPA. Specifically, the concept revealed the redundancy levels of groups of plant species used to treat different diseases in the MPA (paper 1). This paper further assessed the threat level of all medicinal plant species and highlighted those that are highly threatened, and therefore of highest conservation priority. Also, important to note is that the paper identified the areas and assemblages where some of these highly threatened species were found.

2. The second approach mapped the richness of medicinal plant species, and those used against common diseases, and suggested different conservation strategies for the medicinal plants groups (paper 2 and 3). Since species richness is a measure of biodiversity, this approach provides an ecological basis for making conservation decisions (Gould, 2000). As shown in paper 2, current anti-malarial plants conservation strategies and malaria control measures will need to be revised so as to take into consideration the impacts of climate change on anti-malarial plants and malaria vector species. Paper 3 demonstrates that mapping of the distribution of medicinal plant species in a remote and data-limited area is feasible using remote sensing satellite data. The study estab-

lished that the distribution patterns of plant species used to treat stomach ache had a strong spatial congruence with most medicinal plants, while the patterns of those species used to treat wounds and diarrhoea were different from most medicinal plant species. Therefore, differing conservation strategies should be adopted for the different groups of medicinal plant species. As shown in the paper, the Suit-SDM best predicts the richness of medicinal plant species, and should therefore be adopted in predicting medicinal plant species richness as well as other species of conservation concern.

5.2. Outlook

This thesis selected and applied two main approaches to investigate medicinal plants distribution and supply, as well as bringing forward recommendations regarding their conservation, and evaluating their implications for conservation. The first approach- comparing medicinal service supply by wild plants among MPA- can considerably enhance the understanding of the MPA with the highest supply diversity (number of medicinal plant species) and supply security, as well as the factors that influence the co-occurrence of medicinal plant species among the assemblages. Despite the promising outcome of previous studies on ordination and classification (Russell-Smith et al., 2006), comprehensive identification of factors that determine the distribution of medicinal plants remains difficult because of the difficulty in reconstructing the impact of site history on the co-occurrence of medicinal plants. This thesis did not investigate the impact of site history on the co-occurrence and distribution of medicinal plant species. More knowledge could be harnessed in order to understand the impact of site history on medicinal plants distribution and co-occurrences. Future research could use Landsat time series since they cover a long time period. Time series of each band and vegetation related indices such as NDVI can be analyzed for differences at medicinal plant species presence and absence sites, to establish the impact of site history on medicinal plants co-occurrences. Whereas the locals in the study area frequently burn vegetation (Gafna et al., 2017), our work established that the impact of fire on medicinal plants co-occurrence was insignificant, probably because we only focused on the recent fire history during our field observations. Further assessment could be conducted using both ground observation and MODIS burned product to understand the impact of fire history on medicinal plants co-occurrence. Regarding grazing intensity, it would be also interesting to conduct further assessment on its impact on medicinal plant species co-occurrences, given that other studies reported showed it had significant impact on medicinal plants (Adnan et al., 2015). For instance, poisson mixed model (Kéry, 2010), with fixed effects as distance to the corral, and the medicinal plant species abundance as the variable of interest may yield more comprehensive results on the impact of grazing intensity on medicinal plants.

As evidenced in the first paper, the application of redundancy concept in the evaluation of medicinal service supply security was based on medicinal plants richness. Thus, to ensure a more comprehensively estimate of the medicinal service supply security, medicinal plants species abundance may be a promising measure. This is because species richness alone may not stand out as a surrogate in explaining medicinal service supply security. As suggested by Oldeland et al. (2010), analysis based on species richness alone without incorporating abundance may overlook crucial information about the species. Considering that the phyto-chemical constituent of the medicinal plant is as important as the occurrence of the plant, impact of environmental site conditions on the phyto-chemical metabolites is important. Future research should focus on understanding the relationship between accumulation of phyto-chemical constituents in medicinal plants and the environmental conditions, as some medicinal plant species may become toxic in certain environmental conditions. Such an undertaking could be done in collaboration with pharmacologists.

The second approach (chapter 3 and 4)- mapping of the distribution of medicinal plant species, and those used against common diseases. This approach can be used to identify area which require conservation actions currently and in the face of changing climate. The effectiveness of protected areas in the conservation of anti-malarial plants was tested. The procedure used in this thesis seems promising but further work is needed to test different procedures of estimating the species richness found inside and outside the protected areas. In this thesis we only tested the effectiveness of the protected areas in *in-situ* conservation of anti-malarial plants. Additionally, future research should also integrate mapping of medicinal plants with conservation gap analysis aimed at understanding both the *ex-situ* and *in-situ* conservation gap analysis of medicinal plant species. Such gap analysis approach would provide a detailed information on the conservation systems that are needed to enhance conservation efficiency and identification of conservation priority areas (Carver et al., 2021), since such areas should not solely be selected based on medicinal plant species richness predictions. This gap analysis could not only be conducted in medicinal plant species but also other species of conservation value such as wild food plants. The procedure presented in the third paper seems promising but additional work is still necessary to test its applicability across different target classes, areas and time period. Regarding the third paper, further research is also needed in regards to threshold selection to minimize overprediction. In our case, we selected the threshold which yielded the highest overall accuracy.

A. Bibliography

Abrha, H., E. Birhane, H. Hagos, and A. Manaye, 2018: Predicting suitable habitats of endangered juniperus procera tree under climate change in northern ethiopia. *Journal of Sustainable Forestry*, **37 (8)**, 842–853, doi:10.1080/10549811.2018.1494000, place: Philadelphia Publisher: Taylor & Francis Inc WOS:000454941300006.

Acheson, E. S., A. A. Plowright, and J. T. Kerr, 2015: Where have all the mosquito nets gone? spatial modelling reveals mosquito net distributions across tanzania do not target optimal anopheles mosquito habitats. *Malaria Journal*, **14 (1)**, 322–336, doi:10.1186/s12936-015-0841-x, URL https://doi.org/10.1186/s12936-015-0841-x.

Adnan, M., A. Tariq, and Z. Shinwari, 2015: Effects of human proximity and nomadic grazing on the diversity of medicinal plants in temperate hindukush. *Pakistan Journal of Botany*, **47 (1)**, 149–157.

Aguilar-Støen, M., and S. R. Moe, 2007: Medicinal plant conservation and management: distribution of wild and cultivated species in eight countries. *Biodiversity and Conservation*, **16 (6)**, 1973–1981, doi:10.1007/s10531-006-9125-7, URL https://doi.org/10.1007/s10531-006-9125-7.

Ahmad, I., M. S. A. Ahmad, M. Hussain, M. Hameed, M. Y. Ashraf, M. Saghir, and S. Koukab, 2009: Spatio-temporal effects on species classification of medicinal plants in soone valley of pakistan. *International Journal of Agriculture and Biology*, **11 (1)**, 64–68, URL https://www.cabdirect.org/cabdirect/abstract/20093063822, publisher: Friends Science Publishers.

Aiello-Lammens, M. E., R. A. Boria, A. Radosavljevic, B. Vilela, and R. P. Anderson, 2015: spthin: an r package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, **38 (5)**, 541–545, doi:10.1111/ecog.01132, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.01132, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.01132.

Akerele, O., V. Heywood, and H. Synge, 1991: *Conservation of Medicinal Plants*. Cambridge University Press, google-Books-ID: mZZOAAAAIAAJ.

Albuquerque, U. P. d., L. d. H. C. Andrade, and A. C. O. d. Silva, 2005: Use of plant resources in a seasonal dry forest (northeastern brazil). *Acta Botanica Brasilica*, **19 (1)**, 27–38, doi:10.1590/S0102-33062005000100004, URL http://www.scielo.br/scielo.php?script=sci_abstract&pid=S0102-33062005000100004&lng=en&nrm=iso&tlng=en.

Albuquerque, U. P. d., and R. F. d. Oliveira, 2007: Is the use-impact on native caatinga species in brazil reduced by the high species richness of medicinal plants? *Journal of Ethnopharmacology*, **113 (1)**, 156–170, doi:10.1016/j.jep.2007.05.025, URL http://linkinghub.elsevier.com/retrieve/pii/S0378874107002711.

Allouche, O., A. Tsoar, and R. Kadmon, 2006: Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (tss). *Journal of Applied Ecology*, **43 (6)**, 1223–1232, doi:10.1111/j.1365-2664.2006.01214.x, URL https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2664.2006.01214.x.

Alsterberg, C., F. Roger, K. Sundbäck, J. Juhanson, S. Hulth, S. Hallin, and L. Gamfeldt, 2017: Habitat diversity and ecosystem multifunctionality-the importance of direct and indirect effects. *Science Advances*, **3 (2)**, e1601 475, doi:10.1126/sciadv.1601475.

Amuka, O., A. k. Machocho, P. K. Mbugua, and P. O. Okemo, 2014: Ethnobotanical survey of selected medicinal plants used by the ogiek communities in kenya against microbial infections. *Ethnobotany Research and Applications*, **12 (0)**, 627–641, doi:10.17348/era.12.0.627-641, URL http://journals.sfu.ca/era/index.php/era/article/view/805.

Anderson, J., E. Hardy, J. Roach, and R. Witmer, 1976: A land use and land cover classification system for use with remote sensor data. Tech. rep., U.S. Geological Survey Professional Paper, USA, 28–29 pp.

Araújo, M. B., and R. G. Pearson, 2005: Equilibrium of species distributions with climate. *Ecography*, **28 (5)**, 693–695, doi:10.1111/j.2005.0906-7590.04253.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.2005.0906-7590.04253.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.2005.0906-7590.04253.x.

Asase, A., and A. T. Peterson, 2019: Predicted impacts of global climate change on the geographic distribution of an invaluable african medicinal plant resource, alstonia boonei de wild. *Journal of Applied Research on Medicinal and Aromatic Plants*, **14 (1)**, 100–106, doi:10.1016/j.jarmap.2019.100206, URL https://www.sciencedirect.com/science/article/pii/S2214786118300743.

Asfaw, Z., P. Sebsebe Demissew, and Z. Kassa, 2016: Plant diversity and community analysis of the vegetation around tulu korma project centre, ethiopia. *Tropical Plant Research*, **3 (2)**, 292–319, URL https://www.academia.edu/27383802/Plant_diversity_and_community_analysis_of_the_vegetation_around_Tulu_Korma_project_centre_Ethiopia.

Baddeley, A., and R. Turner, 2005: spatstat: An r package for analyzing spatial point patterns. *Journal of Statistical Software*, **12 (1)**, 1–42, doi:10.18637/jss.v012.i06, URL https://doi.org/10.18637/jss.v012.i06.

BAK, 2017: *Plant Species Richness of Kenya*. Kenya Literature Bureau, Nairobi, Kenya.

Baldeck, C. A., M. S. Colgan, J.-B. Féret, S. R. Levick, R. E. Martin, and G. P. Asner, 2014: Landscape-scale variation in plant community composition of an african savanna from airborne species mapping. *Ecological Applications*, **24 (1)**, 84–93, doi:10.1890/13-0307.1, URL http://onlinelibrary.wiley.com/doi/10.1890/13-0307.1/abstract.

Baldwin, R. A., 2009: Use of maximum entropy modeling in wildlife research. *Entropy*, **11 (4)**, 854–866, doi:10.3390/e11040854, URL https://www.mdpi.com/1099-4300/11/4/854, number: 4 Publisher: Molecular Diversity Preservation International.

Balogun, F., and A. Ashafa, 2019: A review of plants used in south african traditional medicine for the management and treatment of hypertension. *Planta Medica*, **85 (4)**, 312–334, doi:10.1055/a-0801-8771, URL http://www.thieme-connect.de/DOI/DOI?10.1055/a-0801-8771.

Beretta, A. N., A. V. Silbermann, L. Paladino, D. Torres, D. Bassahun, R. Musselli, and A. García-Lamohte, 2014: Soil texture analyses using a hydrometer: modification of the bouyoucos method. *Ciencia e investigación agraria*, **41 (2)**, 25–26, doi:10.4067/S0718-16202014000200013, URL http://www.scielo.cl/scielo.php?script=sci_arttext&pid=S0718-16202014000200013&lng=en&nrm=iso&tlng=en.

Beyene, B., B. Beyene, and H. Deribe, 2016: Review on application and management of medicinal plants for the livelihood of the local community. *Journal of Resources Development and Management*, **22 (1)**, 33–39.

Bussmann, R. W., 2006: Ethnobotany of the samburu of mt. nyiru, south turkana, kenya. *Journal of Ethnobiology and Ethnomedicine*, **2 (1)**, 350–358, doi:10.1186/1746-4269-2-35, URL http://dx.doi.org/10.1186/1746-4269-2-35.

Cahyaningsih, R., J. Phillips, J. Magos Brehm, H. Gaisberger, and N. Maxted, 2021: Climate change impact on medicinal plants in indonesia. *Global Ecology and Conservation*, **30**, e01 752, doi:10.1016/j.gecco.2021.e01752, URL https://www.sciencedirect.com/science/article/pii/S2351989421003024.

Calabrese, J. M., G. Certain, C. Kraan, and C. F. Dormann, 2014: Stacking species distribution models and adjusting bias by linking them to macroecological models. *Global Ecology and Biogeography*, **23 (1)**, 99–112, doi:10.1111/geb.12102, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/geb.12102, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/geb.12102.

Cao, S., and D. G. I. Kingston, 2009: Biodiversity conservation and drug discovery: Can they be combined? the suriname and madagascar experiences. *Pharmaceutical biology*, **47 (8)**, 809–823, doi:10.1080/13880200902988629, URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2746688/.

Carver, D., C. C. Sosa, C. K. Khoury, H. A. Achicanoy, M. V. Diaz, S. Sotelo, N. P. Castañeda-Álvarez, and J. Ramirez-Villegas, 2021: Gapanalysis: an r package to calculate conservation indicators using spatial information. *Ecography*, **44 (7)**, 1000–1009, doi:10.1111/ecog.05430, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.05430, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.05430.

Chaianunporn, T., and T. Hovestadt, 2015: Evolutionary responses to climate change in parasitic systems. *Global Change Biology*, **21 (8)**, 2905–2916, doi:10.1111/gcb.12944.

Chalo, M., C. Buchanan, and P. Mutiso, 2016: An ethnobotanical study of medicinal plants used by the masaai people of losho, kenya. *International Journal of Pharmacological Research*, **6 (2)**, 68–74, URL https://www.researchgate.net/publication/296812962_An_ethnobotanical_study_of_medicinal_plants_used_by_the_Masaai_people_of_Losho_Kenya.

Chaturvedi, R., and A. Raghubanshi, 2018: Soil water availability influences major ecosystem processes in tropical dry forest. *International Journal of Hydrology*, **2 (1)**, 46–57, doi:10.15406/ijh.2018.02.00042.

Chen, S.-L., H. Yu, H.-M. Luo, Q. Wu, C.-F. Li, and A. Steinmetz, 2016: Conservation and sustainable use of medicinal plants: problems, progress, and prospects. *Chinese Medicine*, **11 (1)**, 37–46, doi:10.1186/s13020-016-0108-7, URL https://doi.org/10.1186/s13020-016-0108-7.

Coley, P. D., and Coauthors, 2003: Using ecological criteria to design plant collection strategies for drug discovery. *Frontiers in Ecology and the Environment*, **1 (8)**, 421–428, doi:10.2307/3868139, URL https://www.jstor.org/stable/3868139, publisher: Ecological Society of America.

D'Amen, M., A. Dubuis, R. F. Fernandes, J. Pottier, L. Pellissier, and A. Guisan, 2015: Using species richness and functional traits predictions to constrain assemblage predictions from stacked species distribution models. *Journal of Biogeography*, **42 (7)**, 1255–1266, doi:10.1111/jbi.12485, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jbi.12485, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jbi.12485.

Dar, R. A., M. Shahnawaz, and P. H. Qazi, 2017: General overview of medicinal plants: A review. *The Journal of Phytopharmacology*, **6 (6)**, 349–351, doi:10.31254/phyto.2017.6608, URL http://www.phytopharmajournal.com/Vol6_Issue6_08.pdf.

Davis, M. B., 2000: Palynology after y2kunderstanding the source area of pollen in sediments. *Annual Review of Earth and Planetary Sciences*, **28 (1)**, 1–18, URL https://experts.umn.edu/en/publications/palynology-after-y2k-understanding-the-source-area-of-pollen-in-s.

Dewitte, O., and Coauthors, 2013: Harmonisation of the soil map of africa at the continental scale. *Geoderma*, **211-212 (1)**, 138–153, doi:10.1016/j.geoderma.2013.07.007, URL http://linkinghub.elsevier.com/retrieve/pii/S0016706113002401.

Dharani, N., 2011: *Field guide to common TREES AND SHRUBS of East Africa.* 2nd ed., Pippa Parker, Cape Town, South Africa.

Dharani, N., G. Rukunga, A. Yenesew, A. Mbora, L. Mwaura, I. Dawson, and R. Jamnadass, 2010: *Common Antimalarial Trees and Shrubs of East Africa–A Description of Species and a Guide to Cultivation and Conservation through Use*. ICRAF Book, The World Agroforestry Centre, Nairobi, Kenya.

Dharani, N., and A. Yenesew, 2010: *Medicinal Plants of East Africa. An illustrated guide.* Drongo Editing and Publishing, Nairobi, Kenya.

Ding, R., J. Luo, C. Wang, L. Yu, J. Yang, M. Wang, S. Zhong, and R. Gu, 2023: Identifying and mapping individual medicinal plant lamiophlomis rotata at high elevations by using unmanned aerial vehicles and deep learning. *Plant Methods*, **19 (1)**, 38, doi:10.1186/s13007-023-01015-z, URL https://doi.org/10.1186/s13007-023-01015-z.

Dubuis, A., J. Pottier, V. Rion, L. Pellissier, J.-P. Theurillat, and A. Guisan, 2011: Predicting spatial patterns of plant species richness: a comparison of direct macroecological and species stacking modelling approaches. *Diversity and Distributions*, **17 (6)**, 1122–1131, doi:10.1111/j.1472-4642.2011.00792.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1472-4642.2011.00792.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1472-4642.2011.00792.x.

Dudík, M., S. J. Phillips, and R. E. Schapire, 2007: Maximum entropy density estimation with generalized regularization and an application to species distribution modeling. *Journal of Machine Learning Research*, **8**, 1217–1260, URL http://dl.acm.org/citation.cfm?id=1314498.1314540.

Dunn, O. J., 1964: Multiple comparisons using rank sums. *Technometrics*, **6 (3)**, 241–252, doi:10.2307/1266041, URL https://www.jstor.org/stable/1266041.

Eldridge, D. J., and M. E. Tozer, 1997: Environmental factors relating to the distribution of terricolous bryophytes and lichens in semi-arid eastern australia. *The Bryologist*, **100 (1)**, 28–39, doi:10.2307/3244384, URL https://www.jstor.org/stable/3244384.

Elith, J., and J. R. Leathwick, 2009: Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, **40 (1)**, 677–697, doi:10.1146/annurev.ecolsys.110308.120159, URL http://www.annualreviews.org/doi/abs/10.1146/annurev.ecolsys.110308.120159.

Eliá, P., and P. Mariniová, 2017: Ecological functions of vegetation as potentials of ecosystem services (floodplain alder forest in the tríbe microregion). *Journal of Forest Science*, **63 (3)**, 126–135, doi: DOI:10.17221/58/2016-JFS.

Essenfelder, A., 2016: Swat weather database: A quick guide. version: v.0.16.06. URL doi:10.13140/RG.2.1.4329.1927.

Etterson, J. R., and R. G. Shaw, 2001: Constraint to adaptive evolution in response to global warming. *Science*, **294 (5540)**, 151–154, doi:10.1126/science.1063656.

Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, **9 (5)**, 1937–1958, doi:10.5194/gmd-9-1937-2016, URL https://gmd.copernicus.org/articles/9/1937/2016/, publisher: Copernicus GmbH.

FAO, 2009: International treaty on plant genetic resources for food and agriculture. Tech. rep., Rome, Italy.

FAO, 2021: Standard operating procedure for soil ph determinatio. Tech. rep., Rome, Italy, 1–19 pp.

Farr, T. G., and Coauthors, 2007: The shuttle radar topography mission. *Reviews of Geophysics*, **45 (2)**, 34–37, doi:10.1029/2005RG000183, URL https://onlinelibrary.wiley.com/doi/abs/10.1029/2005RG000183, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2005RG000183.

Ferrier, S., 2002: Mapping spatial pattern in biodiversity for regional conservation planning: Where to from here? *Systematic Biology*, **51 (2)**, 331–363, doi:10.1080/10635150252899806, URL https://doi.org/10.1080/10635150252899806.

Fick, S. E., and R. J. Hijmans, 2017: Worldclim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, **37 (12)**, 4302–4315, doi:10.1002/joc.5086, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/joc.5086, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/joc.5086.

Franklin, J., and J. A. Miller, 2009: *Mapping species distributions: spatial inference and prediction*. Ecology, biodiversity and conservation, Cambridge University Press, Cambridge ; New York.

Gafna, D. J., K. Dolos, I. O. Mahiri, J. G. Mahiri, and J. A. Obando, 2017: Diversity of medicinal plants and anthopogenic threats in the samburu central sub-county of kenya. *African Journal of Traditional, Complementary and Alternative Medicines*, **14 (5)**, 72–79, doi:10.21010/ajtcam.v14i5.10, URL https://journals.athmsi.org/index.php/ajtcam/article/view/4856.

Gafna, D. J., J. A. Obando, J. M. Kalwij, K. Dolos, and S. Schmidtlein, 2023: Climate change impacts on the availability of anti-malarial plants in kenya. *Climate Change Ecology*, **5 (1)**, 30–44, doi:10.1016/j.ecochg.2023.100070, URL https://www.sciencedirect.com/science/article/pii/S2666900523000060.

Gafna, D. J., J. A. Obando, M. Reichelt, S. Schmidtlein, and K. Dolos, 2021: Medicinal service supply by wild plants in samburu, kenya: Comparisons among medicinal plant assemblages. *Global Ecology and*

Conservation, **30**, e01 749, doi:10.1016/j.gecco.2021.e01749, URL https://www.sciencedirect.com/science/article/pii/S2351989421002997.

Gaikwad, J., P. D. Wilson, and S. Ranganathan, 2011: Ecological niche modeling of customary medicinal plant species used by australian aborigines to identify species-rich and culturally valuable areas for conservation. *Ecological Modelling*, **222 (18)**, 3437–3443, doi:10.1016/j.ecolmodel.2011.07.005, URL https://www.sciencedirect.com/science/article/pii/S0304380011003759.

Gakuya, D. W., S. M. Itonga, J. M. Mbaria, J. K. Muthee, and J. K. Musau, 2013: Ethnobotanical survey of biopesticides and other medicinal plants traditionally used in meru central district of kenya. *Journal of Ethnopharmacology*, **145 (2)**, 547–553, doi:10.1016/j.jep.2012.11.028.

Gakuya, D. W., M. O. Okumu, S. G. Kiama, J. M. Mbaria, P. K. Gathumbi, P. M. Mathiu, and J. M. Nguta, 2020: Traditional medicine in kenya: Past and current status, challenges, and the way forward. *Scientific African*, **8**, e00 360, doi:10.1016/j.sciaf.2020.e00360, URL https://www.sciencedirect.com/science/article/pii/S2468227620300983.

Gao, B.-c., 1996: Ndwia normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, **58 (3)**, 257–266, doi:10.1016/S0034-4257(96)00067-3, URL https://www.sciencedirect.com/science/article/pii/S0034425796000673.

Gauch, H. G., 1982: *Multivariate Analysis in Community Ecology*. 1st ed., Cambridge University Press, doi:10.1017/CBO9780511623332, URL https://www.cambridge.org/core/product/identifier/9780511623332/type/book.

GBIF.org, 2019: Gbif occurrence download. URL https://doi.org/10.15468/dl.oufswz.

Gessler, M. C., M. H. Nkunya, L. B. Mwasumbi, M. Heinrich, and M. Tanner, 1994: Screening tanzanian medicinal plants for antimalarial activity. *Acta Tropica*, **56 (1)**, 65–77, doi:10.1016/0001-706x(94)90041-8.

Gitelson, A. A., Y. J. Kaufman, and M. N. Merzlyak, 1996: Use of a green channel in remote sensing of global vegetation from eosmodis. *Remote Sensing of Environment*, **58 (3)**, 289–298, doi:10.1016/S0034-4257(96)00072-7, URL https://www.sciencedirect.com/science/article/pii/S0034425796000727.

GOK, 2016: National development plan: 2010-2016. Tech. rep., Government printer Nairobi, Nairobi, Kenya, 12–16 pp.

Golding, N., M. A. Nunn, and B. V. Purse, 2015: Identifying biotic interactions which drive the spatial distribution of a mosquito community. *Parasites & Vectors*, **8 (1)**, 367–378, doi:10.1186/s13071-015-0915-1, URL https://doi.org/10.1186/s13071-015-0915-1.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, 2017: Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, **202 (1)**, 18–27, doi:10.1016/j.rse.2017.06.031, URL https://www.sciencedirect.com/science/article/pii/S0034425717302900.

Gould, W., 2000: Remote sensing of vegetation, plant species richness, and regional biodiversity hotspots. *Ecological Applications*, **10 (6)**, 1861–1870, doi:10.1890/1051-0761(2000)010[1861:RSOVPS]2.0.CO;2, URL https://onlinelibrary.wiley.com/doi/abs/10.1890/1051-0761%282000%29010%5B1861%3ARSOVPS%5D2.0.CO%3B2, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1890/1051-0761%282000%29010%5B1861%3ARSOVPS%5D2.0.CO%3B2.

Grabherr, G., K. Reiter, and W. Willner, 2003: Towards objectivity in vegetation classification: the example of the austrian forests. *Plant Ecology*, **169 (1)**, 21–34, doi:10.1023/A:1026280428467, URL https://doi.org/10.1023/A:1026280428467.

Gray, C. L., and Coauthors, 2016: Local biodiversity is higher inside than outside terrestrial protected areas worldwide. *Nature Communications*, **7 (1)**, 12–19, doi:10.1038/ncomms12306, URL https://www.nature.com/articles/ncomms12306, number: 1 Publisher: Nature Publishing Group.

Greig-Smith, P., 2010: *Quantitative Plant Ecology*. Butterworths, google-Books-ID: J7G_tgAACAAJ.

Groom, M. J., G. K. Meffe, and C. R. Carroll, 2006: *Principles of conservation biology*. 3rd ed., Sinauer Associates, Sunderland, Mass., oCLC: 60651075.

Guisan, A., and W. Thuiller, 2005: Predicting species distribution: offering more than simple habitat models. *Ecology Letters*, **8 (9)**, 993–1009, doi:10.1111/j.1461-0248.2005.00792.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1461-0248.2005.00792.x.

Guo, H., X.-b. Zhou, Y. Tao, J.-f. Yin, L. Zhang, X. Guo, C.-h. Liu, and Y.-m. Zhang, 2023: Perennial herb diversity contributes more than annual herb diversity to multifunctionality in dryland ecosystems of north-western china. *Frontiers in Plant Science*, **14 (1)**, 21–33, doi:https://doi.org/10.3389/fpls.2023.1099110, URL https://www.frontiersin.org/articles/10.3389/fpls.2023.1099110.

Guo, J.-X., M.-X. Zhang, C.-C. Wang, R. Zhang, T.-T. Shi, X.-Y. Wang, X.-B. Zhang, and M.-H. Li, 2021: Application of remote sensing technology in medicinal plant resources. *Journal of Chinese Materia Medica*, **46 (18)**, 4689–4696, doi:10.19540/j.cnki.cjcmm.20210620.101.

Guyon, I., J. Weston, S. Barnhill, and V. Vapnik, 2002: Gene selection for cancer classification using support vector machines. *Machine Learning*, **46 (1)**, 389–422, doi:10.1023/A:1012487302797, URL https://doi.org/10.1023/A:1012487302797.

Hamann, O., 1991: The joint iucnwwf plants conservation programme and its interest in medicinal plants. *Conservation of Medicinal Plants*, Cambridge University Press, Great Britain, 13–22.

Hamilton, A. C., 2004: Medicinal plants, conservation and livelihoods. *Biodiversity & Conservation*, **13 (8)**, 1477–1517, doi:10.1023/B:BIOC.0000021333.23413.42, URL https://doi.org/10.1023/B:BIOC.0000021333.23413.42.

Hansen, M., and Coauthors, 2013: High-resolution global maps of 21st-century forest cover change.

Haq, F., H. Ahmad, Z. Iqbal, M. Alam, and A. Aksoy, 2017: Multivariate approach to the classification and ordination of the forest ecosystem of nandiar valley western himalayas. *Ecological Indicators*, **80**, 232–241, doi:10.1016/j.ecolind.2017.05.047, URL https://www.sciencedirect.com/science/article/pii/S1470160X17303023.

Haralick, R., 1979: Statistical and structural approaches to texture. *Proceedings of the IEEE*, **67 (5)**, 786–804, doi:10.1109/PROC.1979.11328, conference Name: Proceedings of the IEEE.

Haralick, R. M., K. Shanmugam, and I. Dinstein, 1973: Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, **SMC-3 (6)**, 610–621, doi:10.1109/TSMC.1973.4309314, conference Name: IEEE Transactions on Systems, Man, and Cybernetics.

Harris, I., T. J. Osborn, P. Jones, and D. Lister, 2020: Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, **7 (1)**, 109–127, doi:10.1038/s41597-020-0453-3, URL https://www.nature.com/articles/s41597-020-0453-3, bandiera_abtest: a Cc_license_type: cc_publicdomain Cg_type: Nature Research Journals Number: 1 Primary_atype: Research Publisher: Nature Publishing Group Subject_term: Atmospheric dynamics;Climate and Earth system modelling Subject_term_id: atmospheric-dynamics;climate-and-earth-system-modelling.

Heine, B., I. Heine, and C. Koenig, 1988: Plant use and concepts an ethnobotanical survey of the semi-arid and arid lands of eastafrica. part v plants of the samburu (kenya). *Cologne Development Studies*, Vol. 10, Cambridge University Press, 1–286, URL http://www.africabib.org/rec.php?RID=119547422.

Hernández-Stefanoni, J. L., and J. M. Dupuy, 2007: Mapping species density of trees, shrubs and vines in a tropical forest, using field measurements, satellite multiespectral imagery and spatial interpolation. *Biodiversity and Conservation*, **16 (13)**, 3817–3833, doi:10.1007/s10531-007-9182-6, URL https://doi.org/10.1007/s10531-007-9182-6.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis, 2005: Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, **25 (15)**, 1965–1978, doi:10.1002/joc.1276, URL http://onlinelibrary.wiley.com/doi/10.1002/joc.1276/abstract.

Hijmans, R. J., S. Phillips, J. L. Elith, and Jane, 2022: dismo: Species distribution modeling. URL https://CRAN.R-project.org/package=dismo.

Hitimana, J., F. Warinwa, and D. Sumba, 2011: Challenges of linking socio-economic significance and conservation value of forests in drylands of kenya: Case study of kirisia forest-samburu pastoralists coexistence. Tech. rep., Kabianga University College, Kabianga Kenya, Nairobi, Kenya, 15–20 pp.

Huete, A. R., H. Q. Liu, K. Batchily, and W. van Leeuwen, 1997: A comparison of vegetation indices over a global set of tm images for eosmodis. *Remote Sensing of Environment*, **59 (3)**, 440–451, doi:10.1016/S0034-4257(96)00112-5, URL https://www.sciencedirect.com/science/article/pii/S0034425796001125.

Hurskainen, A., 1994: Plant taxonomy of the parakuyo (tanzania). *Nordic Journal of African Studies*, **3 (2)**, 117–158, URL https://www.researchgate.net/publication/249685859_Plant_Taxonomy_of_the_Parakuyo_Tanzania.

Hutchinson, G. E., 1957: Concluding remarks. *Cold Spring Harbor Symposia on Quantitative Biology*, **22 (1)**, 415–427, doi:10.1101/SQB.1957.022.01.039, URL http://symposium.cshlp.org/content/22/415, publisher: Cold Spring Harbor Laboratory Press.

IPCC, 2014: Climate change 2014: synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change. Tech. rep.

IPCC, 2021: Climate change 2021: synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change. Tech. rep., Switzerland.

IUCN, 2008: *Strategy on Drylands and Desertation*. IUCN, Nairobi.

IUCN, 2021: The iucn red list of threatened species. URL https://www.iucnredlist.org/en.

Jones, H. G., and R. A. Vaughan, 2010: *Remote Sensing of Vegetation: Principles, Techniques, and Applications*. OUP Oxford, google-Books-ID: sTmcAQAAQBAJ.

Junninen, K., and A. Komonen, 2011: Conservation ecology of boreal polypores: A review. *Biological Conservation*, **144 (1)**, 11–20, doi:10.1016/j.biocon.2010.07.010, URL https://www.sciencedirect.com/science/article/pii/S0006320710003162.

Kaky, E., and F. Gilbert, 2016: Using species distribution models to assess the importance of egypt's protected areas for the conservation of medicinal plants. *Journal of Arid Environments*, **135**, 140–146, doi:10.1016/j.jaridenv.2016.09.001, place: London Publisher: Academic Press Ltd- Elsevier Science Ltd WOS:000387836500018.

Kaky, E., and F. Gilbert, 2017: Predicting the distributions of egypt's medicinal plants and their potential shifts under future climate change. *PloS One*, **12 (11)**, e0187 714, doi:10.1371/journal.pone.0187714.

Kaky, E., V. Nolan, A. Alatawi, and F. Gilbert, 2020: A comparison between ensemble and maxent species distribution modelling approaches for conservation: A case study with egyptian medicinal plants. *Ecological Informatics*, **60 (1)**, 101–119, doi:10.1016/j.ecoinf.2020.101150, URL https://www.sciencedirect.com/science/article/pii/S157495412030100X.

Kamau, L., P. Mbaabu, J. Mbaria, P. K. Gathumbi, and S. Kiama, 2016: Ethnobotanical survey and threats to medicinal plants traditionally used for the management of human diseases in nyeri county, kenya. *Humanitas Medicine*, **6 (3)**, 167–176.

Kareru, P. G., G. M. Kenji, A. N. Gachanja, J. M. Keriko, and G. Mungai, 2006: Traditional medicines among the embu and mbeere peoples of kenya. *African journal of traditional, complementary, and alternative medicines: AJTCAM / African Networks on Ethnomedicines*, **4 (1)**, 75–86.

Kass, J. M., and Coauthors, 2020: Biotic predictors with phenological information improve range estimates for migrating monarch butterflies in mexico. *Ecography*, **43 (3)**, 341–352, doi:10.1111/ecog.04886, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.04886, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.04886.

Kearney, M., 2006: Habitat, environment and niche: what are we modelling? *Oikos*, **115 (1)**, 186–191, doi:10.1111/j.2006.0030-1299.14908.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.2006.0030-1299.14908.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.2006.0030-1299.14908.x.

Khakurel, D., Y. Uprety, G. Ahn, J.-Y. Cha, W.-Y. Kim, S.-H. Lee, and S. Rajbhandary, 2022: Diversity, distribution, and sustainability of traditional medicinal plants in kaski district, western nepal. *Frontiers in Pharmacology*, **13 (1)**, 1–15, doi:https://doi.org/10.3389/fphar.2022.1076351, URL https://www.frontiersin.org/articles/10.3389/fphar.2022.1076351.

Khalifehzadeh, R., and M. Ghazani, 2014: Using gis, ordination and discriminant analysis for study in habitat characteristics of medicinal plants from compositae family; case study: Boushehr province, iran. *Journal of Biodiversity and Environmental Sciences*, **5 (6)**, 18–23.

Khan, A. M., Q. Li, Z. Saqib, N. Khan, T. Habib, N. Khalid, M. Majeed, and A. Tariq, 2022: Maxent modelling and impact of climate change on habitat suitability variations of economically important chilgoza pine (pinus gerardiana wall.) in south asia. *Forests*, **13 (5)**, 715, doi:10.3390/f13050715, URL https://www.mdpi.com/1999-4907/13/5/715, number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

Kikoti, I. A., and C. Mligo, 2015: Impacts of livestock grazing on plant species composition in montane forests on the northern slope of mount kilimanjaro, tanzania. *International Journal of Biodiversity Science, Ecosystem Services & Management*, **11 (2)**, 114–127, doi:10.1080/21513732.2015.1031179, URL https://www.tandfonline.com/doi/full/10.1080/21513732.2015.1031179.

Kimuyu, J. S., N. J. Muthama, and S. M. Musyoka, 2017: Ecological niche modeling for spatial-temporal quantification of the changing dynamics of malaria vector distribution in kenya under climate change forcing. *International Journal of Scientific & Technology Research*, **6 (6)**, 324–337.

Kioko, J., J. W. Kiringe, and S. O. Seno, 2012: Impacts of livestock grazing on a savanna grassland in kenya. *Journal of Arid Land*, **4 (1)**, 29–35, doi:10.3724/SP.J.1227.2012.00029, wOS:000300387600004.

Kipkore, W., B. Wanjohi, H. Rono, and G. Kigen, 2014: A study of the medicinal plants used by the marakwet community in kenya. *Journal of Ethnobiology and Ethnomedicine*, **10 (1)**, 165–183, doi: 10.1186/1746-4269-10-24, URL http://dx.doi.org/10.1186/1746-4269-10-24.

Kirira, P. G., and Coauthors, 2006: Anti-plasmodial activity and toxicity of extracts of plants used in traditional malaria therapy in meru and kilifi districts of kenya. *Journal of Ethnopharmacology*, **106 (3)**, 403–407, doi:10.1016/j.jep.2006.01.017, URL https://www.sciencedirect.com/science/article/pii/S0378874106000535.

Kishor, C., and K. Amit, 2018: Identification and classification of medicinal plants of the indian himalayan region using hyperspectral remote sensing and random forest techniques, India. 177–180.

Kitula, R. A., 2007: Use of medicinal plants for human health in udzungwa mountains forests: a case study of new dabaga ulongambi forest reserve, tanzania. *Journal of Ethnobiology and Ethnomedicine*, **3 (1)**, 7, doi:10.1186/1746-4269-3-7, URL https://doi.org/10.1186/1746-4269-3-7.

Kleinschmidt, I., and Coauthors, 2001: An empirical malaria distribution map for west africa. *Tropical medicine & international health*, **6 (10)**, 779–786, doi:10.1046/j.1365-3156.2001.00790.x.

KMD, 2019: *Climatological Statistics for Kenya*. Kenya Gazatte, Nairobi, Kenya.

KMS, 2019: Kenya malaria strategy 20192023. Tech. rep., Ministry of Health, Nairobi, Kenya, 1–73 pp.

KNBS, 2019: The 2009 kenya population and housing census. Population survey, Kenya National Bureau of Statistics, Nairobi, 65–76 pp.

Koch, A., P. Tamez, J. Pezzuto, and D. Soejarto, 2005: Evaluation of plants used for antimalarial treatment by the maasai of kenya. *Journal of Ethnopharmacology*, **101 (1)**, 95–99, doi:10.1016/j.jep.2005.03.011, URL https://www.sciencedirect.com/science/article/pii/S0378874105002436.

Kokwaro, J. O., 2009: *Medicinal plants of East Africa*. 3rd ed., University of Nairobi Press, Nairobi, Kenya.

Kotir, J. H., 2011: Climate change and variability in sub-saharan africa: a review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability*, **13 (3)**, 587–605, doi:10.1007/s10668-010-9278-0, URL https://doi.org/10.1007/s10668-010-9278-0.

KSS, 2011: Soil and terrain database for kenya. Soil and Terrain in Kenya 4, Nairobi, Kenya, 44–45 pp. URL http://www.isric.org/data/soil-and-terrain-database-kenya-ver-20-kensoter.

Kuhn, M., 2008: Building predictive models in r using the caret package. *Journal of Statistical Software*, **28 (1)**, 1–26, doi:10.18637/jss.v028.i05, URL https://www.jstatsoft.org/index.php/jss/article/view/v028i05, number: 1.

Kulkarni, M. A., R. E. Desrochers, and J. T. Kerr, 2010: High resolution niche models of malaria vectors in northern tanzania: A new capacity to predict malaria risk? *PLOS ONE*, **5 (2)**, e9396, doi:10.1371/journal.pone.0009396, URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0009396, publisher: Public Library of Science.

Kuria, K. A. M., S. De Coster, G. Muriuki, W. Masengo, I. Kibwage, J. Hoogmartens, and G. M. Laekeman, 2001: Antimalarial activity of ajuga remota benth (labiatae) and caesalpinia volkensii harms (caesalpiniaceae): in vitro confirmation of ethnopharmacological use. *Journal of Ethnopharmacology*, **74 (2)**, 141–148, doi:10.1016/S0378-8741(00)00367-6, URL https://www.sciencedirect.com/science/article/pii/S0378874100003676.

KWS, 2010: National parks, game reserves and sanctuaries in kenya. Kenya Gazatte, Nairobi, Kenya.

Kéry, M., 2010: Poisson mixed-effects model (poisson glmm). 203–209, doi:10.1016/B978-0-12-378605-0.00016-8.

Lawler, J. J., D. White, R. P. Neilson, and A. R. Blaustein, 2006: Predicting climate-induced range shifts: model differences and model reliability. *Global Change Biology*, **12 (8)**, 1568–1584, doi:10.1111/j.1365-2486.2006.01191.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2486.2006.01191.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2486.2006.01191.x.

Legendre, P., and L. F. J. Legendre, 1998: *Numerical Ecology*. 2nd ed., Elsevier Science, Amsterdam, Netherlands, google-Books-ID: KBoHuoNRO5MC.

Lemenkova, P., 2020: Hyperspectral vegetation indices calculated by qgis using landsat tm image: a case study of northern iceland. *Advanced Research in Life Sciences*, **4 (1)**, 70–78, doi:10.2478/arls-2020-0021, URL https://sciendo.com/article/10.2478/arls-2020-0021.

Li, L.-p., B.-g. Zhang, P.-g. Xiao, Z. Zhang, Y.-d. Qi, X.-j. Li, G.-p. Wang, and H.-t. Liu, 2015: Native medicinal plant richness distribution patterns and environmental determinants of xinjiang, northwest china. *Chinese Herbal Medicines*, **7 (1)**, 45–53, doi:10.1016/S1674-6384(15)60019-3, URL https://www.sciencedirect.com/science/article/pii/S1674638415600193.

Li, W., and Q. Guo, 2010: A maximum entropy approach to one-class classification of remote sensing imagery. *International Journal of Remote Sensing*, **31 (8)**, 2227–2235, doi:10.1080/

01431161003702245, URL https://doi.org/10.1080/01431161003702245, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01431161003702245.

Lindsay, S. W., and M. N. Bayoh, 2004: Mapping members of the anopheles gambiae complex using climate data. *Physiological Entomology*, **29 (3)**, 204–209, doi:10.1111/j.0307-6962.2004.00405.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0307-6962.2004.00405.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0307-6962.2004.00405.x.

Linstädter, A., J. Schellberg, K. Brüser, C. A. Moreno García, R. J. Oomen, C. C. du Preez, J. C. Ruppert, and F. Ewert, 2014: Are there consistent grazing indicators in drylands? testing plant functional types of various complexity in south africas grassland and savanna biomes. *PLoS ONE*, **9 (8)**, e104 672, doi:10.1371/journal.pone.0104672, URL http://dx.plos.org/10.1371/journal.pone.0104672.

Liu, B., Y. Dai, X. Li, W. S. Lee, and P. S. Yu, 2003: Building text classifiers using positive and unlabeled examples. *Proceedings of the Third IEEE International Conference on Data Mining*, IEEE Computer Society, USA, 179, ICDM '03.

Liu, C., P. M. Berry, T. P. Dawson, and R. G. Pearson, 2005: Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, **28 (3)**, 385–393, doi:10.1111/j.0906-7590.2005.03957.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0906-7590.2005.03957.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0906-7590.2005.03957.x.

Liu, C., G. Newell, and M. White, 2016: On the selection of thresholds for predicting species occurrence with presence-only data. *Ecology and Evolution*, **6 (1)**, 337–348, doi:10.1002/ece3.1878, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/ece3.1878, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ece3.1878.

Liu, C., M. White, and G. Newell, 2013: Selecting thresholds for the prediction of species occurrence with presence-only data. *Journal of Biogeography*, **40 (4)**, 778–789, doi:10.1111/jbi.12058, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jbi.12058.

Liu, X., H. Liu, P. Datta, J. Frey, and B. Koch, 2020: Mapping an invasive plant spartina alterniflora by combining an ensemble one-class classification algorithm with a phenological ndvi time-series analysis approach in middle coast of jiangsu, china. *Remote Sensing*, **12 (24)**, 4010, doi:10.3390/rs12244010, URL https://www.mdpi.com/2072-4292/12/24/4010, number: 24 Publisher: Multidisciplinary Digital Publishing Institute.

Lloyd, C. T., A. Sorichetta, and A. J. Tatem, 2017: High resolution global gridded data for use in population studies. *Scientific Data*, **4 (1)**, 1–17, doi:10.1038/sdata.2017.1, URL https://www.nature.com/articles/sdata20171.

Ma, Y., L. Qu, W. Wang, X. Yang, and T. Lei, 2016: Measuring soil water content through volume/mass replacement using a constant volume container. *Geoderma*, **271 (1)**, 42–49, doi:10.1016/j.geoderma.2016.02.003, URL https://www.sciencedirect.com/science/article/pii/S0016706116300532.

Machault, V., and Coauthors, 2010: Spatial heterogeneity and temporal evolution of malaria transmission risk in dakar, senegal, according to remotely sensed environmental data. *Malaria Journal*, **9 (1)**, 1–14, doi:10.1186/1475-2875-9-252, URL https://doi.org/10.1186/1475-2875-9-252.

Mack, B., R. Roscher, and B. Waske, 2014: Can i trust my one-class classification? *Remote Sensing*, **6 (9)**, 8779–8802, doi:10.3390/rs6098779, URL https://www.mdpi.com/2072-4292/6/9/8779, number: 9 Publisher: Multidisciplinary Digital Publishing Institute.

Mack, B., and B. Waske, 2017: In-depth comparisons of maxent, biased svm and one-class svm for one-class classification of remote sensing data. *Remote Sensing Letters*, **8 (3)**, 290–299, doi:10.1080/2150704X.2016.1265689, URL https://doi.org/10.1080/2150704X.2016.1265689, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/2150704X.2016.1265689.

Mahomoodally, M. F., 2013: Traditional medicines in africa: An appraisal of ten potent african medicinal plants. *Evidence-Based Complementary and Alternative Medicine*, **2013**, 1–14, doi:10.1155/2013/617459, URL http://www.hindawi.com/journals/ecam/2013/617459/.

Malahlela, O. E., C. Adjorlolo, and J. M. Olwoch, 2019: Mapping the spatial distribution of lippia javanica (burm. f.) spreng using sentinel-2 and srtmderived topographic data in malaria endemic environment. *Ecological Modelling*, **392 (1)**, 147–158, doi:10.1016/j.ecolmodel.2018.11.020, URL https://www.sciencedirect.com/science/article/pii/S0304380018304083.

Manach, C., A. Scalbert, C. Morand, C. Rémésy, and L. Jiménez, 2004: Polyphenols: food sources and bioavailability. *The American Journal of Clinical Nutrition*, **79 (5)**, 727–747, doi:10.1093/ajcn/79.5.727.

MARA/ARMA, 1996: An atlas of malaria in africa. URL http://www.mara.org.za.

Mariem, H., and M. Chaieb, 2017: Climate change impacts on the distribution of stipa tenacissima l ecosystems in north african arid zone - a case study in tunisia. *Applied Ecology and Environmental Research*, **15 (3)**, 67–82, doi:10.15666/aeer/1503_067082, place: Budapest Publisher: Corvinus Univ Budapest WOS:000403811200006.

McCoy, D., G. Kembhavi, J. Patel, and A. Luintel, 2009: The bill & melinda gates foundation's grant-making programme for global health. *The Lancet*, **373 (9675)**, 1645–1653, doi:10.1016/S0140-6736(09)60571-7, URL https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(09)60571-7/abstract, publisher: Elsevier.

Meine, C., 2010: Conservation biology: past and present. *Conservation Biology for All*, Oxford University Press, United Kingdom, 7–26.

Meine, C., M. Soulé, and R. E. Noss, 2006: "a mission-driven discipline": the growth of conservation biology. *Conservation Biology*, **20 (3)**, 631–651, doi:10.1111/j.1523-1739.2006.00449.x.

Merow, C., M. J. Smith, and J. A. Silander Jr, 2013: A practical guide to maxent for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, **36 (10)**, 1058–1069, doi:10.1111/j.1600-0587.2013.07872.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1600-0587.2013.07872.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1600-0587.2013.07872.x.

Meynard, C. N., and D. M. Kaplan, 2012: The effect of a gradual response to the environment on species distribution modeling performance. *Ecography*, **35 (6)**, 499–509, URL https://www.jstor.org/stable/41510689, publisher: Wiley.

Mitchell, S. C., 2005: How useful is the concept of habitat? a critique. *Oikos*, **110 (3)**, 634–638, doi:10.1111/j.0030-1299.2005.13810.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0030-1299.2005.13810.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0030-1299.2005.13810.x.

Mordecai, E. A., S. J. Ryan, J. M. Caldwell, M. M. Shah, and A. D. LaBeaud, 2020: Climate change could shift disease burden from malaria to arboviruses in africa. *The Lancet. Planetary health*, **4 (9)**, 416–423, doi:10.1016/S2542-5196(20)30178-9, URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7490804/.

Moustafa, A. R. A., and J. M. Klopatek, 1995: Vegetation and landforms of the saint catherine area, southern sinai, egypt. *Journal of Arid Environments*, **30 (4)**, 385–395, doi:10.1006/jare.1995.0033, URL https://www.sciencedirect.com/science/article/pii/S014019638570033X.

Mukungu, N., K. Abuga, F. Okalebo, R. Ingwela, and J. Mwangi, 2016: Medicinal plants used for management of malaria among the luhya community of kakamega east sub-county, kenya. *Journal of Ethnopharmacology*, **194 (1)**, 98–107, doi:10.1016/j.jep.2016.08.050, URL http://www.sciencedirect.com/science/article/pii/S0378874116305840.

Muscarella, R., P. J. Galante, M. SoleyGuardia, R. A. Boria, J. M. Kass, M. Uriarte, and R. P. Anderson, 2014: Enmeval: An r package for conducting spatially independent evaluations and estimating optimal model complexity for maxent ecological niche models. *Methods in Ecology and Evolution*, **5 (11)**, 1198–1205, doi:10.1111/2041-210X.12261, URL https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/2041-210X.12261.

Muturi, E. J., J. Mwangangi, J. Shililu, B. G. Jacob, C. Mbogo, J. Githure, and R. J. Novak, 2008: Environmental factors associated with the distribution of anopheles arabiensis and culex quinquefasciatus in a rice agro-ecosystem in mwea, kenya. *Journal of Vector Ecology*, **33 (1)**, 56–63, doi: 10.3376/1081-1710(2008)33[56:efawtd]2.0.co;2.

Márialigeti, S., F. Tinya, A. Bidló, and P. Ódor, 2016: Environmental drivers of the composition and diversity of the herb layer in mixed temperate forests in hungary. *Plant Ecology*, **217 (5)**, 549–563, URL https://www.jstor.org/stable/24751032, publisher: Springer.

Nabarro, D., 1999: Roll back malaria. *Parassitologia*, **41 (1-3)**, 501–504.

Nanyingi, M. O., J. M. Mbaria, A. L. Lanyasunya, C. G. Wagate, K. B. Koros, H. F. Kaburia, R. W. Munenge, and W. O. Ogara, 2008: Ethnopharmacological survey of samburu district, kenya. *Journal of Ethnobiology and Ethnomedicine*, **4 (1)**, 143–151, doi:10.1186/1746-4269-4-14, URL http://ethnobiomed.biomedcentral.com/articles/10.1186/1746-4269-4-14.

Nasseri, S., B. Farhadi Bansouleh, and A. Azari, 2023: Estimation of land surface temperature in agricultural lands using sentinel 2 images: A case study for sunflower fields. *Irrigation and Drainage*, **1 (2)**, 1–11, doi:10.1002/ird.2802, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/ird.2802, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ird.2802.

Newman, J. E., and J. E. Oliver, 2005: Palmer index/palmer drought severity index. *Encyclopedia of World Climatology*, J. E. Oliver, Ed., Springer Netherlands, Dordrecht, 571–573, doi:10.1007/1-4020-3266-8_159, URL https://doi.org/10.1007/1-4020-3266-8_159.

Ngari, E., L. Chiur, S. Kariuk, and S. Huckett, 2010: Ethnomedicine of ogiek of river njoro watershed, nakuru- kenya. *Ethnobotany Research & Applications*, **8 (1)**, 135–152.

Njoroge, G., 2012: Traditional medicinal plants in two urban areas in kenya (thika and nairobi): Diversity of traded species and conservation concerns. *Ethnobotany Research and Applications*, **10 (0)**, 329–338, URL http://journals.sfu.ca/era/index.php/era/article/view/511.

Nourani, V., G. Elkiran, and S. I. Abba, 2018: Wastewater treatment plant performance analysis using artificial intelligence - an ensemble approach. *Water Science and Technology*, **78 (10)**, 2064–2076, doi:10.2166/wst.2018.477.

Ogutu, Z. A., 1996: Multivariate analysis of plant communities in the narok district, kenya: The influence of environmental factors and human disturbance. *Vegetatio*, **126 (2)**, 181–189, URL https://www.jstor.org/stable/20048748, publisher: Springer.

Oksanen, J., 2006: vegan: Community ecology package.

Oldeland, J., N. Dreber, and D. Wesuls, 2010: Diversity measures in comparative rangeland studies: application and advantages of species abundance distributions and diversity profiles. *Dinteria*, **31**, 50–66.

Omara, T., 2020: Antimalarial plants used across kenyan communities. *Evidence-Based Complementary and Alternative Medicine*, **2020 (1)**, 53–74, doi:10.1155/2020/4538602, URL https://www.hindawi.com/journals/ecam/2020/4538602/, publisher: Hindawi.

Omori, E. O., O. Calistus, P. K. Mbugua, and P. O. Okemo, 2012: Ethnobotanical identification and anti-microbial evaluation of some anti- diarrhoreal plants used by the samburu community, kenya. *Malaysian Journal of Microbiology*, **8 (2)**, 68–74, URL https://www.researchgate.net/publication/266011300_Ethnobotanical_Identification_and_Anti-microbial_Evaluation_of_Some_Anti-_Diarrhoreal_Plants_Used_by_the_Samburu_Community_Kenya.

Omwenga, E. O., P. K. Mbugua, and P. Okemo, 2014: Ethno-medicinal survey of important plants of samburu community (wamba)-samburu district in kenya. *Research and Reviews: Journal of Botanical Sciences*, **3 (3)**, 25–29.

OpenStreetMap, 2021: Planet dump retrieved from https://planet.osm.org |bibsonomy. URL https://www.bibsonomy.org/bibtex/2fb98b96ccfd5a338c4486f521ef5c8d4/lautenschlager.

Ouko, E., and Coauthors, 2020: Modeling invasive plant species in kenyas northern rangelands. *Frontiers in Environmental Science*, **8 (1)**, 23–42, doi:https://doi.org/10.3389/fenvs.2020.00069, URL https://www.frontiersin.org/articles/10.3389/fenvs.2020.00069.

Owens, H., and G. Robert, 2019: climate stability: An r package to estimate climate stability from time-slice climatologies. *Biodiversity Informatics*, **14 (1)**, 8–13, doi:10.17161/bi.v14i0.9786.

Palmer, M. W., 1993: Putting things in even better order: The advantages of canonical correspondence analysis. *Ecology*, **74 (8)**, 2215–2230, doi:10.2307/1939575, URL http://doi.wiley.com/10.2307/1939575.

Pearson, R. G., and T. P. Dawson, 2003: Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global Ecology and Biogeography*, **12 (5)**, 361–371, doi:10.1046/j.1466-822X.2003.00042.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1046/j.1466-822X.2003.00042.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1046/j.1466-822X.2003.00042.x.

Pearson, R. G., C. J. Raxworthy, M. Nakamura, and A. T. Peterson, 2007: Original article predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in madagascar. *Journal of Biogeography*, **34 (1)**, 102–117, doi:10.1111/j.1365-2699.2006.01594.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2699.2006.01594.x.

Pearson, R. G., and Coauthors, 2006: Model-based uncertainty in species range prediction. *Journal of Biogeography*, **33 (10)**, 1704–1711, doi:10.1111/j.1365-2699.2006.01460.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2699.2006.01460.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2699.2006.01460.x.

Peet, R. K., 1980: Ordination as a tool for analyzing complex data sets. *Classification and Ordination: Symposium on advances in vegetation science, Nijmegen, The Netherlands, May 1979*, E. van der Maarel, Ed., Advances in vegetation science, Springer Netherlands, Dordrecht, 171–174, doi:10.1007/978-94-009-9197-2_20, URL https://doi.org/10.1007/978-94-009-9197-2_20.

Phillips, S. J., R. P. Anderson, and R. E. Schapire, 2006: Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, **190 (3)**, 231–259, doi:10.1016/j.ecolmodel.2005.03.026, URL http://www.sciencedirect.com/science/article/pii/S030438000500267X.

Pielou, E. C., 1984: *Interpretation of Ecological Data: Primer on Classification and Ordination by Pielou*. Wiley-Interscience.

Piiroinen, R., F. E. Fassnacht, J. Heiskanen, E. Maeda, B. Mack, and P. Pellikka, 2018: Invasive tree species detection in the eastern arc mountains biodiversity hotspot using one class classification. *Remote Sensing of Environment*, **218**, 119–131, doi:10.1016/j.rse.2018.09.018, URL https://www.sciencedirect.com/science/article/pii/S0034425718304292.

Pimm, S. L., G. J. Russell, J. L. Gittleman, and T. M. Brooks, 1995: The future of biodiversity. *Science*, **269 (5222)**, 347–350, doi:10.1126/science.269.5222.347.

Prince, S. D., and S. N. Goward, 1995: Global primary production: A remote sensing approach. *Journal of Biogeography*, **22 (4/5)**, 815–835, doi:10.2307/2845983, URL https://www.jstor.org/stable/2845983, publisher: Wiley.

Qi, J., A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian, 1994: A modified soil adjusted vegetation index. *Remote Sensing of Environment*, **48 (2)**, 119–126, doi:10.1016/0034-4257(94)90134-1, URL https://www.sciencedirect.com/science/article/pii/0034425794901341.

Qian, J., and Coauthors, 2020: Selecting flagship species to solve a biodiversity conservation conundrum. *Plant Diversity*, **42 (6)**, 488–491, doi:10.1016/j.pld.2021.01.004, URL https://www.sciencedirect.com/science/article/pii/S2468265921000044.

Rafieian-Kopaei, M., 2012: Medicinal plants and the human needs. *Journal of Herbmed Pharmacology*, **1 (1)**, 1–2, URL http://herbmedpharmacol.com/Article/JHP_20150526152110, number: 1 Publisher: Shahrekord University of Medical Sciences.

Rahmati, O., and Coauthors, 2019: Spatial modeling of snow avalanche using machine learning models and geo-environmental factors: Comparison of effectiveness in two mountain regions. *Remote Sensing*, **11 (24)**, 2995, doi:10.3390/rs11242995, URL https://www.mdpi.com/2072-4292/11/24/2995, number: 24 Publisher: Multidisciplinary Digital Publishing Institute.

Rajasekharan, P. E., and S. H. Wani, 2020: Distribution, diversity, conservation and utilization of threatened medicinal plants. *Conservation and Utilization of Threatened Medicinal Plants*, P. Rajasekharan, and S. H. Wani, Eds., Springer International Publishing, Cham, 3–30, doi:10.1007/978-3-030-39793-7_1, URL https://doi.org/10.1007/978-3-030-39793-7_1.

Rana, S. K., H. K. Rana, S. K. Ghimire, K. K. Shrestha, and S. Ranjitkar, 2017: Predicting the impact of climate change on the distribution of two threatened himalayan medicinal plants of liliaceae in nepal. *Journal of Mountain Science*, **14 (3)**, 558–570, doi:10.1007/s11629-015-3822-1, URL https://doi.org/10.1007/s11629-015-3822-1.

Rao, K. P. C., W. G. Ndegwa, K. Kizito, and A. Oyoo, 2011: Climate variability and change: Farmer perceptions and understanding of intraseasonal variability in rainfall and associated risk in semiarid kenya. *Experimental Agriculture*, **47 (2)**, 267–291, doi:10.1017/S0014479710000918, URL https://www.cambridge.org/core/journals/experimental-agriculture/article/climate-variability-and-change-farmer-perceptions-and-understanding-of-intraseasonal-variability-in-rainfall-and-assoc 83A1E65D5058A633E35F773BFB726ED9, publisher: Cambridge University Press.

Rasool, A., K. M. Bhat, A. A. Sheikh, A. Jan, and S. Hassan, 2020: Medicinal plants: Role, distribution and future. *Journal of Pharmacognosy and Phytochemistry*, **9 (2)**, 2111–2114, URL https://www.phytojournal.com/archives/2020.v9.i2.11165/medicinal-plants-role-distribution-and-future, publisher: AkiNik Publications.

Ray, R., K. V. Gururaja, and T. V. Ramchandra, 2011: Predictive distribution modeling for rare himalayan medicinal plant berberis aristata dc. *Journal of Environmental Biology*, **32 (6)**, 725–730.

Ribeiro, A., M. M. Romeiras, J. Tavares, and M. T. Faria, 2010: Ethnobotanical survey in canhane village, district of massingir, mozambique: medicinal plants and traditional knowledge. *Journal of Ethnobiology and Ethnomedicine*, **6 (1)**, 33, doi:10.1186/1746-4269-6-33, URL https://doi.org/10.1186/1746-4269-6-33.

Richter, D. D., D. Markewitz, W. A. Reiners, and P. Sánchez, 2007: *Understanding Soil Change: Soil Sustainability over Millennia, Centuries, and Decades*. Reissue edition ed., Cambridge University Press.

Rokaya, M. B., Z. Münzbergová, M. R. Shrestha, and B. Timsina, 2012: Distribution patterns of medicinal plants along an elevational gradient in central himalaya, nepal. *Journal of Mountain Science*, **9 (2)**, 201–213, doi:10.1007/s11629-012-2144-9, URL https://link.springer.com/article/10.1007/s11629-012-2144-9.

Russell-Smith, J., N. S. Karunaratne, and R. Mahindapala, 2006: Rapid inventory of wild medicinal plant populations in sri lanka. *Biological Conservation*, **132 (1)**, 22–32, doi:10.1016/j.biocon.2006.03.009, URL https://www.sciencedirect.com/science/article/pii/S0006320706001121.

Ryan, C., and P. Elsner, 2016: The potential for sand dams to increase the adaptive capacity of east african drylands to climate change. *Regional Environmental Change*, **16 (7)**, 2087–2096, doi:10.1007/s10113-016-0938-y, URL https://doi.org/10.1007/s10113-016-0938-y.

Ryan, S. J., C. A. Lippi, and F. Zermoglio, 2020: Shifting transmission risk for malaria in africa with climate change: a framework for planning and intervention. *Malaria Journal*, **19 (1)**, 170–184, doi:10.1186/s12936-020-03224-6, URL https://doi.org/10.1186/s12936-020-03224-6.

Sankaran, M., and Coauthors, 2005: Determinants of woody cover in african savannas. *Nature*, **438 (7069)**, 846–849, doi:DOI:10.1038/nature04070.

SCBD, 2010: Global biodiversity outlook 3. Tech. rep., Montréal, Canada.

Schmidtlein, S., L. Tichý, H. Feilhauer, and U. Faude, 2010: A brute-force approach to vegetation classification. *Journal of Vegetation Science*, **21 (6)**, 1162–1171, doi:10.1111/j.1654-1103.2010.01221.x, URL http://onlinelibrary.wiley.com/doi/10.1111/j.1654-1103.2010.01221.x/abstract.

Schölkopf, B., J. Platt, J. Shawe-Taylor, A. Smola, and R. Williamson, 2001: Estimating support of a high-dimensional distribution. *Neural Computation*, **13 (1)**, 1443–1471, doi:10.1162/089976601750264965.

Segurado, P., and M. B. Araújo, 2004: An evaluation of methods for modelling species distributions. *Journal of Biogeography*, **31 (10)**, 1555–1568, doi:10.1111/j.1365-2699.2004.01076.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2699.2004.01076.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2699.2004.01076.x.

Seyoum, A., K. Pålsson, S. Kung'a, E. W. Kabiru, W. Lwande, G. F. Killeen, A. Hassanali, and B. G. J. Knols, 2002: Traditional use of mosquito-repellent plants in western kenya and their evaluation in semi-field experimental huts against anopheles gambiae: ethnobotanical studies and application by thermal expulsion and direct burning. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, **96 (3)**, 225–231, doi:10.1016/s0035-9203(02)90084-2.

Shammi, S. A., and Q. Meng, 2021: Use time series ndvi and evi to develop dynamic crop growth metrics for yield modeling. *Ecological Indicators*, **121 (1)**, 107–124, doi:10.1016/j.ecolind.2020.107124, URL https://www.sciencedirect.com/science/article/pii/S1470160X20310633.

Shanley, P., and L. Luz, 2003: The impacts of forest degradation on medicinal plant use and implications for health care in eastern amazonia. *BioScience*, **53 (6)**, 573–584, doi:10.1641/0006-3568(2003)053[0573:TIOFDO]2.0.CO;2, URL https://academic.oup.com/bioscience/article/53/6/573/224740.

Sharma, N., and C. P. Kala, 2018: Patterns in distribution, population density and uses of medicinal plants along the altitudinal gradient in dhauladhar mountain range of indian himalayas. *Current Science*, **114 (11)**, 2323–2328, doi:10.18520/cs/v114/i11/2323-2328, URL http://www.redi-bw.de/db/ebsco.php/search.ebscohost.com/login.aspx%3fdirect%3dtrue%26db%3daph%26AN%3d130119360%26site%3deds-live.

Sheldon, J. W., M. J. Balick, S. A. Laird, and G. M. Milne, 1997: Medicinal plants: Can utilization and conservation coexist? *Advances in Economic Botany*, **12 (1)**, 91–104, URL https://www.jstor.org/stable/43931401, publisher: New York Botanical Garden Press.

Silva, J. L. S., O. Cruz-Neto, M. Tabarelli, U. P. Albuquerque, and A. V. Lopes, 2022: Climate change will likely threaten areas of suitable habitats for the most relevant medicinal plants native to the caatinga dry forest. *Ethnobiology and Conservation*, **11 (1)**, 24–48, doi:10.15451/ec2022-06-11.15-1-24, URL https://ethnobioconservation.com/index.php/ebc/article/view/537.

Singh, J. S., 2002: The biodiversity crisis: A multifaceted review. *Current Science*, **82 (6)**, 638–647, URL https://www.jstor.org/stable/24106689, publisher: Temporary Publisher.

Soberón, J., 2007: Grinnellian and eltonian niches and geographic distributions of species. *Ecology Letters*, **10 (12)**, 1115–1123, doi:10.1111/j.1461-0248.2007.01107.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1461-0248.2007.01107.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1461-0248.2007.01107.x.

Soberón, J., and A. T. Peterson, 2005: Interpretation of models of fundamental ecological niches and species distributional areas. *Biodiversity Informatics*, **2 (1)**, 1–10, doi:https://doi.org/10.17161/bi.v2i0.4, URL https://www.academia.edu/5331193/INTERPRETATION_OF_MODELS_OF_FUNDAMENTAL_ECOLOGICAL_NICHES_AND_SPECIES_DISTRIBUTIONAL_AREAS.

Sofowora, A., 1993: *Medicinal Plants and Traditional Medicine in Africa*. Spectrum Books, Ibadan, Nigeria, google-Books-ID: ZdaxQwAACAAJ.

Song, N., B. Xu, and J. Zhang, 2022: Self-organizing feature map classification and ordination of endangered medicinal plant (glycyrrhiza uralensis) comunities in north china. *Applied Ecology and Environmental Research*, **4 (20)**, 3619–3629, URL http://dx.doi.org/10.15666/aeer/2004_36193629.

Srivastava, J., J. Lambert, and N. Vietmeyer, 1996: *Medicinal Plants: An Expanding Role in Development*. World Bank Publications, google-Books-ID: BoUhhYHim08C.

Steinhoff, B., 2005: Laws and regulation on medicinal and aromatic plants in europe. *Acta Horticulturae*, **1 (678)**, 13–22, doi:10.17660/ActaHortic.2005.678.1, URL https://www.actahort.org/books/678/678_1.htm.

Stenzel, S., F. E. Fassnacht, B. Mack, and S. Schmidtlein, 2017: Identification of high nature value grassland with remote sensing and minimal field data. *Ecological Indicators*, **74**, 28–38, doi:10.1016/j.ecolind.2016.11.005, URL https://www.sciencedirect.com/science/article/pii/S1470160X16306422.

Syfert, M. M., M. J. Smith, and D. A. Coomes, 2013: The effects of sampling bias and model complexity on the predictive performance of maxent species distribution models. *PLOS ONE*, **8 (2)**, e55 158, doi:10.1371/journal.pone.0055158, URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0055158, publisher: Public Library of Science.

Tatian, M., H. Arzani, M. K. Reihan, M. A. Bahmanyar, and H. Jalilvand, 2010: Effect of soil and physiographic factors on ecological plant groups in the eastern elborz mountain rangeland of iran. *Grassland Science*, **56 (2)**, 77–86, doi:10.1111/j.1744-697X.2010.00178.x.

Tavili, A., and M. Jafari, 2009: Interrelations between plants and environmental variables. *International Journal of Environmental Research*, **3 (2)**, 32–44, doi:10.22059/ijer.2009.51, URL https://doi.org/10.22059/ijer.2009.51.

Thuiller, W., S. Lavorel, M. B. Araújo, M. T. Sykes, and I. C. Prentice, 2005: Climate change threats to plant diversity in europe. *Proceedings of the National Academy of Sciences*, **102 (23)**, 8245–8250, doi:10.1073/pnas.0409902102, URL https://www.pnas.org/doi/abs/10.1073/pnas.0409902102, publisher: Proceedings of the National Academy of Sciences.

Ticktin, T., P. Nantel, F. Ramirez, and T. Johns, 2002: Effects of variation on harvest limits for nontimber forest species in mexico. *Conservation Biology*, **16 (3)**, 691–705, URL https://www.jstor.org/stable/3061216, publisher: [Wiley, Society for Conservation Biology].

Tonnang, H. E. Z., R. Y. M. Kangalawe, and P. Z. Yanda, 2010: Predicting and mapping malaria under climate change scenarios: the potential redistribution of malaria vectors in africa. *Malaria Journal*, **9 (1)**, 111–121, doi:10.1186/1475-2875-9-111.

Tshabalala, T., E. M. Abdel-Rahman, B. Ncube, A. R. Ndhlala, and O. Mutanga, 2021: Leveraging of hyperspectral remote sensing on estimating biomass yield of moringa oleifera lam. medicinal plant. *South African Journal of Botany*, **140 (1)**, 37–49, doi:10.1016/j.sajb.2021.03.035, URL https://www.sciencedirect.com/science/article/pii/S0254629921001162.

Tshabalala, T., O. Mutanga, and E. M. Abdel-Rahman, 2022: Predicting the geographical distribution shift of medicinal plants in south africa due to climate change. *Conservation*, **2 (4)**, 694–708, doi:10.3390/conservation2040045, URL https://www.mdpi.com/2673-7159/2/4/45, number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

Tsigemelak, D., N. Dharani, J. Kinyamario, and S. Kibo, 2016: The utilization of medicinal plants by the maasai community in arid lands of kajiado county, kenya. *International Journal of Plant, Animal and Environmental Sciences*, **6 (3)**, 151–159.

Tucker, C. J., 1979: Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, **8 (2)**, 127–150, doi:10.1016/0034-4257(79)90013-0, URL https://linkinghub.elsevier.com/retrieve/pii/0034425779900130.

Tugume, P., and C. Nyakoojo, 2019: Ethno-pharmacological survey of herbal remedies used in the treatment of paediatric diseases in buhunga parish, rukungiri district, uganda. *BMC Complementary and Alternative Medicine*, **19 (1)**, 78–89, doi:10.1186/s12906-019-2763-6, URL https://link.springer.com/epdf/10.1186/s12906-019-2763-6.

UN, 2015: The 2030 agenda and the sustainable development goals. Tech. rep., World Health Organization, Switzerland.

UNEP, 1992: World atlas of desertification. Tech. rep., Edward Arnold :, London, UK. URL https://digitallibrary.un.org/record/246740.

Uprety, Y., H. Asselin, A. Dhakal, and N. Julien, 2012: Traditional use of medicinal plants in the boreal forest of canada: review and perspectives. *Journal of Ethnobiology and Ethnomedicine*, **8 (1)**, 7, doi:10.1186/1746-4269-8-7, URL https://doi.org/10.1186/1746-4269-8-7.

USGS, 2019: Africa land cover characteristics data base version 2.0. URL https://www.usgs.gov/media/images/africa-land-cover-characteristics-data-base-version-20.

Valderrama, L., S. Ayala, C. Reyes, and C. R. González, 2021: Modeling the potential distribution of the malaria vector anopheles (ano.) pseudopunctipennis theobald (diptera: Culicidae) in arid regions of northern chile. *Frontiers in Public Health*, **9 (1)**, 140–147, doi:https://doi.org/10.3389/fpubh.2021.611152, URL https://www.frontiersin.org/article/10.3389/fpubh.2021.611152.

van Andel, T., and R. Havinga, 2008: Sustainability aspects of commercial medicinal plant harvesting in suriname. *Forest Ecology and Management*, **256 (8)**, 1540–1545, doi:10.1016/j.foreco.2008.06.031, URL https://www.sciencedirect.com/science/article/pii/S0378112708005331.

van Andel, T. R., S. Croft, E. E. van Loon, D. Quiroz, A. M. Towns, and N. Raes, 2015: Prioritizing west african medicinal plants for conservation and sustainable extraction studies based on market surveys and species distribution models. *Biological Conservation*, **181 (1)**, 173–181, doi:10.1016/j.biocon.2014.11.015, URL https://www.sciencedirect.com/science/article/pii/S0006320714004406.

Van Wyk, B.-E., 2015: A review of commercially important african medicinal plants. *J. Ethnopharmacol.*, **176 (1)**, 118–134, doi:10.1016/j.jep.2015.10.031.

VanDerWal, J., F. Falconi, S. Januchowski, L. Shoo, and C. Storlie, 2019: Sdmtools - species distribution modelling tools: Tools for processing data associated with species distribution modelling exercises -r package ver. 1.1-221.1. URL https://CRAN.R-project.org/package=SDMTools.

Vanlauwe, B., K. Descheemaeker, K. Giller, J. Huising, R. Merckx, G. Nziguheba, and J. Wendt, 2015: Integrated soil fertility management in sub-saharan africa: unravelling local adaptation. *Soil*, **1**, 491–508.

Verma, A., 2017: Genetic diversity as buffer in biodiversity. *Indian Journal of Biology*, **4 (1)**, 61–63, doi:10.21088/ijb.2394.1391.4117.9.

Vesperinas, E. S., A. G. Moreno, M. S. Elorza, E. D. Sánchez, D. S. Mata, and R. Gavilán, 2001: The expansion of thermophilic plants in the iberian peninsula as a sign of climatic change. *Fingerprints of Climate Change: Adapted Behaviour and Shifting Species Ranges*, G.-R. Walther, C. A. Burga, and P. J. Edwards, Eds., Springer US, Boston, MA, 163–184, doi:10.1007/978-1-4419-8692-4_11, URL https://doi.org/10.1007/978-1-4419-8692-4_11.

Walter, H., and H. Lieth, 1980: *Klimadiagramm Weltatlas*. s.n., S.l., oCLC: 67575811.

Wambugu, S. N., P. M. Mathiu, D. W. Gakuya, T. I. Kanui, J. D. Kabasa, and S. G. Kiama, 2011: Medicinal plants used in the management of chronic joint pains in machakos and makueni counties, kenya. *Journal of Ethnopharmacology*, **137 (2)**, 945–955, doi:10.1016/j.jep.2011.06.038.

Wang, J., Y. Wang, M. Li, N. He, and J. Li, 2021: Divergent roles of environmental and spatial factors in shaping plant beta diversity of different growth forms in drylands. *Global Ecology and Conservation*, **26**, e01 487, doi:10.1016/j.gecco.2021.e01487, URL https://www.sciencedirect.com/science/article/pii/S2351989421000378.

Warman, L. D., D. M. Forsyth, A. R. E. Sinclair, K. Freemark, H. D. Moore, T. W. Barrett, R. L. Pressey, and D. White, 2004: Species distributions, surrogacy, and important conservation regions in canada. *Ecology Letters*, **7 (5)**, 374–379, doi:10.1111/j.1461-0248.2004.00590.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1461-0248.2004.00590.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1461-0248.2004.00590.x.

Whiting, D., A. Card, C. Wilson, and J. Reeder, 2011: Estimating soil texture sandy, loamy or clayey? Tech. rep., Colorado State University, Colorado, USA, 1–5 pp.

WHO, Ed., 2013: *WHO traditional medicine strategy. 2014-2023*. World Health Organization, Geneva.

WHO, 2014: Progress on the health-related millennium development goals (mdgs). Tech. Rep. 22, United Nations, Geneva, Switzerland.

WHO, 2015: Global technical strategy for malaria 20162030. Tech. rep., Geneva, Switzerland, 1–29 pp.

Wisz, M. S., R. J. Hijmans, J. Li, A. T. Peterson, C. H. Graham, A. Guisan, and N. P. S. D. W. Group, 2008: Effects of sample size on the performance of species distribution models. *Diversity and Distributions*, **14 (5)**, 763–773, doi:10.1111/j.1472-4642.2008.00482.x, URL http://doi.wiley.com/10.1111/j.1472-4642.2008.00482.x.

Xiao, X., S. Boles, J. Liu, D. Zhuang, and M. Liu, 2002: Characterization of forest types in northeastern china, using multi-temporal spot4 vegetation sensor data. *Remote Sensing of Environment*, **82 (2)**, 335–348, doi:10.1016/S0034-4257(02)00051-2, URL https://www.sciencedirect.com/science/article/pii/S0034425702000512.

Xiao, X., and Coauthors, 2005: Satellite-based modeling of gross primary production in a seasonally moist tropical evergreen forest. *Remote Sensing of Environment*, **94 (1)**, 105–122, doi:10.1016/j.rse.2004.08.015, URL https://www.sciencedirect.com/science/article/pii/S0034425704002883.

Yang, Q., L. Wang, J. Huang, L. Lu, Y. Li, Y. Du, and F. Ling, 2022: Mapping plant diversity based on combined sentinel1/2 dataopportunities for subtropical mountainous forests. *Remote Sensing*, **14 (3)**, 492, doi:10.3390/rs14030492, URL https://www.mdpi.com/2072-4292/14/3/492, number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

Yang, S., Z. Zhang, B. Zhang, and Y. Lin, 2000: Counter measures to overcome the present inadequate means for the protection of near extinct species of chinese medicinal plant. *Chinese traditional and herbal drugs*, **426 (31)**, 401–403, doi:https://europepmc.org/article/cba/343676, issue: 6 Journal Abbreviation: Zhong Cao Yao Pages: 401-403,426 Volume: 31.

Yang, X.-Q., S. Kushwaha, S. Saran, J. Xu, and P. Roy, 2013: Maxent modeling for predicting the potential distribution of medicinal plant, justicia adhatoda l in lesser himalayan foothills. *Ecological Engineering*, **51 (1)**, 83–87, doi:10.1016/j.ecoleng.2012.12.004, URL http://linkinghub.elsevier.com/retrieve/pii/S0925857412003588.

Yi, Y.-j., X. Cheng, Z.-F. Yang, and S.-H. Zhang, 2016: Maxent modeling for predicting the potential distribution of endangered medicinal plant (h riparia lour) in yunnan, china. *Ecological Engineering*, **92**, 260–269, doi:10.1016/j.ecoleng.2016.04.010, URL https://www.sciencedirect.com/science/article/pii/S0925857416302245.

Yibing, Q., W. Zhaoning, Z. Liyun, S. Qingdong, J. Jin, and T. Lisong, 2004: Impact of habitat heterogeneity on plant community pattern in gurbantunggut desert. *Journal of Geographical Sciences*, **14 (4)**, 447–455, doi:10.1007/BF02837488, URL https://doi.org/10.1007/BF02837488.

Zar, J. H., 2009: *Biostatistical Analysis*. 5th ed., Pearson, Upper Saddle River, N.J.

Zhang, Y. M., Y. N. Chen, and B. R. Pan, 2005: Distribution and floristics of desert plant communities in the lower reaches of tarim river, southern xinjiang, people's republic of china. *Journal of Arid Environments*, **63 (4)**, 772–784, doi:10.1016/j.jaridenv.2005.03.023, URL https://www.sciencedirect.com/science/article/pii/S0140196305000790.

Zhao, Y., X. Deng, W. Xiang, L. Chen, and S. Ouyang, 2021: Predicting potential suitable habitats of chinese fir under current and future climatic scenarios based on maxent model. *Ecological Informatics*, **64**, 101 393, doi:10.1016/j.ecoinf.2021.101393, URL https://www.sciencedirect.com/science/article/pii/S1574954121001849.

Zhu, G., W. Ju, J. M. Chen, and Y. Liu, 2014: A novel moisture adjusted vegetation index (mavi) to reduce background reflectance and topographical effects on lai retrieval. *PLOS ONE*, **9 (7)**, e102 560, doi:10.1371/journal.pone.0102560, URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0102560, publisher: Public Library of Science.

Zurell, D., 2020: Introduction to species distribution modelling (sdm) in r.

Zvoleff, A., 2020: glcm: Calculate textures from grey-level co-occurrence matrices (glcms). URL https://CRAN.R-project.org/package=glcm.

B. List of Figures

C. List of Tables

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E. Acronyms and Abbreviations

BSVM	Biased Support Vector Machine
Bin-SDM	Ensemble Binary Species Distribution Model
DEM	Digital Elevation Model
eOCC	Ensemble One Class Classifier
EVI	Enhanced Vegetation Index
FC	Feature Class
FPAR	Fraction of Photoysnthetically Active Radiation
GCM	Global Climate Model
GLCM	Grey Level Co-occurrence Matrix
GNDVI	Green Normalized Difference Vegetation Index
CLRE	Red-Edge Chlorophyll Index
GPP	Gross Primary Production
LSWI	Land Surface Water Index
MPA	Medicinal Plant Assemblage
MSAVI	Modified Soil Adjusted Vegetation Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near-infrared
NRMSE	Normalized Root Mean Squared Error
OA	Overall Accuracy
OCC	One Class Classifier
OCSVM	One Class Support Vector Machine
PA	Producers Accuracy
RBF	Radial Basis Function
RM	Regularization Multiplier
RS	Remote Sensing

RVI	Ratio Vegetation Index
SAC	Spatial Auto-Correlation
SDM	Species Distribution Model
SR	Species Richness
SSP	Shared Socioeconomic Pathway
Suit-SDM	Ensemble Suitability Species Distribution Model
SWC	Soil Water Content
SWIR	Shortwave-infrared
S-2	Sentinel 2
TPI	Topographic Position Index
TSS	True Skill Statistical
UA	Users Accuracy

Eidesstattliche Versicherung

Eidesstattliche Versicherung gemäSS ğ 13 Absatz 2 Satz 1 Ziffer 4 der Promotionsordnung des Karlsruher Instituts für Technologie (KIT) für die KIT-Fakultät für Bauingenieur-, Geo- und Um- weltwissenschaften
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