THESIS

PARTNERING INDIGENOUS AND WESTERN KNOWLEDGE SYSTEMS: A CASE STUDY OF MAASAI PERSPECTIVES ON PROBLEMATIC PLANTS IN NORTHERN TANZANIA'S DRYLANDS

Submitted by

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In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2024

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ABSTRACT

PARTNERING INDIGENOUS AND WESTERN KNOWLEDGE SYSTEMS:
A CASE STUDY OF MAASAI PERSPECTIVES ON PROBLEMATIC PLANTS AS LANDSCAPE CHANGE INDICATORS IN NORTHERN TANZANIA'S DRYLANDS

Maasai are an Indigenous group native to the East African drylands who traditionally practice pastoralism, but their livelihoods are undergoing drastic changes as they become increasingly dependent on cultivation, adapt to climate change, and endure socio-political pressures, including for wildlife conservation. We wanted to understand Maasai communities' views on this landscape-level change using their Indigenous knowledge of plants as an indicator. In the first part of this research project, we asked members of five Maasai villages located in Tanzania's Simanjiro Plains about their experiences with problematic plants to identify and rank which plant species and plant characteristics they found to be most problematic from their perspective without influence from our team's biases. In the second part of the project, we introduced a participatory science tool, CitSci, into the community to collect geospatial data on these plants to created habitat suitability models for the three most problematic plants – *Oltelemet* (*Ipomoea hildebrandtii*), *Alairahirah* (*Crotalaria polysperma*), and *Gugu caroti* (*Parthenium hysterophorus*). Using quantitative and qualitative analyses, we evaluated participatory science's challenges and benefits in the community as a source of continuous engagement, collaboration, and local utility. This speaks to our greater goal: to embed two-eyed seeing in participatory social-ecological research. By utilizing both Indigenous knowledge and scientific tools from the Western scientific world, there is potential to improve academic research and help Indigenous researchers carry out locally focused and community-led projects without the oversight, influence, or harm from external forces common with Western-focused approaches. Using this project as an exploratory case study, our conceptual framework shows great promise.

ACKNOWLEDGEMENTS

I would first like to thank the Maasai Communities that allowed us to conduct our research – Sukuro, Kitiengare, Loiborsoit, Emboreet, and Terat. All (well most) of the people we met were enthusiastic and curious about the research and always hospitable with a cup of homemade *chai*. Along that note, thank you also to the Regional, District, and Village leadership who helped us get boots on the ground. A special thanks also to participants of focus groups and surveys as well as the CitSci signups all helped provide incredible information and data. None of this would have happened if not for your knowledge and insight.

Our local research team also deserves immense gratitude. Isaya Rumas, our local research partner, deserves extra thanks for enduring weeks away from his home as a translator, driver, and mediator, as well as a friend. His son, Joshua Rumas, was also able to join us for much of the journey. He learned invaluable research skills while being my guide in the villages and the cities. It was comforting having someone to talk to. Our camp each day included our cook, Asiya, and our guard each night, Rumas Angela; thank you both for many laughs.

I would also like to thank my graduate committee: Stacy Lynn, Jody Voegler, and Melinda Smith. Stacy, you provided encouragement, understanding, and wisdom throughout the whole journey. All your tips, tricks, and advice were incredibly helpful, and I would have been much worse off had it not been for you. Jody and Mendy, you asked thoughtful questions and gave me incredible feedback during my defense. This thesis is now at least moderately digestible thanks to the two of you.

The Center for Collaborative Conservation provided me with the funds and logistical capacity to safely arrive in and depart from Tanzania…twice. To Allison Brody and John

Sanderson, I appreciate you both for your unwavering support and quick responses while overcoming the many logistical hurdles. I am also incredibly grateful for the funds, so that I could carry out this research.

Lastly, thank you to my family. To my in-laws, the Hultgrens and Pynes, you have been such positive cheerleaders. You were always kind and sympathetic to my position, but also forceful; no words could be more applicable than “just get it done”. To the McCartys, thanks for giving me intelligent, collegiate level feedback. And thanks for being flexible with my schedule/ I needed it. Finally, to the most important person, which has now become people: my wife, Erin, and our daughter Hadley. Erin, you have been so patient, when a two-year degree became three and then nearly four. You provided me with the motivation when I couldn’t provide any of my own and watched our daughter when my attention was elsewhere. I’m sorry I dragged you through this: the late nights, the missed deadlines, the episodes of inescapable self-pity. But you stuck through it with me and kept me moving forward. I am forever grateful to have you as my partner.

DEDICATION

To our newly born daughter, Hadley. Writing this thesis was good training in sleep deprivation and patience. I don't know how we got so lucky to not need them with you (yet).

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POSITIONALITY STATEMENT

I am a 30-year-old, cisgender, white male. I come from an affluent community in a predominantly white state – Colorado – where I have lived most of my life. I do not identify with any minoritized, marginalized, or underrepresented group. My paternal family descends primarily from Western Europe (France/Germany and Ireland) while my maternal family is of Ashkenazi Jewish descent in Eastern Europe. I am married to a white female with a similar upbringing as me. She earned her MA in Public Policy and Women and Gender Studies, so I have been introduced to many topics related to diversity, equity, and inclusion in an informal way. Together, we have a daughter that was born in 2024.

I have also been privileged to a university-level education. During my undergraduate studies, I was granted the opportunity to design and conduct research in the Manyara Region, Tanzania. My research's objective was to define "problematic" plants and traits in a Tanzanian landscape by consulting Maasai pastoralists and their traditional ecological knowledge. For my graduate thesis, I am continuing this work to delve deeper into both the social and ecological components of these previously defined problematic plants. I understand that my privilege has granted me these opportunities that not everyone gets to experience.

As a non-Indigenous researcher working in Indigenous spaces, I wanted to build a cohesive foundation for myself, and others, to produce more ethical and Indigenous-focused research. During my first field season, I knew there were power dynamics present around race, ethnicity, and organizational affiliation, but I was not aware of the true local history or culture, or even my own ancestry. I learned an extensive amount during that initial introduction about the vast diversity in ways of knowing. However, that was only the first step in a long series of learning opportunities.

Through ongoing self-evaluation during this research, my intentions are to help build the bridge between existing ways of knowing so that we may create better and more comprehensive knowledge for decision-making and problem solving in natural resource management.

INTRODUCTION

Historically, countries of the Western regions have caused damage to untold numbers of communities, knowledge systems, and ecosystems around the world. In the research realm, this has resulted in cultural misrepresentation, marginalization, exploitation, and violence (David-Chavez & Gavin, 2018; Kovach, 2010; Tuhiwai Smith, 2021; van Uitregt, n.d.). Western research needs to move away from its historically extractive and detrimental practices towards usefulness, reciprocity, and empowerment (Anda et al., 2021; Daniels & Walker, 2001; Matson et al., 2021; S. Walker et al., 2020).

This project utilizes a research approach called "two-eyed seeing" to bring to the forefront these once undervalued Indigenous knowledge systems. Two-eyed seeing captures the strengths and knowledge from an Indigenous "eye" while using select knowledge and tools of the more Western scientific "eye." Using both perspectives, we can understand more wholly the social-ecological system, making it more relevant to the locals that are affected, while discovering emergent and novel solutions (Kimmerer & Kimmerer, 2013; K. Whyte, 2018; Wilmer et al., 2021). It uses both ways-of-knowing, allowing them to overlap and coexist. It does not merge them, subsume one into the other, create a singularity that 'others' outliers, or rank their qualities hierarchically. Two-eyed seeing is instead a partnership between disparate and equal knowledge systems that reveals the multiplicity of correct methodologies and conclusions (M. J. Goldman, 2021; Peltier, 2018; Wright et al., 2019). This is the foundation our project was built upon to maximize the amount and suitability of information that is gathered and utilized. Our position was to step back and actively release preconceived notions of what we might find, allowing us to value local knowledge and perspectives to our fullest potential.

Under the two-eyed seeing framework, this research project has been carried out in full collaboration with several Indigenous Maasai pastoralists communities, who live in the semi-arid Simanjiro Plains of Tanzania. For centuries, Maasai have adapted to their highly variable dryland environment through extensive livestock-keeping, i.e., pastoralism, within the social-ecological boundaries of an area known as Maasailand, which stretches from southern Kenya into northern Tanzania (Maimai, 2014). Both the ecosystem and Maasai culture are continuous across the international boundary but have been interrupted by policy differences and restrictions on movement of people, livestock, and goods. Global pressures such as infrastructure development, government land use policies and evictions, wildlife tourism, invasive species, and natural resource restrictions have changed the landscape that Maasai rely heavily on. This has been coupled with an increase in crop cultivation that Maasai have been adopting to supplement their animal-derived diets (Homewood, 2004; Igoe, 2003; S. Lynn, 2010b, 2010a; Mccabe, 2003).

For over two decades, members of the research team have established deep roots in this region and with these communities through social-ecological research (S. Lynn, 2010a). This project is meant to build upon this foundation to collaboratively investigate an interest and concern that was raised by community members themselves: problematic plants. We chose to start with what the landscape looks like on the Simanjiro Plains. First, in Chapter One we ask, "What do the people tell us?" We do this by asking Maasai to define plant species and characteristics that are problematic to their livelihoods and on their landscape, without influence from our Western academic definitions of "problematic." To gather more inclusive opinions, we collected data in male and female groups that contained multiple generational age-sets.

Next in Chapter Two we ask, "What does the land tell us?" by establishing a participatory science project with the community, and modeling key problematic plant distributions based on community members' observations taken with a mobile app. Using these plant presence observations, we assess patterns in their distributions that may exist. We did this using various potentially influential environmental variables and algorithms to determine which combinations would produce the most useful results. To help maintain an Indigenous proclivity in the dataset, we introduced into the community the CitSci mobile app to facilitate information-gathering and sharing. Not only did this enhance our data collection efforts, but it also empowered locals with an additional tool and training to record observations. This half of the project is used as an exploratory two-eyed seeing case study, evaluating how academically oriented Western scientific tools and Indigenous knowledge can benefit each other. This type of information-gathering can assist local stakeholders with natural resource management decisions.

Finally, in Chapter Three, we present a synthetic view of this work's potential applications and ways that collaborations between researchers and local people can continue. We review the obstacles that the project encountered and potential pathways into the future given our current knowledge, feedback from the communities, and future challenges that may arise.

CHAPTER 1: DEFINING PROBLEMATIC PLANTS SPECIES AND THEIR CHARACTERISTICS FOR MAASAI COMMUNITIES IN THE SIMANJIRO PLAINS

Introduction

Prior to pursuing this endeavor, we need to outline the social-ecological system in which it takes part. For millennia Maasai pastoralists have roamed the East Africa drylands, often traversing hundreds of miles to lead their livestock to seasonal pastures. Maasai are an iconic tribal people, but their cultural story is facing rapid transformations in response to climate change, geopolitics, wildlife conservation, and development. These changes have spurred Maasai to adopt "modernity" and more sedentary crop-cultivation lifestyles, modifying their once nomadic livelihoods and accompanying landscapes. This has led to changes in Maasai relationships to various ecological elements, including vegetation and plant species that are viewed as problematic. With this background knowledge, we aimed to identify problematic plant species and the characteristics that cause them to be problematic from the Maasai perspective.

East African Dryland Environments

Our area of interest is East Africa with a focus on the drylands of north-central Tanzania in an area known as the Simanjiro Plains (Figure 1). Collectively, dryland ecosystems are technically defined by their aridity index (AI) value. AI is computed as a ratio of mean annual precipitation (MAP) to potential evapotranspiration (PET) (United Nations Environment Programme, 1992). In drylands, this ratio is $\leq$1:1.5 = 0.65. This means that water is a limiting resource because more water is being lost through evaporation and transpiration (i.e., evapotranspiration) than is being gained in precipitation. The most recent IPCC Special Report on Desertification (Jia et al., 2022) specifies four dryland subcategories: dry sub-humid ($0.50 < AI \leq$

0.65), semi-arid ($0.20 < AI \leq 0.50$), arid ($0.05 < AI \leq 0.20$,) and hyper-arid ($AI < 0.05$). The Simanjiro Plains are semi-arid.

Drylands are characterized by mosaics of semi-desert, grassland, scrub-shrub, and woodland ecosystems (Oesterheld et al., 1999; Safriel et al., 2005). They make up approximately 40% of Earth's land surface area and are home to over two billion people, largely in developing countries. Although drylands are proportionately abundant compared to many other ecosystems, they are relatively ignored by international conservation efforts (Food and Agricultural Organization, 2021; International Union for Conservation of Nature, 2021)

Precipitation falls in a bimodal pattern in northern Tanzania with two rainy seasons and two dry seasons occurring each year. This is because the intertropical convergence zone (ITCZ) – a constantly moving weather zone near the equator where the Northern and Southern hemispheres' trade winds come together based on the Sun's seasonal latitude – passes over the area twice annually. At approximately the summer solstice in June, the ITCZ is at its most northward latitude, and from this point travels southward, crossing over northern Tanzania October-November, producing a short rainy season. As it moves northward after the winter solstice in December, it passes back over the region February-March and then southward again March-May. Without the ITCZ ever having moved off the region February-May, this is what produces a long rainy season (National Oceanic and Atmospheric Administration, 2023).

Long-term annual precipitation averages between 500-1000mm, but the coefficient of variance is high in these regions leading to high interannual variability; the Simanjiro Plains annual precipitation averages approximately 600 mm/year (J. Ellis & Galvin, 1994; Palmer et al., 2023; Prins, 1988). Local factors such as topography, temperature, and trade winds affect these patterns immensely, and there are annual and semi-decadal cyclic changes in ocean and atmospheric thermal circulation, called global teleconnections, that can amplify or dampen these effects (Palmer et al., 2023). The most prominent teleconnections that affect the East African region are the El Niño–Southern Oscillation, Indian Ocean Dipole, Quasi-Biennial Oscillation, and the Madden–Julian Oscillation (Palmer et al., 2023). Independently these can cause great variations in rainfall, but they can also influence each other, resulting in even greater variations season-to-season and year-to-year (Intergovernmental Panel on Climate Change, 2021). In the past 30 years, this has led to annual rainfalls that range from 20-300% the long-term average, resulting in a volatile mix of droughts and deluges (Palmer et al., 2023).

Anthropogenically-induced climate change has had vast implications for weather patterns. Greenhouse gasses warm the Earth's surface which can have two opposing effects: (1) greater atmospheric moisture content leading to more precipitation, and (2) higher evapotranspiration rates which intensify aridity (Palmer et al., 2023). Since the 1980's, both phenomena have been observed in contrasting seasonal trends. The long rainy season is experiencing a drying trend, causing more and worse droughts, while the short rainy season is experiencing a wetting trend, which has the same effect on floods. In the past 30 years, this has led to shifts in MAP of 50-100mm/year, both positive and negative, depending on the season (Palmer et al., 2023). Anomalous precipitation events punctuate these trends, magnifying the system's stochasticity. Between these competing trends, the region has been experiencing less annual rainfall overall. These changes are only expected to increase in magnitude, albeit with substantial spread amongst different climate models (Palmer et al., 2023).

With water being the most limiting factor in arid and semi-arid systems, the changes in these stochastic weather patterns can have drastic landscape effects (J. E. Ellis & Swift, 1988; Safriel et al., 2005). Changing precipitation patterns have led to fluctuations in ecosystem structure, function, dynamics, and services (Borics et al., 2013; Niang et al., 2015). Increased rainfall, such as has been observed during the short rainy season in northern Tanzania, can cause landscape greening (Piao et al., 2020), increased net primary production (Zarei et al., 2021), more erosion(Blake et al., 2018), faster turnover in biogeochemical cycles (Intergovernmental Panel on Climate Change, 2023a; Iverson & Dervan, 2019; X. Zhang et al., 2021), higher rates of water-borne pathogens and vectors (e.g., mosquitoes, ticks, fleas) (Caminade et al., 2019), and depressed fire regimes (Senande-Rivera et al., 2022). Conversely, decreased rainfall is likely to see the opposite effects. Not only can this affect the ecological state of the environment, but it can also affect the social state of the human populations living and relying on these lands.

Land use is directly related to precipitation patterns, and as precipitation patterns change it can alter productivity and the success of land use that was traditionally practiced in that place (Intergovernmental Panel on Climate Change, 2021). Under a bimodal precipitation regime, 600 mm falls in approximately 90-120 days, which is the minimum requirement for rain-fed maize, sorghum, millet, and bean cultivation. Even slight spatial-temporal rainfall distribution variations can greatly affect which species will successfully produce a harvest (J. Ellis & Galvin, 1994).

People are likely to see changes to human appropriated primary production, human and livestock diseases, infrastructure development and maintenance, and adaptive capacity and resilience (Intergovernmental Panel on Climate Change, 2023b). With local weather patterns changing, so too do disturbance regimes, soil properties, plant communities, and vegetation distributions. These cascading effects may allow opportunistic plants to spread, which can potentially negatively impact Maasai land use opportunities. By interrupting the way in which Maasai interact with their environment, these plants, native and introduced alike, become problematic to Maasai livelihoods.

People

Maasai are a Nilotic tribe that migrated southward from Sudan until they settled in Kenya and Tanzania in the 15th century. The word *Maasai* translates to "people speaking *Maa,*" which is their native language (Maimai, 2014). In 2018, the Kenya census reported 1.2 million Maasai (Iverson & Dervan, 2019) and more than 400,000 Maasai are estimated to reside in Tanzania (International Work Group for Indigenous Affairs, 2018). Maasai inhabit a region that is 150,000 km^2 which lies within the East African Rift Valley, stretching from southern Kenya into northern Tanzania. Although they are an iconic tribe, and the most well-known tribe of the region, this area is also home to over 100 other Indigenous tribes (Maimai, 2014). Semi-arid and arid woodlands, bushlands, and grasslands define the ecosystem. Quintessential mammalian migrations of wildebeest (*Connochaetes taurinus*), zebra (*Equus burchelli*), and elephant (*Loxodonta africana*) have historically crossed these lands along with iconic predators, such as lions (*Panthera leo*) and hyenas (*Crocuta crocuta*) (Lamprey, 1964). The botany of this region's botanical makeup includes many species of *Acacia* trees, the swollen baobab trees (*Adansonia digitata*), and seas of biodiverse grasses and shrubs (Turner et al., 2022).

The Simanjiro Plains is an area within Maasailand that is composed of zones ranging from village lands to protected areas (PAs), some of which exclude people and livestock. Simanjiro PAs include national parks and a game reserve that exclude people and livestock: Tarangire National Park (TNP), Lake Manyara National Park (LMNP), and Nkungunero Game Reserve (NGR). They also include several less restrictive Game Controlled Areas and Wildlife Management Areas: Simanjiro Game Controlled Area, Lolkisale Game Controlled Area, and several wildlife management areas (Bluwstein, 2018). The game-controlled areas are managed by surrounding villages, as the village lands themselves form an important wildlife dispersal area.

TNP, located to the west of our study villages, is a fully protected area that excludes all consumptive land use. Historically, TNP provided reliable forage reserves during dry seasons and drought (J. Ellis & Galvin, 1994; S. Lynn, 2010a; S. J. Lynn, 2009) for centripetal grazing patterns – keeping animals further from permanent water sources in the wet season and moving them inward toward water sources as the dry season progresses (Holechek et al., 2010) – but the Park is now not accessible to people (other than paying tourists) and livestock. This is problematic for Maasai because TNP is where Simanjiro's perennial water sources exist. Maasai are cut off from already limited resources.

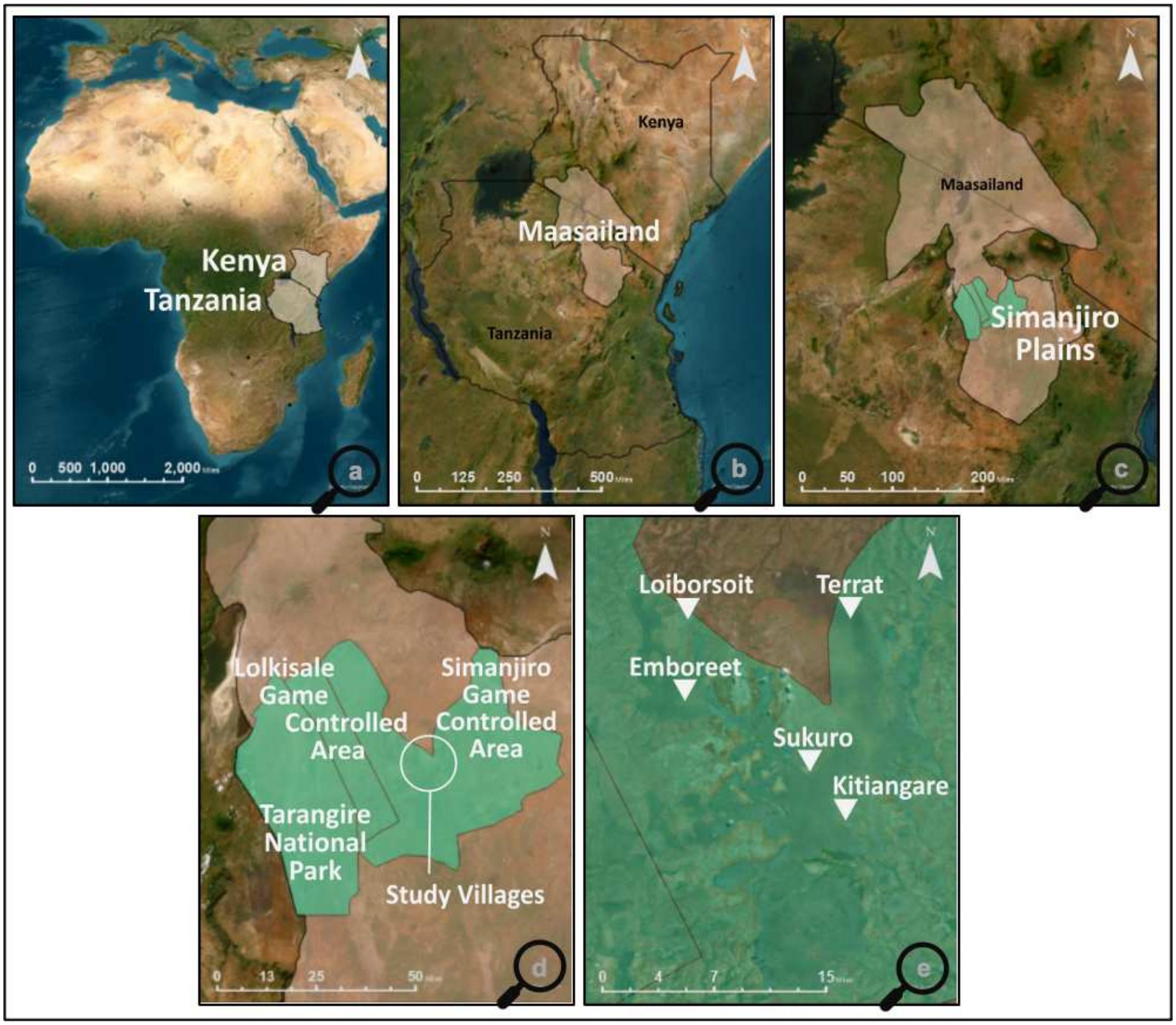


Figure 1. Maps of increasing spatial definition from (a) the African continent to (b) the countries of Kenya and Tanzania to (c) the Maasailand boundaries showing the Simanjiro Plains to (d) Tarangire National Park, Simanjiro Game Controlled Area, and Lolkisale Game Controlled Area which are the protected areas that comprise the Simanjiro Plains and finally to (e) the study villages where the research project was conducted.

To survive in and adapt to their environment's stochastic nature, Maasai ground their culture deeply in pastoralism, the practice of extensive animal herding. There are many definitions of "pastoral," but they all include nomadic or semi-nomadic animal husbandry on open pastures, with movement patterns occurring over varying time periods. Pastoralism can be seasonal, supplemented by other professions, or an exclusive lifestyle (K. Homewood et al., 2019).

Pastoralists access forage and water that are dispersed across time and space according to rainfall patterns by moving their animals across the heterogeneous landscape. It is favored in comparison to cultivation in an area with bimodal wet seasons, which results in less consistent vegetation growth (J. Ellis & Galvin, 1994). Excluding years of unfavorable conditions, continuous and extensive movement allows their animals to graze year-round, taking advantage of forage resources where they grow.

Livestock convert grasses – an energy source that is indigestible and unusable for humans – into milk and meat resources that humans can exploit (Lamprey, 1983). In the Simanjiro Plains, Maasai keep hardy, mixed livestock herds of Zebu cattle (*Bos indicus*), Tanganyika sheep (*Ovis aries*), and Maasai goats (*Cabra hircus*). In addition to food production, these animals are used for exchange, gift giving, investment collateral, as a symbol of social standing. Donkeys are also used for resource transportation, like water hauling (K. Homewood et al., 2019; Maimai, 2014). Most importantly, however, livestock provide sustenance. Although occasionally used for their meat and blood, these animals are kept primarily as female-dominated dairy herds because the continuous caloric production is more sustainable than intermittent slaughter (K. Homewood et al., 2009).

Maasai livestock coexist with wildlife that also use these habitats for grazing and reproduction and follow similar landscape movements searching for forage and water (K. Homewood et al., 2019; Mccabe, 2003; Wojtkowski Barbeau, 2017). Zebra and wildebeest can be seen alongside cattle, sheep, and goats in the Simanjiro Plains (Figure 2). Livestock diversity parallels wildlife herd diversity in that each species can coexist by filling specialized ecological niches that respond to fluctuations in environmental conditions. This maximizes the landscape's biological productivity and provides risk reduction for Maasai (Lamprey, 1964; Swift et al., 1996).

However, changes in land-use-land-cover (LULC) are causing cascading effects on the entire Simanjiro Plains social-ecological system.

Figure 2. In the foreground, young Maasai men herd cattle while zebras graze nearby in the midground and wildebeest in the background (photo credit: The EastAfrican, 2022).

Indigenous Knowledge Systems

Sustained interactions between people and their environment results from generations of acquired and transmitted Indigenous traditional ecological knowledge (TEK) (K. Whyte, 2018). These knowledge systems are based on information pertaining to the local environment that is learned by experience and transmitted to each successive generation, typically through practice and oral communication (Ruddle, 1991; Ruiz-Mallén & Corbera, 2013; K. P. Whyte, 2013). It is their pedagogy, the foundation of how human communities learn and choose to interact with their natural surroundings as well as their capacity to adapt to environmental changes and disturbances (Fernández-Llamazares et al., 2021).

Unfortunately, traditional ways-of-knowing have been largely undervalued and ignored by Western science, causing valuable insights and information to be overlooked by other systematic information-gathering methods used in Western science (M. Goldman, 2003; M. J. Goldman & Milliary, 2014; Ruiz-Mallén & Corbera, 2013). Traditional scientific approaches tend to devalue Indigenous insights because observations are not necessarily made systematically as called for by Western scientific methods. We propose that it is important to value Indigenous ways-of-knowing *because* of their different observational approaches. Therefore, rather than neglect these knowledge systems, we centered our project around Maasai Indigenous knowledge to ensure that it is relevant and informative for all stakeholders.

While the central tendencies of Western and Indigenous approaches may differ, they are also remarkably similar. Scott (Scott, 1998) uses the concept *metis* to describe practical place-based knowledge, skills, and experiences that are often held by local people or practitioners. Traditionally, *metis* contrasts with formal, standardized knowledge imposed by "states", such as Western science. But Goldman (2003) argues that "rather than a separate type of knowledge from what is considered 'scientific', *metis* is a part of all knowledge production processes, including scientific. That is, personal, practical knowledge is a part of all knowledge." Therefore, our individual ontologies and epistemologies – philosophical branches concerned with understanding reality and knowledge, respectively – shape our outlook(Grier, 2010; Hume, 2016). "Facts" become ambiguous, objectivity versus subjectivity becomes obscured, and seemingly divergent knowledge systems begin to incorporate each other. This belief spearheaded our journey into this project.

A Changing Landscape

In the 1950's after independence for many East African countries, foreign pressures for biodiversity conservation, particularly megafauna, caused an eruption of protected areas, largely as national parks. These were modeled after the American National Park's philosophy to exclude all consumptive land uses like settlement, grazing, and crop cultivation. In 2018, PAs encompassed 48.2% of the terrestrial land surface, 20.4% of which is considered "strict," excluding *all* human use (Riggio et al., 2019), including 22 national parks (Tanzania Wildlife Management Authority, 2024). This has led to evictions of Indigenous people from their traditional homelands and in many areas compressed human populations into smaller areas. This is made more problematic because PAs tend to encompass important water resources and dry season grazing pastures, which leads to greater stresses on less productive pastures.

Land tenure has also changed on the landscape. All land is owned by the Tanzanian government. What was once communally shared land has become increasingly parceled and leased long-term following a villagization program that began in the 1970s (S. Lynn, 2010b). People who once herded their livestock freely were forcibly settled on specific centralized tracts. In addition, according to the Village Land Act V (United Republic of Tanzania, 1999) land that does remain communal requires *active use* in order for people to maintain their allocated rights. This framework rejects the centuries-old practice of allowing select pastures to remain fallow for emergency purposes (i.e., drought). Immobilization and the threat of losing land access have forced Maasai to keep hold of their allotments by cultivating them (Lynn, 2010a, 2010b).

Local people are becoming increasingly dependent on cultivation as a supplementary economic investment to diversify their livelihoods (Lynn, 2010a, 2010b; Goldman, 2003). Whereas the livestock rearing is dependent on the previous year's success, crop cultivation is independent year to year based primarily on precipitation. Maasai in this region recognize that following a drought when a good rainy season transpires, crop cultivation is immediately profitable while livestock herds need several years to recover their numbers (Lynn, 2010a). However, over-investment in crop cultivation can prove detrimental to food security if seed-sowing is followed by lack of rain during the long rains that happen approximately February through May. This is becoming more precarious since an initial analysis of changing cultivation patterns completed by our team indicates that between 2013-2023 cultivated land coverage in Simanjiro increased nearly 400%, including both household and commercial plots.

Climate change is altering patterns of productivity for all human land uses and, thus, livelihoods. As mentioned before, the East African region has been greatly affected by less overall precipitation, less predictable precipitation, and more extreme precipitation events since the 1980's (Palmer et al., 2023). In 2022, a Red Cross Emergency Plan of Action reported 62,000 cows, sheep, goats, and donkeys had died in northern Tanzania's Manyara and Arusha Districts after extreme drought continued for four months (International Federation of Red Cross and Red Crescent Societies, 2022). Just one year later, from November to December 2023, extreme flooding in the Manyara Region resulted in over 6,000 destroyed/displaced households, a 60% increase in food insecurity, and at least 130 human fatalities, in addition to "numerous livestock" fatalities (International Federation of Red Cross and Red Crescent Societies, 2024a, 2024b).

Climate changes are occurring simultaneously with growing human populations and infrastructure development. Access to healthcare has increased life expectancy and decreased child mortality for these rural environments (Afnan-Holmes et al., 2015; Hategeka et al., 2019). Based on estimates from census data, the Maasai population grew nearly 60% in 20 years, from one million in 1998, to more than one-and-a-half million in 2018 (International Work Group for Indigenous Affairs, 2019; Iverson & Dervan, 2019). Roads and information and communication technologies (i.e., cellphones) have also brought in drastically more human traffic (Butt, 2015; Summers et al., 2020). Government-built highways divide the landscape by introducing more and larger vehicles as well as physical barriers, such as fencing. Since their introduction into Kenya in the 1980s (Maliro, 2023), motorcycles – locally named '*boda-boda'* or '*piki-piki*' – have become a primary transportation mode across East Africa. They've become so popular that motorcycle imports rose 10,000% in the first decade of the 21st century alone (Automobile Association of Tanzania, 2012). This has resulted in an explosion of unofficial "social" roads/trails observable on aerial images in nearly every environment due to motorcycles' ease of off-road use (Isaya Rumas, personal communication, November 1, 2022).

The consequences of these social-ecological changes have a snowball effect on LULC and culture. Land fragmentation and land loss by PAs, roads, and villages decreases land connectivity. Exclusion from PAs and land loss require increased crop cultivation. Financial and labor investment in cultivation and pastureland loss in turn leads to smaller livestock herds, requiring better crop yields to feed a growing population (K. Homewood & Brockington, 1999; K. M. Homewood, 2004; Igoe, 2003; S. Lynn, 2010b; Mccabe, 2003). The land-cover and land-use changes are reciprocal, affecting Maasai livelihoods. They are forced to adapt their natural resource management knowledge and practices in an attempt to maintain livelihoods to support their families and communities (Bekure et al., 1991; Maimai, 2014).

Because Maasai are so directly reliant on the landscape around them, we wanted to look at one of the primary changing factors that dictate the system: plants. Based on discussions in the 2010's between members of the research team and Maasai living in the Simanjiro Plains, problematic plants became a notable system component requiring investigation. Without knowing the specific problems caused, we began a pilot study in 2017 to ascertain (1) what problems can be caused by plants and (2) which plants cause them. We quickly learned that we had to reverse the order of these questions to figure out which plants were problematic and the problematic characteristics those plants exhibited. This subtle but profound shift was one of the first that followed an Indigenous thought process rather than our preconceived notions.

Problematic Plants

Great ecological perturbations, such as flood and drought, are becoming more destructive and less predictable in the Simanjiro Plains (Community communications, 2023). One fallout of these disturbances is that recovering lands produce environmental resources that are increasingly intermittent in space and time. This allows plants, animals, fungi, or microbes with competitive characteristics – rapid proliferation, efficient resource extraction, economical nutrient allocation, aggressive behavior, etc. – to recolonize disturbed areas and fill vacant niches (Lekevičius, 2009). As certain plants utilize these opportunities to spread, the ecosystem's biodiversity, structure, and function can change dramatically in a relatively short period. These changes can alter land cover and composition, land use, and land productivity (Borics et al., 2013; Dornelas, 2010; Potapov et al., 2022). This is a reciprocal cycle as land use, subsequently affecting land cover and productivity, can also drive plant distribution patterns. The feedback of disturbance and anthropogenic reaction is deterministic for certain plants' spreading rates and patterns (Gerstner et al., 2014). Oftentimes these plants can be problematic by posing harm to the social-ecological systems they exist in (Boone et al., 2011; Galvin et al., 2001).

From a scientific viewpoint, some common types of problematic plants are weeds and pests, but the most notorious are invasive alien species (IAS). IAS are those that have historically been absent from a location and are anthropogenically introduced, causing disturbances to newly inhabited foreign ecosystems. IAS have an uncanny ability to spread due to diminished predation, reduced competition, and/or increased resource availability (Clinton, 1999; Colautti & MacIsaac, 2004). This can result in non-native species dominating over essential resources, outcompeting native plants, changing biological makeup, and further destabilizing ecosystem functions oftentimes in an irreversible manner (CBD, 2009; Gichua et al., 2013; Lowe et al., 2007; Obiri, 2011).

However, invasive species are just a single category of problematic plants experienced and studied and applied through science and academia. For Indigenous communities, these might be entirely different. For example, they can prove poisonous and even fatal for humans, domestic animals, and/or wildlife. Another example is that these plants can change soil processes on small- and large-scales including hydrologic infiltration and runoff, evapotranspiration, and nutrient cycling. Lastly, they may outcompete plants beneficial to humans, such as crops and forage. For subsistence populations that require some semblance of reliability from their environment, these disturbances can prove extremely detrimental.

The Project

While a great amount of research has been conducted on plants considered to be problematic from a Western point of view, very little research has been done to understand what problematic means from a non-Western perspective. We wanted to flip this narrative to allow the identification of problematic plant characteristics and species to be emergent by investigating this issue from Indigenous Maasai ontologies, taking the approach of two-eyed seeing. This would allow us to determine plant species and characteristics that are most disruptive and damaging to local livelihoods Additionally, we wanted to represent many voices by including all ages and genders in the conversations, and to then determine how differences in gender and generation may contribute to what characteristics and species are identified as problematic.

With over 20 collective years of research experience by members of the team in the Simanjiro Plains, this region became the perfect candidate to test the conceptual two-eyed seeing framework. It gave us an opportunity to engage with community members who were comfortable with our presence and intentions, greatly reducing our access to entry. Because of this familiarity with the communities, we were able to wholly focus on the project, trial-and-error more ideas, and receive more honest feedback.

Research Questions

1. What are the characteristics that define problematic plants for Simanjiro Maasai communities?
2. What plants do Maasai in the Simanjiro Plains find to be most problematic as measured by a salience index (a metric of frequency x severity) and why?
3. How do patterns of problematic plant species and characteristic identification vary by various groups in the community, specifically by generation and gender?

Methods

All procedures conformed to Institutional Review Board Human Subjects protocol #3284, approved by Colorado State University on 5/16/2022 based on Free, Prior, and Informed Consent (FPIC). This is a principle that respects the rights of Indigenous peoples and local communities to make autonomous decisions about developments, projects, or activities that may affect their lands, territories, and resources. It is a crucial component of international human rights standards, particularly in the context of environmental and developmental projects (Food and Agricultural Organization, 2016) FPIC entails:

- **Free**: Consent must be given voluntarily, without coercion, intimidation, or manipulation. Indigenous peoples and local communities must be able to make decisions freely, based on their own understanding and without external pressures.
- **Prior**: Consent must be sought in advance of any project or activity taking place giving communities sufficient time to consider the potential impacts and alternatives, and to engage in meaningful dialogue with the project's proponents.
- **Informed**: Consent must be based on accurate, objective, and accessible information about the project or activity, including its potential impacts on the environment, health, culture, and livelihoods of the affected communities. This requires clear and understandable communication of relevant information, often facilitated through culturally appropriate methods and languages.
- **Consent**: Indigenous peoples and local communities have the right to accept or reject the proposed project or activity. Their consent is not merely procedural but reflects their authority to make decisions over their lands, territories, and resources.

Implementing FPIC requires genuine partnership, respect for local knowledge and governance systems, and a commitment to equitable and sustainable development that respects human rights and environmental integrity.

In addition to FPIC, we also strive to follow the FAIR and CARE principles of data governance. FAIR includes making the data findable, accessible, interoperable, and reusable (GO FAIR, 2016). CARE focuses on the collective benefit, authority over control, responsibility, and ethics (Global Indigenous Data Alliance, 2018). These principles reflect a shift towards more inclusive and ethical practices in data governance, moving beyond conventional frameworks to incorporate Indigenous perspectives, values, and rights. They aim to empower Indigenous communities to manage and benefit from their data in ways that are respectful, equitable, and supportive of community self-determination and well-being.

Data Collection

A participatory rapid appraisal method (PRA) was used to collect data for this study. This methodological category allows researchers to gather ample information efficiently and cost-effectively (Beebe, 1995, 2004; Chambers, 1981; Kumar, 1993). It uses mixed qualitative-quantitative methods to elicit responses from individuals or groups about the researcher's topic and scope. This process is iterative and reciprocal because, as new ideas emerge so will new questions, and vice versa. Overtime, it produces themes, or "piles", that allows the researcher to ask more focused questions, in both immediate and future discussions (Ager et al., 2010, 2011). This is an inclusive community-driven process that draws upon Indigenous knowledge and perceptions, creates open discussion, values differing viewpoints, and ultimately sheds insight on what is most relevant to locals.

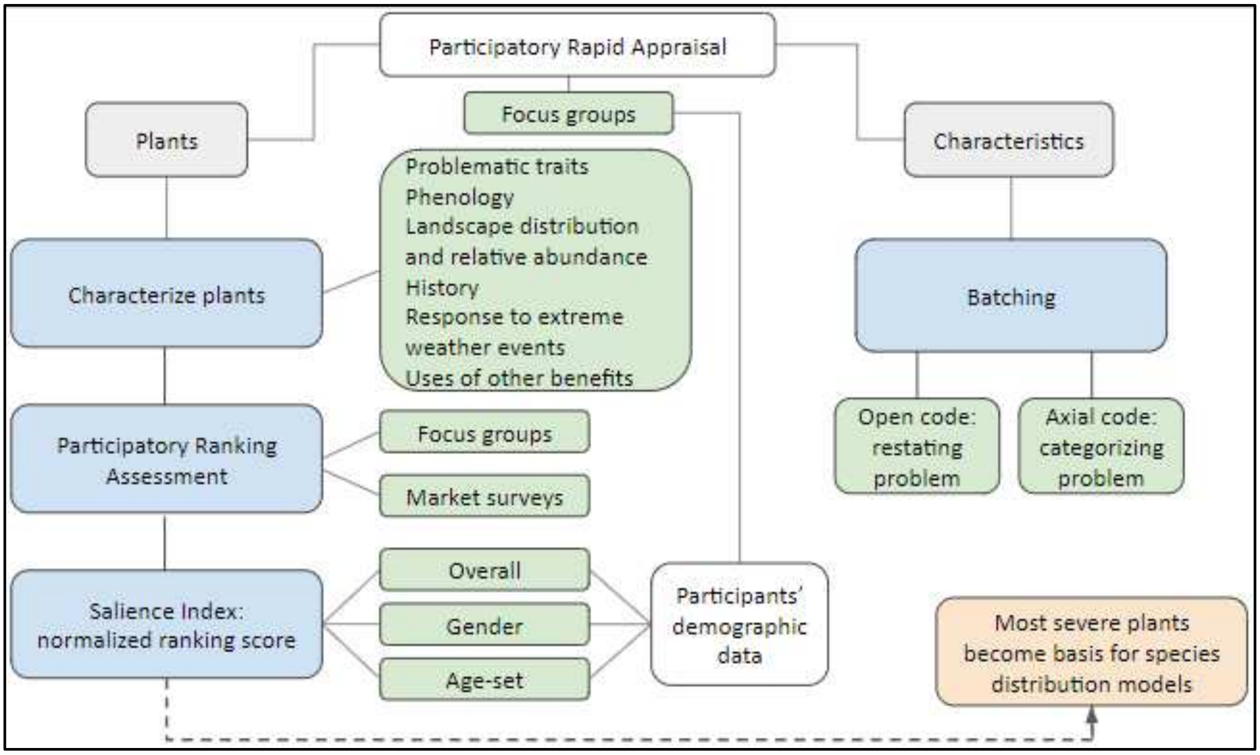


Figure 3. A conceptual diagram showing the steps (blue) of the methodology with details (green) about characterizing and ranking the problematic plants and characteristics.

Our methodologies are based on and adapted from a pilot study using a PRA approach by McCarty (McCarty, 2018) in the same location (Figure 3). Thirteen focus groups were set up across three study villages with the help from village leaders: Sukuro (n=6), Kitiengare (n=5), and Loiborsoit (n=2). Two additional focus groups were attempted but were not completed and, so, were excluded from the study. Each completed focus group involved between five and 12 participants and lasted between 90-180 minutes. (See Table 1 for the total number of participants by age-set and gender; see Appendix A for focus group questions).

Focus groups followed a standard procedure. They were gendered, either male or female. First, participants' generational age-set cohorts were recorded, which are an important component of Maasai culture. Upon circumcision in early puberty, Maasai men are incorporated into a generational age-set that each span ~15 years. Each age-set adopts a name, a set of responsibilities, and group norms. Every eight years the men will advance with their peers to the next grade, gaining additional authority and decision-making in village affairs (Fosbrooke, 1956; Mccabe et al., 2011). While these traditions and rankings are at times superseded by the authority of non-tribal governments and individual's level of education, a man's socio-political status in the tribe is still largely a reflection of his age-set (Bekure et al., 1991). Women adopt the name, but not the responsibilities, of their husbands' age set when they marry. However, they are often referred to by their general age-group: *Endito*: young girl, pre-marriage; *Esiangiki*: new wife; *Yeiyo*: mother; and *Koko*: grandmother.

Age-sets that contributed to this 2022 study included: *Nyongulo* (junior warriors, *Moran*): 15-30 years old; *Korianga* (senior warriors): 30-45 years old; *Landis* (junior elders): 45-60 years old; *Makaa* (senior elders): 60-75 years old; *Seuri* (retired elders): 75-90 years old (retired elders). There are additional age-sets with living members, including *Nyangusi* (retired elders): 90-105 years old and *Ilterito* (retired elders): 105+ years old, but none of their members participated in the data collection. The age cutoffs between these age-sets are more obscure than what is captured here but our stated age ranges are generally representative. It should be noted that no *Nyongulo* under the age of 18 took part in the research.

Second, each focus group concentrated on listing problematic plant species and then defining and characterizing problematic plant characteristics (Figure 4). Participants were asked to free-list all the plant species they found to be problematic. Follow-up questions helped define each plant species' problematic characteristics and basic phenology (see Appendix A for Focus Group Questions), as well as recognized uses, benefits, and other characteristics.

Third, after the focus groups' members agreed that there were no additional problematic plants to be listed, we performed a guided ranking exercise. Participatory ranking methodology

(PRM) builds on the PRA in a similar quantitative-qualitative manner by producing numeric rankings for each “pile” (i.e., problematic plant) discussed in the first part of the focus group (Ager et al., 2010, 2011). In this instance, each participant was given three color-coded stickers labeled with their own unique identification number, which was linked to the individual’s self-identified age-set and gender (without personal identifiers), allowing analysis by these categories. Red/pink stickers corresponded with that individual’s opinion of the most problematic plant, yellow stickers with the second most problematic plant, and green stickers with the third most problematic plant (Figure 5). Plant names were then written on a posterboard, and participants identified the top three plant species they independently perceived to be most problematic by placing stickers next to the corresponding plant. Participants were invited up individually to reduce bias and influence from others, and each plant name was read off by our local Maasai facilitator to ensure that non-literate individuals could mark their plants without error. Immediately after completing the sticker placement exercise, each ranking was assigned an inverted score – number one rankings were assigned a score of three, second was assigned a score of two, and third was assigned a score of one. Scores were summed for each plant, converting individual rankings into collective ranking *severity* categories for each species, while also allowing us to document *frequency* of mentions as a top-three problematic species.

Lastly, the three overall top-ranked species were identified, and further questions were asked about historical and current landscape dispersion, relative abundance in various environments, responses to extreme weather events (i.e. flood and drought), any used or known management approaches, and other information volunteered by participants. These follow-up questions gave us more information on the most problematic plant species and allowed us to evaluate the response similarities across villages and genders. This way we could discern if there was spatial variability or perceived valuation differences.

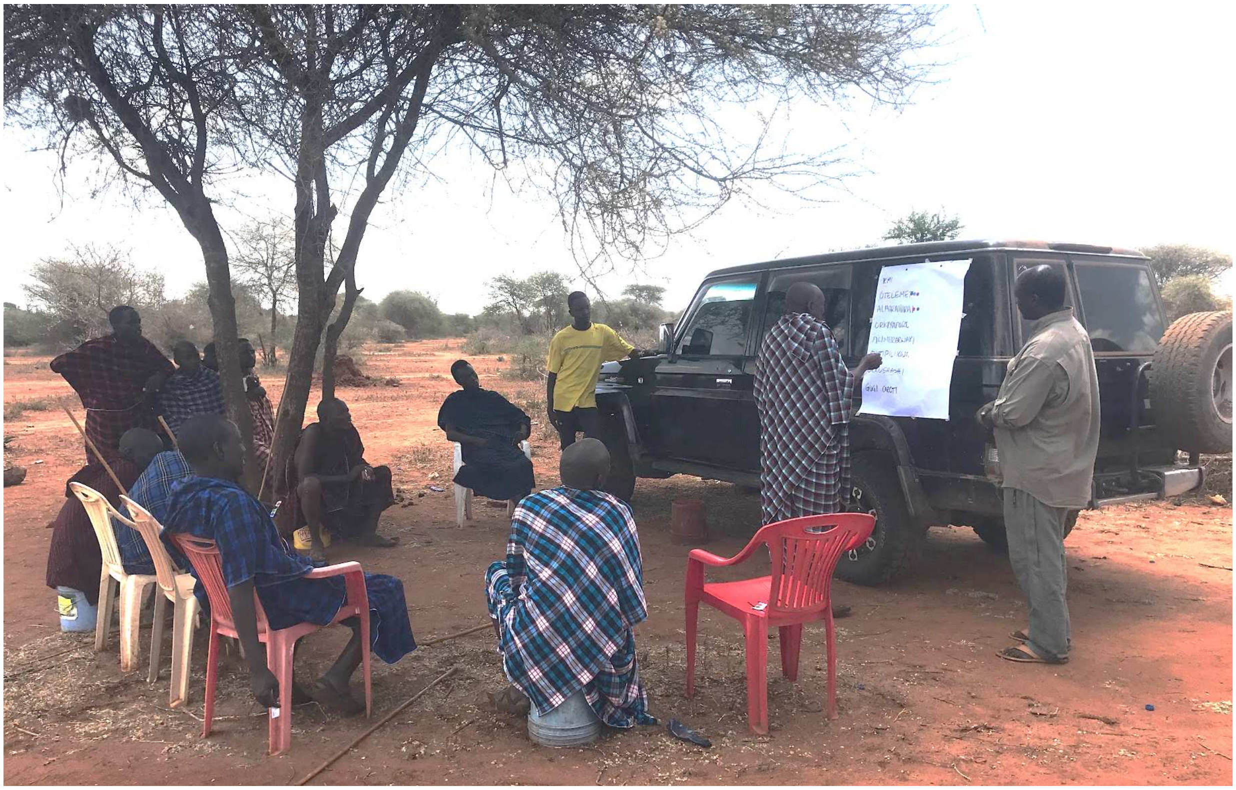


Figure 4. Example of a ranking exercise occurring during a focus group. Groups were structured so that ideas and conversation could be expressed communally, but rankings occurred individually (photo credit. C. McCarty, 2023).

Once all focus groups were completed, an aggregate list was created that contained all mentioned problematic plants. This list was then utilized to perform a similar ranking exercise on a larger scale via a survey conducted on market days in nearby villages. At the two largest market days in neighboring villages – Terat and Emboreet – passersby were asked to participate in a brief ranking exercise. Taped to the research vehicle was a posterboard that contained a list of all the problematic plants that had been mentioned during focus groups. One at a time, participants were given the same three-colored-sticker set, but these were marked with two letters that corresponded with their gender and age-set (for example "NM" indicated "*Nyongulo* Male"). Our local research team used a predetermined script to guide participants through the exercise, reading off each of the 23 plant names, and helping them place their stickers accordingly. This helped to both increase species ranking sample size and increase geographic representation.

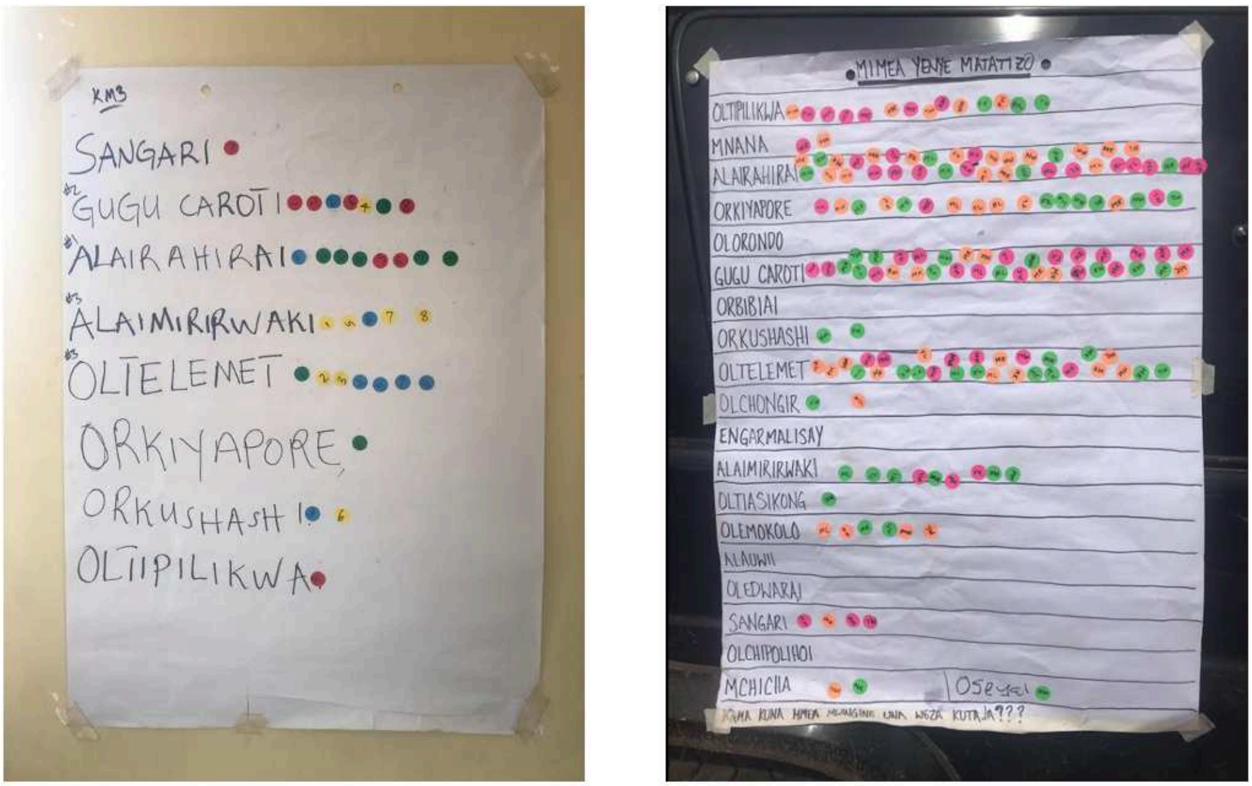


Figure 5. Examples of ranking posterboards from a focus group (left) and market survey (right) [photo credit: C. McCarty, 2023].

Data Processing

During the original data collection, all plants were identified in Maa or Swahili languages (Table 2). We attempted to find the English common name (sometimes non-specific, e.g., Morning Glory) and/or Latin scientific name for all species listed but were unable to identify all the plants to the species level because of field limitations. Therefore, the Maa or Swahili names that were used by participants will be used throughout this first chapter for consistency.

Problematic Plant Ranking: Smith Salience Index

Calculating a score that accounted for each plant's individual ranks, group ranks, and number of ranks required a modified Smith's Salience Index (SSI). Salience represents the frequency and average ranking of an individual item listed in a domain. Our domain consisted of all the items (n=23 plants). This was done by totaling each individual inverted score and dividing it by 220, the total number of participants in both the market and focus groups. This weights the score so that the plants that are ranked more frequently but not as severely (or vice versa) are not misrepresented (Newing, 2010). It should be noted that this index can become biased when there are not many participants, such as with the elder generations.

Problematic Characteristics

To answer the question of what plant characteristics are determined to be most problematic, researchers used a batching methodology, which is qualitative data analysis that "batches" each characteristic into an easily translatable code (Newing, 2010). This process involves two stages of batching into like categories, first to identify each plant's problematic characteristics, and then to thematically cluster these characteristics into groups. The dataset of raw characteristics was batched down to 26 open codes, which eliminated redundant information by consolidating same/similar responses into more precise categories. Some plants had more than one problematic characteristic, each of which was extracted out and coded separately. These codes were refined into secondary axial codes, which were determined by the part of the system that they impacted.

During the data processing step, we established rules for transcribing the raw data to ensure consistency. (1) Each answer was coded as it was stated during the focus group. No inferences were made to answers given for the same plant mentioned in other focus groups. For example, a plant may have caused “Extended hooves" and “Livestock fatality” in one focus group, but only “Extended hooves" in a second focus group. Although the two plants are the same, the two answers were treated independently. Since it was not stated in the second focus group that the plant can cause death, it was not inferred when coding the plant’s problematic characteristics. (2) All impacts for animals were consolidated into the broad category “livestock.” This is because we did not further investigate each animal species’ import to Maasai livelihoods, and thus it was unnecessary to divide them in our analysis. Raw data contain species-specific information that was specified during data collection. (3) Problematic characteristics were not ranked as part of the analysis because if a plant had multiple problematic characteristics, it could not be determined if the plant was ranked as it was because of a singular characteristic, multiple characteristics, or the combination of characteristics. Therefore, they were evaluated only in terms of the number of times they were mentioned during focus groups.

Results

Participant Description

Altogether there were 220 participants (Table 1). 100 participated in focus groups, and 120 participated in market surveys. 59 participants were women, and 161 were men. The male-dominated skew in the data was primarily from the market surveys; men are more likely to socialize with outsiders compared to women due to cultural expectations (Isaya Rumas, personal communication, March 15, 2023) and women's heavy daytime workloads. Thirty-four women and 48 men participated in focus group discussions.

Table 1. Participants for each data collection methodology, disaggregated by gender, age-set (N: Nyongulo [youngest], K: Korianga, L: Landis, M: Makaa, S: Seuri [eldest]), and village.

Identity	**Gender**	**Male**					**Female**					**Total**
	Age-Set	**N**	**K**	**L**	**M**	**S**	**N**	**K**	**L**	**M**	**S**	
Methodology	**Village**											
Focus groups	Sukuro	9	7	1	1	0	9	3	3	1	0	**34**
	Kitiengare	3	14	7	4	1	2	7	8	3	2	**51**
	Loiborsoit	2	5	1	2	0	0	3	1	1	0	**15**
Market surveys	Terat	17	31	14	4	0	0	2	6	4	0	**78**
	Emboreet	12	19	4	3	0	0	2	1	1	0	**42**
Total participants by gender and age-set		**43**	**76**	**27**	**14**	**1**	**11**	**17**	**19**	**10**	**2**	**220**
Total participants of each gender		**161**					**59**					

Smith's Salience Index (SSI)

Smith's Salience Index (SSI) scores were calculated for each plant species by combining focus group individual rankings with market survey results (Table 2). *Oltelemet* (1.20), *Alairahirah* (1.18), and *Gugu caroti* (1.14) received the highest SSI scores, all above 1.00. These three plants were categorized as "Highly Problematic" based on these scores. The fourth, fifth, and sixth most problematic plants, *Orkiyapore* (0.52), *Alaimirirwaki* (0.43), and *Oltipilikwa* (0.24), respectively, were categorized as "Moderately Problematic." The remaining 17 plants were all considered "Minimally Problematic" with SSI scores less than 0.20. These divisions of problematic status emerged as natural breaks in the dataset.

Problematic Characteristics and Thematic Categories

Our multi-staged problematic characteristic batching process progressively clustered like characteristics. Five major themes emerged through this process: *Noxious to livestock* (38.9% of problematic characteristics mentioned during focus groups), *Competitive in pasturelands* (21.3%), *Noxious to humans* (18.1%), *Other* (12.7%), and *Competitive in cultivated fields* (9.0%).

Within these five overarching themes, there are specific characteristics that feature prominently. Of all problematic characteristics that came up, *Livestock fatality* was mentioned 13.6% of the time. This was followed by several other highly ranked livestock-related characteristics including *Pasture/forage loss* (11.8%), *Milk loss* (6.8%), and *Extended hooves* (5.0%). There are a few other noteworthy findings. *No utility* was the sixth highest ranked characteristic (6.3%). The most frequently mentioned characteristic to directly affect humans, *Detrimental to human health* (4.5%), is ninth on the list. Lastly, *Widespread expansion* (7.2%) was mentioned five times more often than *Rapid expansion* (1.4%).

Table 2. Total salience index for all participants in descending order of the plant ranked most problematic to the least. The rows are color coordinated to help separate where significant breaks happen between severity scores. The Highly Problematic plants have a salience score ≥1.00 (red), the Moderately Problematic plants have a score <1.00 but ≥0.20 (blue), and the Minimally Problematic plants have a score <0.20 (green). "(?)" in the Scientific Name column indicates some amount of uncertainty; it could mean that sources conflicted with each other, one common Maasai/Swahili name represented multiple species, or that it is a best guess without verification.

Rank	Maasai/Swahili Name	Scientific Name	Smith's Salience Score	Severity Score	Ranking Frequency	Summary of Participants' Descriptions
1	*Oltelemet*	*Ipomoea hildebrandtii*	**1.20**	252	18%	Detrimental to the environment and pastures because it "takes over" and does not allow anything else to grow. Some consider it poisonous to children and livestock if they eat it. One of the few plants with benefits (firewood, toilet paper).
2	*Alairahirai*	*Crotalaria polysperma*	**1.18**	249	17%	Cows who ingest this plant become weak, thin, lose their milk, and can grow extended hooves, which can cause immobilization, and eventual starvation.
3	*Gugu caroti*	*Parthenium hysterophorus*	**1.14**	240	17%	A rapidly spreading plant that was introduced with the construction of new roads in the past 10 years. It kills all grasses leaving pastures useless. There is suspicion that it causes death to animals who eat it. It is also an irritant/allergen for humans who touch it.
4	*Orkiyapore*	*Tribulus terrestris (?)*	**0.52**	110	10%	White and multicolor cows who ingest this plant develop open wounds on the lighter colors of their hide, which is thought to be sunburn caused by phytotoxins in the plant.
5	*Alaimirirwaki*	*Altanthera pungens (?)*	**0.43**	90	6%	When cows, goats, and sheep eat this plant their stomachs swell, and they die within 2 hours. The seeds are also encased in rough burrs which spread during rain events and make it difficult/painful for humans and animals to walk.

6	*Oltipilikwa*	*Strychnos henningsii*	**0.24**	51	4%	Goats and sheep will die asymptomatically 1-2 months after ingesting, which is made more problematic by animals being attracted to its "sweet scent."
7	*Olchongir*	Unknown	**0.17**	35	5%	Produces a milky substance that causes irritation on the skin and potential blindness if it comes in contact with the eyes.
8	*Sangari*	*Cynodon dactylon* OR *Hyparrhenia rufa (?)*	**0.15**	31	2%	Changes agricultural soil to "hot and hard" making it difficult for other plants to grow. Believed to also cause East Coast Fever in cows.
9	*Olemokolo (Katanijela)*	*Argomona mexicana*	**0.13**	28	3%	Prickly weed that grows in agricultural fields making them difficult to tend.
10	*Mnana*	*Daturis zamonia (?)*	**0.13**	27	2%	Inedible for all animals. Small thorns also make it difficult to weed in cultivated fields. A small amount that is accidentally collected during crop harvest can be poisonous for humans.
11	*Oltiasikong*	Unknown	**0.12**	26	3%	Cows' milk becomes bitter when the animal has eaten this plant. The pollen can also cause eye irritation.
12	*Enundulu*	*Harrisonia abyssinica*	**0.10**	21	1%	It kills all other plants wherever present and is difficult to remove.
13	*Orkushashi*	Unknown	**0.09**	18	2%	The painful thorns "imprison" other plants because animals are unable to get to them. It can also be deadly when donkeys eat it.
14	*Elejai*	Unknown	**0.08**	17	2%	Can cause irritation and painful bumps/bubbles on the skin when it comes in contact.
15	*Olbibiai*	*Leonotis spp. - nepetifolia, mollissima*	**0.07**	14	2%	Detrimental in cultivated fields, including other weedy plants.
16	*Olchopolihoi*	Unknown	**0.06**	13	1%	Causes East Coast Fever in cattle and sheep.
17	*Engarmalisay*	*Aloe vokensii* OR	**0.05**	10	1%	Can be deadly for cows, goats, and sheep that consume it.

		Hyposix spp. - angustifolia, obtusa (?)				
18	*Mchicha*	*Amaranthus cruensis (?)*	**0.03**	6	1%	Kills crops in cultivated fields, especially maize.
19	*Alauwii*	Unknown	**0.02**	5	0%	Fruits are attractive for children that can be deadly when eaten.
20	*Olorrondo*	*Cyphostemma serpens*	**0.02**	5	1%	Fruits are attractive for children that can be deadly when eaten.
21	*Oledwarai*	Unknown	**0.01**	3	0%	Fruits are attractive for children that cause diarrhea and vomiting when eaten.
22	*Emurua*	Unknown	**0.01**	2	0%	The plant attracts a small insect that then causes fainting and potential death for cows, goats, and sheep that eat it. The plant is still considered beneficial for grazing if the insect is not present.
23	*Oseyai*	*Cyperus spp. - rotundus, immensus (?)*	**0.00**	1	0%	(Added onto market survey list, but given no explanation)

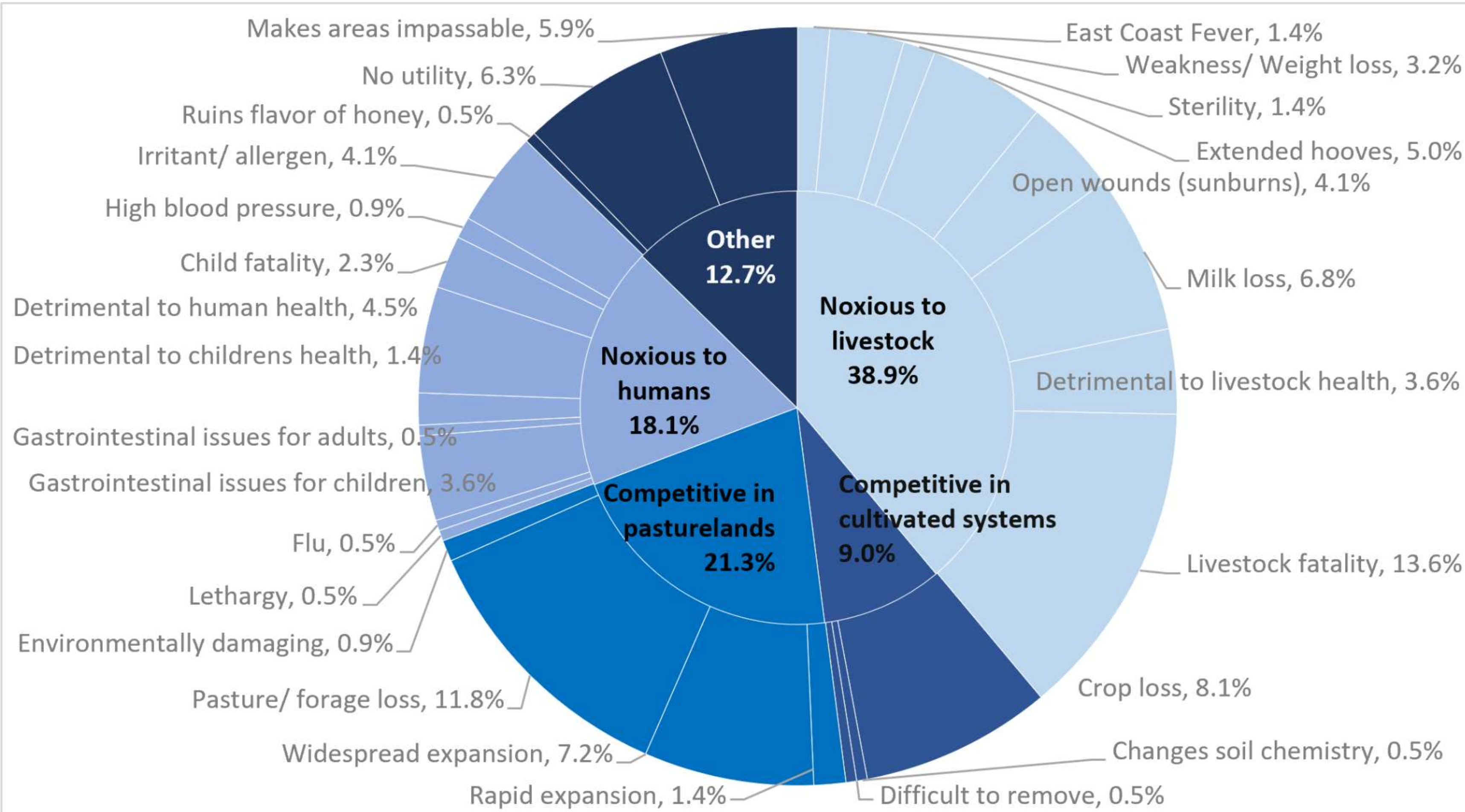


Figure 6. Open Codes of the problematic characteristics comprise the exterior of the graph, which are created by batching raw data into same/similar answers. Each exterior pie slice represents the number of times a particular problematic characteristic was mentioned as a percentage of the total count of all problematic characteristics mentioned throughout all of the focus groups (n = 221). These were then categorized into five Axial Codes, which represent realms of impact seen on the interior of the graph. Each of these pie slices can indicate how important each realm of impact is perceived to be to Maasai livelihoods based on its size.

Gender Perceptions of Problematic Plant Species and Characteristics

A note about sex and gender: The words "male" and "men" are used synonymously, as are "female" with "women". This is not done to be intentionally exclusive. Rather Maasai culture is unanimously cisgender (in our experience), where their gender matches the sex assigned to them at birth. Therefore, we use gender and sex terms interchangeably based on how the word fits colloquially into the writing.

Based on the Chi Square test (p = 0.03) there is evidence to support many gender-specific results/differences (Table 3). Plant characteristics that fall within the *Noxious to livestock* category elicited the greatest proportion of mentions by both women and men, at 31.4% and 45.4%, respectively. While the proportion of men's mentions is nearly 50% greater than that of women, for both groups it was the number one mentioned characteristic class. The next greatest proportion of mentions by women was for characteristics associated with the *Noxious to humans* category, at 26.5%, which only received mentions by 10.9% of male focus groups, a fourth rank. Men's second greatest proportion of mentions was for characteristics associated with being *Competitive in pasturelands* at 20.2% of mentions, which was relatively equal to the proportion of mentions by women at 22.5%, emerging as third rank.

When comparing the plant species rankings, the Chi Square test did not show a significant difference between male and female responses (p = 0.99).

Table 3. Total Axial and Open codes for each gender. The cell colors exist on a spectrum that correlates with the number of mentions by each gender ranging from green (few mentions) → red (many mentions); white correlates to zero mentions. The Chi Square Test revealed that there was moderate evidence ($p = 0.03$) to support a difference between the responses of the two groups. Percentages are of total mentions of all characteristics and therefore sum to 100%.

Axial Codes	Open Codes	Women		Men	
Noxious to livestock	East Coast Fever	0	31.4%	3	45.4%
	Weakness/ Weight loss	3		4	
	Sterility	0		3	
	Extended hooves	5		6	
	Open wounds (sunburns)	3		6	
	Milk loss	10		5	
	Detrimental to livestock health	4		4	
	Livestock fatality	7		23	
Competitive in cultivated fields	Crop loss	8	8.8%	10	9.2%
	Difficult to remove	1		0	
	Changes soil chemistry	0		1	
Competitive in pasturelands	Rapid expansion	0	22.5%	3	20.2%
	Widespread expansion	9		7	
	Pasture/ forage loss	14		12	
	Environmentally damaging	0		2	
Noxious to humans	Lethargy	0	26.5%	1	10.9%
	Gastrointestinal issues for adults	1		0	
	Gastrointestinal issues for children	7		1	
	Detrimental to children's health	2		1	
	Detrimental to human health	6		4	
	Child fatality	4		1	
	Flu	1		0	
	High blood pressure	0		2	
	Irritant/allergen	6		3	
Other	Ruins flavor of honey	1	10.8%	0	14.3%
	No utility	4		10	
	Makes areas impassable	6		7	
Total		**102**		**119**	

Age-Set Perceptions of Problematic Plant Species

In addition to investigating perceptions of problematic plant species by gender, we also investigated whether generational differences exist. We wanted to know if there were any patterns in perceptions of problematic plants based on age-set, potentially informed by generational experiences and values differences, and if we identified patterns whether they were statistically significant.

Separating men and women for focus groups did not allow us to substantiate the number of mentions according to each age-set, therefore not allowing us to investigate perceptions of problematic characteristics by age-set. While it would be possible to link participants' plant rankings to the characteristics that those plants exhibited, this would negate our third guideline to disaggregate plants from their characteristics on the basis that a plant's ranking could not be determined by any single characteristic if it exhibited more than one. Therefore, our inquiry into differences in perceptions of problematic plants by age-set is restricted to looking at differences in SSI by each age-set for each species only. While there are some differences in SSI values across age-sets, ANOVA indicates there is not a statistically significant difference in responses by age-sets across all species ($p = 0.99$).

When we look at individual species, the two species that were reported differently by different age sets are *Oltelemet* and *Oltipilikwa* (Figure 7). It is also interesting to note that the long tail of the last eight species mentioned by few participants were almost exclusively mentioned by the youngest age set, and then by the second-youngest age set. This could be because they are the ones who are actively exploring and taking long foot safaris. They are often also responsible for the livestock.

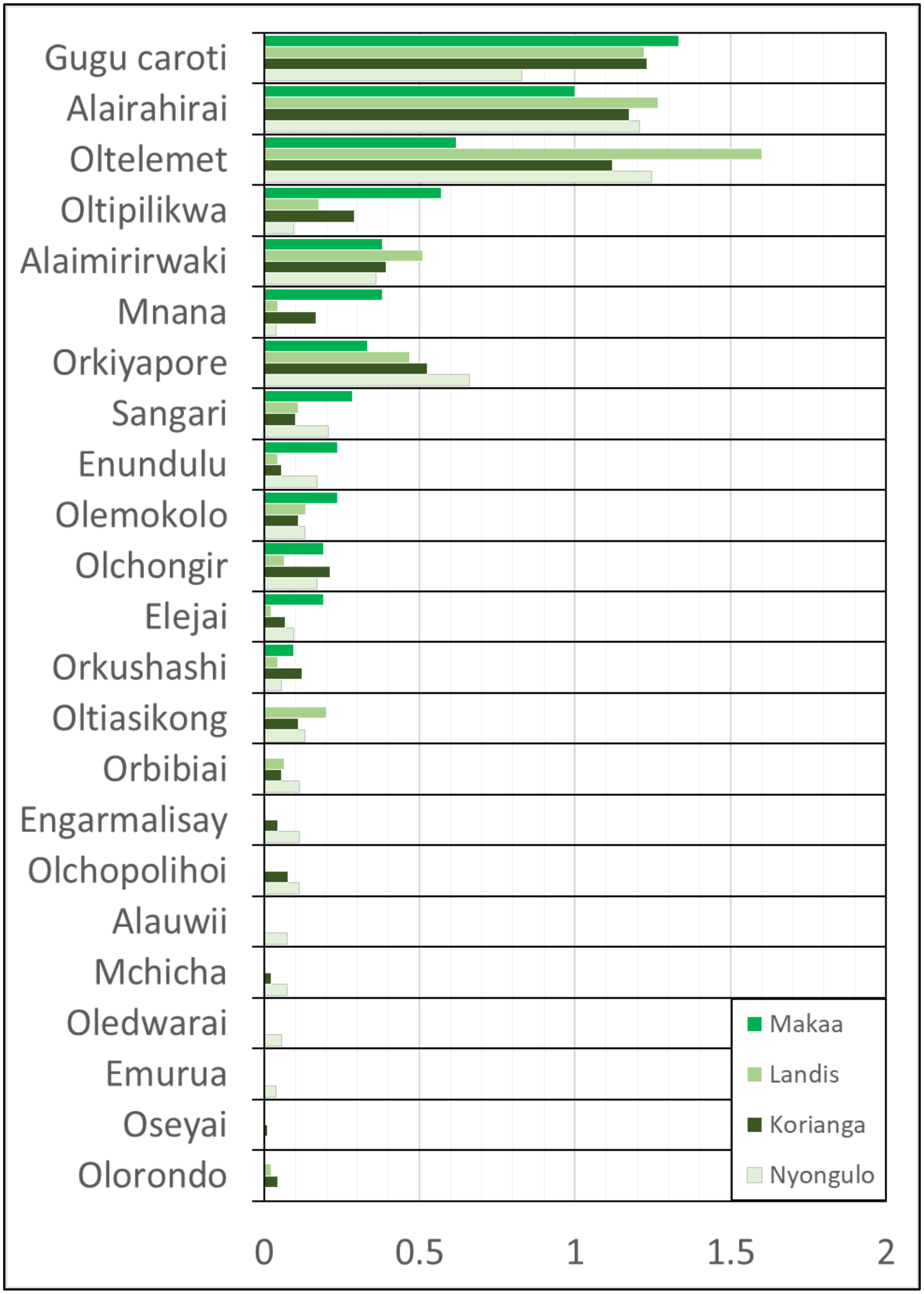


Figure 7. Mean Smith's Salience Index of each species represented by age-set, minus senior elders who were under-represented in the sample and therefore excluded. ANOVA does not support our hypothesis that there are statistically significant differences in SSI perceptions by age-set (p = 0.99). Rather, SSI is shown to be similar across groups.

Discussion

General Perceptions of Problematic Plant Species and Characteristic

There are several lines of evidence from both the problematic plants and problematic characteristics that demonstrate Maasais' deep attachment to tradition and culture in an ever-changing world. As a linchpin of their historical livelihoods, they place immense value on their livestock above other aspects of life and livelihoods. Results indicate that their livestock are their greatest priority, above ecosystem health, personal safety, and cultivation. There were common themes amongst the three problematic tiers. The top six plant species with the highest SSI value – *Oltelemet*, *Alairahirah*, *Gugu caroti*, *Orkiyapore*, *Alaimirirwaki*, *Oltipilikwa* – all cause adverse health effects for livestock that ingest them, which comprises all plants with an SSI ≥ 0.20, the entirety of the top two of three SSI tiers ("Highly Problematic" and "Moderately Problematic"). Of those six species, *Gugu caroti*, *Alairahirah*, *Alaimirirwaki*, and *Oltipilikwa* were reported to be the most concerning in relation to livestock fatalities. *Oltelemet* and *Gugu caroti*, two of the three "Highly Problematic" plants, are considered widespread and detrimental to pasturelands. While *Oltelemet* is native to East Africa (Ojija & Manyanza, 2021b), and *Gugu caroti* is a non-native alien species (Musese, Andrew, et al., 2020; Ojija & Manyanza, 2021a; Patel, 2011), both were mentioned by respondents and some local researchers as being new (i.e. non-native) in this part of the country. Although not deemed invasive, *Alairahirah* can also render large forage patches inaccessible when it drops its spiny seed burrs. These three "Highly Problematic" plants are detrimental to pasture health which has consequences for livestock, prioritizing food for livestock over human food from cultivation or even human safety. This same pattern continues with the problematic characteristics. *Noxious to livestock* and *Competitive in pasturelands* together accounted for over half (60.2%) the problematic characteristics mentioned during focus groups.

Livestock's high value can be attributed to the direct impact they have on day-to-day culture and livelihoods for Maasai. Pastoralism is ingrained in their culture, and they are reliant on a mutually beneficial relationship with their animals in dryland conditions. For example, milk loss equates to calorie loss, and cows with extended hooves typically have trouble walking, which requires specialty care for sustenance. Although the culture is transitioning away from exclusive pastoralism, diversifying land use and livelihoods, these results demonstrate the value that Maasai continue to place on their livestock.

We can also speculate on the lower rankings for problematic species and characteristics related to human safety. All the plant species that cause problems exclusively in human safety are in the "Minimally Problematic" category. There are several theories as to why this might be. One hypothesis is that these plants are infrequently encountered based on landscape distribution and/or human pathways. A second hypothesis is that this may reflect how well Maasai know their plant species and know which ones to avoid based on their TEK. Children (and adults, but to a lesser degree) may be at lower risk of consuming these plants than livestock are because they are more closely watched, making species problematic to livestock more concerning. Lastly, humans simply consume less plant matter than their livestock. There is a greater absolute possibility of livestock encountering a problematic plant making the relative proportion of problematic plants skewed towards livestock health.

Similar to human safety, problematic species related to cultivation are all "Minimally Problematic". This is mirrored by the *Competitive in cultivated fields* theme being the least problematic axial code (9.0%). While this may indicate Maasai do not value cultivation as highly as livestock, there are several other possible explanations. One hypothesis is that tractors have become much more prevalent in the past decade (Isaya Rumas, personal communication, March

28, 2023). This has allowed them to easily till and weed the soil prior to planting, which can help reduce the problematic characteristic. Another, potentially complementary hypothesis is that several species considered problematic in cultivation are not problematic elsewhere, such as in pasturelands where they become forage for livestock. The benefits help balance the problems they cause, reducing the perception of how problematic they are in cultivated fields.

Another intriguing outcome is the high ranking of *No utility* (sixth overall) as a problematic characteristic from multiple species. This reveals that Maasai do not value plants that do not serve a purpose. A similar trend emerged when a land-use-land-change schema was created using Maasai Indigenous knowledge (see Chapter 2 for more details). This work shows how Maasai value natural resources based on functionality, likely because they are more directly reliant on them. From a scholastic definition, the benefits that humans gain from their environment are called *Ecosystem Services* (World Resources Institute, 2005) *Provisioning Services*, one of the four ecosystem service types, are material goods that humans receive from the environment, usually to serve an immediate human need (Briske, 2017; World Resources Institute, 2005). These are the types of services Maasai cultural systems value: an abundance of grass for their livestock, rainfall for their crops, firewood for their cooking, mud for their bomas, herbal medicines, and more (Briske, 2017; Monlezun et al., 2024). Problematic plants can be detrimental by reducing the provisionary services that the environment can provide, upsetting the system's unsteady resource supply-demand balance (Briske, 2017). The other three ecosystem services types – *Supporting, Regulating,* and *Cultural* (World Resources Institute 2005) – may seem peripheral, but are closely linked with the *Provisioning services* in a complex social-ecological system (Goodwin et al., 2023). There is a clear relationship between our emergent data and the ecosystem services concept, but further investigation is outside this project's scope. It is for future inquiry inspired by the community that could bridge Indigenous and Western knowledge frameworks.

Gendered Differences in Perceptions of Problematic Plant Species and Characteristics

There is strong evidence that there are differences between genders in these findings. Although all Maasai value livestock, men may be more concerned with livestock health and safety and potentially more knowledgeable of plants that cause problems for livestock, whereas women may be more concerned with human health and safety and more aware of the plants that make children sick. Based on several lines of evidence, women appear to find plants that are irritants, allergens, and toxic to children more problematic than plants that have non-lethal noxious effects on livestock. First, five plants related to human health ranked "Moderately Problematic" for the women over plants affecting livestock, but these same plants ranked "Minimally Problematic" for the men. Second, there is ~14% discrepancy between men (45%) and women (31%) related to *Noxious to livestock*. This is nearly the exact amount that makes up the difference of proportional mentions to *Noxious to humans* characteristics mentioned between women (27%) and men (11%). Third, *Gastrointestinal issues for children* was mentioned seven times by women, and only once by men. Lastly, *Milk loss* from cows was the women's second most mentioned problematic characteristic (10%), which is a large caloric stock for children throughout the day. Although both groups value livestock health the most, women value human health almost as much. This reflects their daily tasks and gender-based roles and responsibilities within the community: men tend to the cattle and women tend to the family.

Age-Set Perceptions of Problematic Plant Species and Characteristics

There was insufficient evidence to show that there were differences between the age-sets in their plant rankings. Therefore, we might assume that, while each age-set may have grown up in different conditions, they rank based on the current environment or perceptions based on TEK passed generationally.

Conclusion

Maasai living on the Simanjiro Plains are a culture in transition. While they traditionally practice pastoralism, they have increasingly turned to agro-pastoralism, increasing crop cultivation under pressures from federal mandates, development, climate change, and global environmental movements. We have found that success and productivity of both land uses is jeopardized by community-identified problematic native and non-native plant species. To understand the species that are most problematic through a Maasai Indigenous, rather than Western, knowledge lens, we turned to participatory methods to gather relevant, useful data through a modified focus group format that included individual response components. This helped us answer (1) What plants do Maasai of Simanjiro find to be most problematic, (2) What are the characteristics that define those plants, and (3) How do these responses differ by gender and/or generational age-set?

Although this project faced sample size, spatial extent, and geopolitical power dynamic challenges, our mixed quantitative and qualitative methodologies not only led to our findings, but also led us to new lines of inquiry. We found that Maasai overall find species that reduce pasture productivity and harm livestock to be the most problematic. The worst also exhibits invasive and aggressive qualities as recognized through a Western lens. Additionally, men and women differ in their knowledge and concern for certain species. While both groups prioritize livestock health and safety, women show the same level of concern and knowledge for plants that affect humans, especially children.

CHAPTER 2: COMBINING INDIGENOUS KNOWLEDGE, PARTICIPATORY SCIENCE, AND HABITAT SUITABILITY MODELING TO VIEW PROBLEMATIC PLANT DISTRIBUTIONS IN MAASAILAND

Introduction

Maasai community study participants in the Simanjiro Plains of northern Tanzania identified and ranked three local plant species as the most problematic species: *Oltelemet*, *Alairahirah*, and *Gugu caroti* (see Chapter 1). With help from local botanist Benjamin Rumas (personal communication, March 15, 2023), and verified by in-depth literature reviews, we were able to identify these three local plants, respectively, as *Ipomoea hildebrandtii* (Manyanza, 2018; Ojija & Manyanza, 2021b), *Crotalaria polysperma* (Gender Biodiversity and Local Knowledge Systems to Strengthen Agricultural and Rural Development & Vetaid Tz, 2000), and *Parthenium hysterophorus* (Adkins & Shabbir, 2014; Musese, Andrew, et al., 2020; Ojija & Manyanza, 2021a).

Our next overarching goal was to bring together Indigenous knowledge with Western scientific methods and community participation to determine where on the landscape these three species were present. Using participatory science methods and a mobile application, community members collected observations of these and other plants, which we used as baseline data to develop preliminary models of habitat suitability across Maasailand. These methods help us to explore the advantages and obstacles of two-eyed seeing in participatory research to create a conceptual framework that can potentially be reproduced and adapted in this and other Indigenous communities globally. We hope to spur new Indigenous-focused research projects that emerge under the guidance of local (as opposed to foreign) authority in collaboration with Western academic scientists. This is a learning opportunity, a step in the iterative process of participatory research.

Habitat Suitability Models

Habitat suitability models (HSMs) are called by many names: species distribution models, environmental/ecological niche models, predictive habitat distribution, and more. These often can be interchangeable in the literature, but for consistency throughout this report we will use only one term. HSMs attempt to define a species niche in ecological space and project that into geographic space. They use statistical algorithms to generate the likelihood that a species of interest exists in a/any location based on various environmental factors of known locations fed to the model (Engelstad et al., 2022; Jarnevich et al., 2023; S. B. Phillips et al., 2006). HSMs represent the capacity of provided predictors to support the theoretical existence of a species at any given point.

When used appropriately by governing agencies, HSMs can be powerful tools in natural resource conservation for various applications, such as protecting rare species, informing surveillance design, and establishing invasion risks (Jiménez-Valverde et al., 2011; Smithsonian Environmental Research Center, 2024; Sofaer et al., 2019). They can help natural resource managers, like Maasai pastoralists, answer the questions “What species should we be looking for?”, “Where might these species occur?”, and “Are our actions possibly contributing to their presence?” Agencies and managers typically have limited resources, so optimizing their impacts in time and space is necessary (O’Donnell et al., 2012).

Participatory Science (PS)

Participatory science (PS) – alternatively called citizen science – is the use of the non-scientific, general public for data collection efforts in research (Association for Advancing

Participatory Sciences, 2023; Smithsonian Environmental Research Center, 2024). Together with community-based monitoring, PS can utilize both traditional ecological knowledge and Western science tools and approaches (Chiaravalloti et al., 2022; McKinley et al., 2017). They have the ability to solve complex problems by engaging the public with boots on the ground, identify local-level problems, provide locally grounded perspectives, and find locally driven solutions (Conrad & Hilchey, 2011; Eitzel et al., 2017).

One notable participatory framework is Extreme Citizen Science (ECS) designed by University College London (Haklay, 2012), which is a model our work approximates. This interdisciplinary model invites members from marginalized and remote communities to contribute their local knowledge and observations to scientific research projects aimed at solving problems relevant to involved communities through genuine partnerships and iterative improvements (Smith, 2022). According to projects' self-evaluations, it has been successfully utilized in several studies around the globe (Chiaravalloti et al., 2022; Skarlatidou et al., 2020).

Scientific engagement is essential for democratic science governance. In addition to its empowering effect for communities to engage in science, PS has proven to expand the spatial and temporal scale of data collection beyond conventional research, accelerating scientific discovery (Danielsen et al., 2019; Loss et al., 2015; Theobald et al., 2015). For at-risk or marginalized communities, it perpetuates members' access to the data and preserves local knowledge within the community via platform-mediated information governance systems. This helps preserve the community's social and cultural values, while also preventing misappropriation by external forces (Árnason, 2013; Irwin, 2014). Lastly, it creates a more meaningful connection between the public and science, which has historically been an underdeveloped relationship (Requier et al., 2020).

Problematic Plants of Interest

The problematic plant species are described in two ways. First, background information is given based on literature reviews. Then, information is provided based on focus group responses, which were conducted in three parts: (1) participants were asked to free-list and briefly characterize all plants they found to be problematic to their livelihood; (2) the top three problematic plants were ranked by each individual member of the group; (3) the three most severely ranked plants (collectively) were characterized further through follow-up questions. Rankings were also conducted on a larger scale through market surveys, but no additional information regarding plant characteristics was gathered from surveys. There was a total of 220 participants: 100 from focus groups and 120 from market surveys. The Smith's Salience Index (SSI), a metric that incorporates both the total number of ranks (i.e., ranking frequency) and each plant's average rank in order to properly weight the rankings, was used to determine the salience score of each species. "Highly Problematic" plants have an SSI ≥1.00, "Moderately Problematic" plants are scored 0.20-0.99, and the "Minimally Problematic" plants have a score <0.20. This chapter focuses on the three plants that scored as "Highly Problematic" – *Oltelemet (Ipomoea hildebrandtii)*, *Alairahirah (Crotalaria polysperma)*, and *Gugu caroti (Parthenium hysterophorus)*.

Oltelemet – Ipomoea hildebrandtii

Ipomoea hildebrandtii was the most significantly ranked plant with an SSI of 1.20 based on data collected for Chapter One of this thesis. This species is called *Oltelemet* in Maasai language and is how we referred to this species throughout our work with communities.

Background Information: As part of the Convolvulaceae family, *I. hildebrandtii* is a woody shrub that grows 1-2.5 m tall and can grow in a range of habitats between 400-1850 m in altitude (1300-6000 ft) (Verdcourt, 1963; Witt et al., 2018). There are, however, local claims of its existence higher than this. It is one of nearly 650 species of flowers all commonly called morning glory (Miller & Rausher, 1999). Although native to East and Central Africa, it is considered invasive by many of its origin countries (Witt & Luke, 2017). Wildfire had traditionally helped to mitigate the spread of *I. hildebrandtii*, but once cultural burning was banned in 1998 by the Forest Act (FAO-Finland Forestry Programme, 2013), a practice that once decreased tsetse fly infestations and increased soil fertility (Wojtkowski Barbeau, 2017), *I. hildebrandtii* grew voraciously (Witt and Luke, 2017).

<u>Informant-provided Information</u>: *I. hildebrandtii* was mentioned in 100% of focus groups and was given a top-three ranking by 72% of participants. “It comes in and takes over everything” is how one study participant described it. Its prolific expansion has been the result of road building and increased travel, pasture degradation, and fire suppression (as noted by a local non-Maasai bowhunter [Michael S., personal communication, March 22, 2023])

The entire *I. hildebrandtii* plant is inedible for both livestock and wildlife, and there are accounts of it poisoning children who attempt to eat it. Usable forage is being outcompeted across entire swaths of pasturelands, dwindling at a staggering rate wherever *I. hildebrandtii* takes over (Manyanza, 2018; Ojija & Manyanza, 2021b; Witt & Luke, 2017). When it invades agricultural fields, it makes manual weeding more difficult because the entire root must be pulled up. The plant can sprout just one week after the first rainfall following the dry season, and it is able to develop an extensive root system and mature more rapidly than other plants, which allows it to remain green year-round, even during the dry season (Simanjiro community, personal communication, March 1-30, 2022). This gives the plant a competitive advantage over local grasses and crops in Simanjiro.

On the other hand, it was one of the few plants that had named benefits: using dried branches for biofuel, increased honey production for apiarists, and using the leathery leaves as toilet paper. There was also a second "type" of *Oltelemet* described by Maasai during focus groups. It is suspected that this may be a second species, *Ipomoea kituiensis*, but it was not determined definitively.

Figure 8. Oltelemet - Ipomoea hildebrandtii (photo credit: C. McCarty, 2017).

Alairahirah – Crotalaria polysperma

Crotalaria polysperma had the second highest salience score of 1.18 based on data collected for Chapter One of this thesis. This species is called *Alairahirah* in Maasai language and is how we referred to this species throughout our work with communities.

Background Information: *C. polysperma* is an annual herb belonging to the legume family, Fabaceae (Polhill, 1968). It grows between 0.3-1.5 m (1-5 ft) tall, and its flowers in Simanjiro are typically violet or light blue, although other colors exist. It grows at altitudes from sea level up to 2500 m (8200 ft), predominantly in grasslands with various shrub and/or wood coverage, preferring temperatures between 24-34°C (73-94°F) (Polhill, 1968). It originated in southern

Africa (Zimbabwe, Mozambique, Zambia) and migrated northward into East Africa (Polhill, 1968). A distinct feature of *Crotalaria* spp. are their pubescent seed pods; when they dry the seeds will rattle around inside the pod, which is where they get their common name “rattlepod” (Polhill, 1968).

There are several species of *Crotalaria* that have been shown to bioaccumulate selenium from their soils (Polhill, 1968). This is important because cows who ingest this plant at any phenological stage can be poisoned by consuming toxic levels of selenium resulting in lethargy and weakness, nursing cows losing their milk, mating bulls losing fertility, and some even developing a condition called laminitis. This is when the hooves grow to awkward lengths and angles making walking extremely painful for the animal (Barri & Adam, 1981; Dhillon et al., n.d.; Dhillon & Dhillon, 2003; Plants Poisonous to Livestock, 2019). Depending on the severity of growth it can leave the cow immobilized, which requires extra care by owners lest the animal starves. There are no known treatments for selenium toxicity except to avoid the seleniferous soils to prevent further intake.

<u>Informant-provided Information</u>: Knowledge shared by Simanjiro community members about *C. polysperma* and its effects on Maasai livestock aligns with what Western science has found about this plant's capacity to lead to selenium toxicity. Many groups mentioned it as being new to their village within the past 10-20 years or greatly increasing within that timeframe. Nearly every focus group had at least one member who had had a cow that had experienced laminitis recently.


Figure 9. Alairahirah - Crotalaria polysperma (left; photo credit: S. Brown, 2020). Laminitis on a Zebu cattle in Botswana (right; photo credit: T. Basine, 2013).

Gugu caroti – Parthenium hysterophorus

Parthenium hysterophorus was the third most problematic plant with an SSI of 1.14, which is quite remarkable, given that this plant was simply called "roadside plant" and was not perceived as a serious threat during a 2017 proof-of-concept study by the research team (McCarty, 2018). This species is now called *Gugu caroti* by Simanjiro Maasai (directly translates to "carrot weed" in Swahili language) and is how we referred to it throughout our work with communities. In five years, it has notoriously established itself in many habitats leading to a decline in grazing forage and a threat to animal safety.

<u>Background Information</u>: In 2011, *P. hysterophorus* was considered one of the world's seven most devastating weeds (Patel, 2011). It was likely brought to Tanzania in the 1980s through a shipment of tainted USAID grain and quickly spread along disturbed sites, such as roads, degraded fields, and train tracks(Musese, Andrew, et al., 2020; Musese, Macrice, et al., 2020; Ojija & Manyanza, 2021a). It is an annual herb in the Asteraceae family that grows 0.3-2.5 m (1-8 ft) tall with white flowers (Adkins & Shabbir, 2014). Many cultures have likened its appearance to a

carrot. In fact, the name *Gugu caroti* translates to the English common name “carrot weed” (Patel, 2011).

P. hysterophorus has been so successful as an invader because of its phenotypic plasticity, rapid germination, large seed bank, and allelopathic capabilities (Rathee et al., 2021). Originating in the neotropics of Central America, it has invaded tropical, semiarid, and temperate regions across the globe, and has been found up to 2000 m (6500 ft) in the Himalayan Range (Adkins & Shabbir, 2014; Rathee et al., 2021; Shrestha et al., 2019). Similarly, it has been found in climates between -2-36°C (28-96°F) with >900 mm (35 in) annual precipitation and/or ample soil moisture but can withstand conditions outside these ranges (Awais, 2020; Kaur et al., 2017). It can be found in a wide variety of habitats and soil types: roadsides, waste sites, pastures, cultivated plots, wetlands, grasslands, shrublands, and woodlands (Evans, 1997). In just one month after germination, a single plant can produce up to 20,000 seeds, which can remain viable for up to six years in the soil seed bank (Adkins and Shabbir, 2014). Lastly, it exhibits a characteristic called allelopathy, the release of chemical(s) into the environment to inhibit the germination or growth of neighboring plant species (Ramos et al., 2002). In addition to disrupted plant growth, parthenin, the allelopathic compound produced by *P. hysterophorus*, is thought to also be the culprit for the plant’s deleterious effects on animals (Ramos et al., 2002).

<u>Informant-provided Information</u>: After *I. hildebrandtii*, *Parthenium hysterophorus* received the most top-three rankings by individual participants in both focus groups and market groups. While at the market, one woman began shouting, and our translator told us, “she is using foul language to curse *Gugu caroti*. It has caused a lot of suffering.” When consumed, the plant is poisonous to livestock and humans with reports of fatalities. It is also an irritant and allergen to eyes, skin, and lungs.

Figure 10. Gugu caroti - Parthenium hysterophorus (photo credit: C. McCarty, 2023).

These plants are perceived by Maasai in Simanjiro to be the most highly problematic to their livelihoods. Using these three plants and the Simanjiro Maasai community as case study examples, we wanted to explore the uses of participatory science in a two-eyed seeing framework. To further study these three problematic plant species in partnership with the communities that are being affected, we determined that a participatory approach to collecting *in-situ* data on plant presence would be beneficial. This portion of the project is a pilot study of implementing participatory approaches to see what works and what requirements there are for such a project. It also is a pilot study for creating HSMs based on participatory data and for evaluating how participatory approaches can best serve our partner communities.

Research Questions

1. How successful are Maasai in the Simanjiro Plains at adopting participatory science tools, such as CitSci? What challenges were faced? What improvements can be made to this conceptual framework to overcome those challenges?

2. How statistically reliable can habitat suitability models be using data collected through participatory methods?
3. What other emergent two-eyed seeing applications could participatory data collection methods help the Maasai of the Simanjiro Plains achieve?

Methods

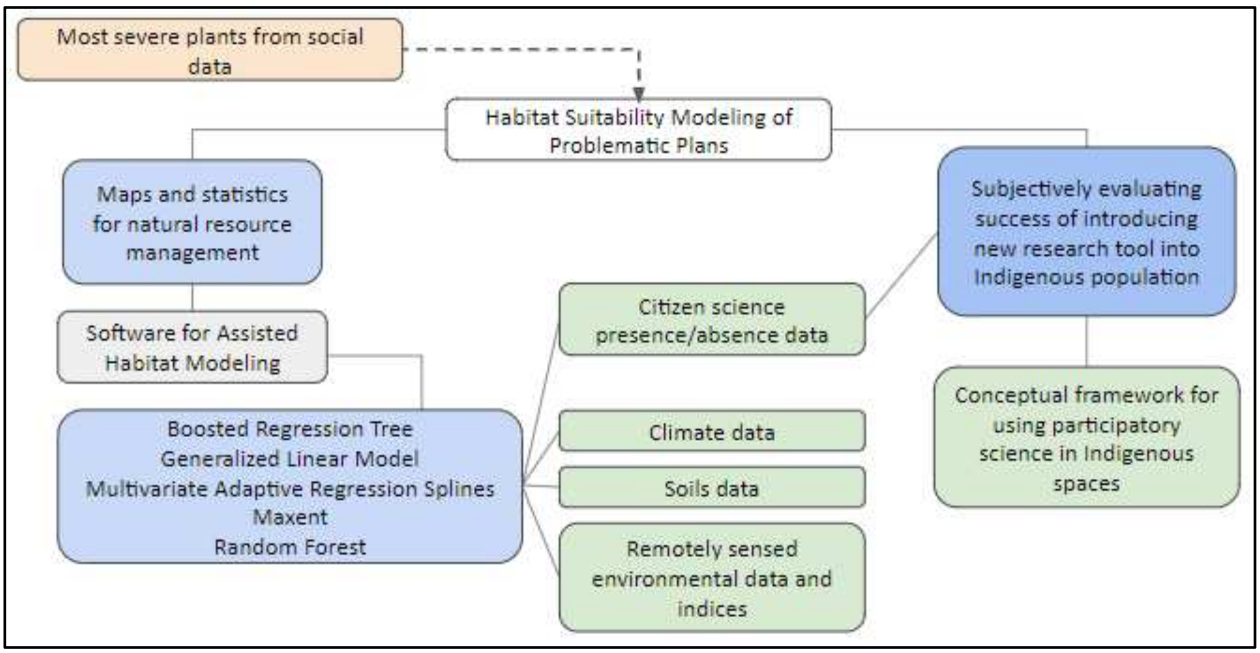


Figure 11. A conceptual diagram showing the steps (blue) of the methodology with details (green) for the models and framework.

Data Collection

Participatory Science Presence/Absence Points

CitSci is a participatory science organization that was developed at Colorado State University to provide secure, free, and globally accessible cyberinfrastructure to support participatory science projects (S. J. Lynn et al., 2019; Newman et al., 2017). These features allow project managers to personalize their projects according to local interests, specific areas of inquiry, data sensitivity levels, and the communities' privacy needs, which are all essential for protecting TEK from appropriation by external forces. Tanzania has a long history of scientific and land disenfranchisement that has been devastating to communities (Goldman, 2003). The integration of TEK and PS technologies engages the best local approaches alongside technologies designed for identification, monitoring, remote sensing, and modeling. Use of CitSci platform gives full access and ownership of the data to the communities themselves.

We created a project on CitSci called "*Mimea ya Simanjiro*" (translated from Swahili as "Plants of Simanjiro"). Settings require that participants must be given permission to join the project by the project's manager (i.e., research team including our local partner, Isaya Rumas, a CSU researcher, Lynn, and CSU graduate student, McCarty). This ensures that the data cannot be shared on or off the CitSci platform with anyone other than those that have been admitted.

We held workshops for joining the project, where two to eight participants at a time would join at a central location for several hours with food and beverages provided. Village leaders helped recruit participants based on two criteria.: (1) ownership of or access to a smartphone, and (2) literate, at least in Swahili and preferably also in English. During workshops, we set each individual up with an email address (required to verify the CitSci account), downloaded and set up the app on each person's phone, went through the datasheet in the app, and then collected test points nearby. During market surveys, we also had a posterboard attached to the vehicle with instructions on downloading and using the app.

It took several iterations to develop a datasheet that was detailed enough to gather the necessary information without overwhelming participants or discouraging them from using the app (see Appendix C for the CitSci datasheet questions). The resulting datasheet, entitled "*Uchunguzi wa mimea*" ("Problems of plants"), auto-populates the user's name, observation date, and location when first pulled up in the app. The datasheet consists of 13 questions that were written in Swahili, translated from English by our local research partner and written in a way that was culturally understandable. Over time, we realized that emojis, small digital images/icons that can be strung into the text, could be included as characters in the questions and answers. We used these whenever applicable to be more easily interpreted by users. For example, a camera emoji was placed next to the questions that request photos. Only one photo was required, but optional, supplementary questions allowed users to take photos of specific plant anatomy and the surrounding environment. Additional questions were asked about the species prevalence, problematic characteristics exhibited, land classification, soil color, and any nearby land disturbance that may have occurred (e.g., overgrazing, crop cultivation, roads).

In addition to the community's participatory observation data collected using CitSci, we incorporated observations from the Global Diversity Information Facility (GBIF). GBIF is "an international network and data infrastructure funded by the world's governments and aimed at providing anyone, anywhere, open access to data about all types of life on Earth." In the context of this project, GBIF was a central hub for PS data gathered from a multitude of other platforms. For each species of interest, data was downloaded from GBIF within the Maasailand boundaries, according to its taxonomic name on 12/20/2023. We filtered for physical observations only (no museum specimens), recorded from 1980-present, and with a geospatial accuracy ≤30 meters.

A note about *Crotalaria polysperma*: There were no points collected on CitSci by locals for this plant and only seven points that fell within Maasailand in the GBIF database. Lacking sufficient data, we were unable to complete any habitat suitability models for this plant. This same circumstance arose for the next three most concerning plants, and so we chose only to focus on *Ipomoea hildebrandtii* and *Parthenium hysterophorus*.

Ecological Data

Following focus groups, we intended to complete ecological site descriptions (ESDs). A composite TM image was created using 20 or fewer Landsat-8 Collection 2 Tier 1 (LC08C02T1) scaled, at-sensor calibrated radiance values captured between 01/01/2020–12/31/2023, each in the 50th percentile with ≤5% cloud cover. A supervised classification was carried out in the *Classification Wizard* tool in ArcGIS Pro to create an LULC map using these images for the five-village region based on local descriptors: red soils, black soils, white soils, cultivated soils, bomas, and roadsides. The proportional area of each classification was calculated, and random points were generated using the *Random Points Generator* tool. At least 10 ESDs were to be conducted in each LULC based on GIS-generated randomized locations with an additional 10-ESD minimum for locations where species were noted to exist. A handheld Garmin GPS unit was used to locate selected sites within a 3-meter accuracy. ESDs were intended to be performed soon after the rainy season, which would benefit plant observation and identification efforts. For each ESD we wanted to assess site characteristics, plant communities, soil profiles following the Natural Resource Conservation Service guidelines (adapted from methods in USDA, 2001; USDA et al., 1996), and take several photos. Then, a cardinal direction was to be dictated from a random number generator with parameters set from 0-360. From the ESD, we would complete a 50-meter linear plant transects using the randomly generated bearing, performing 1-meter quadrats at 5-meter intervals with photos. Transects were to follow a random systematic sampling approach and assess associated plant species, percent ground cover, topography (relative position, slope, and aspect), immediate disturbance (degree, source, and distance), and other general observations, such as presence of wildlife for example. All these data were to be captured in a CitSci app datasheet separate from *Uchunguzi wa mimea*.

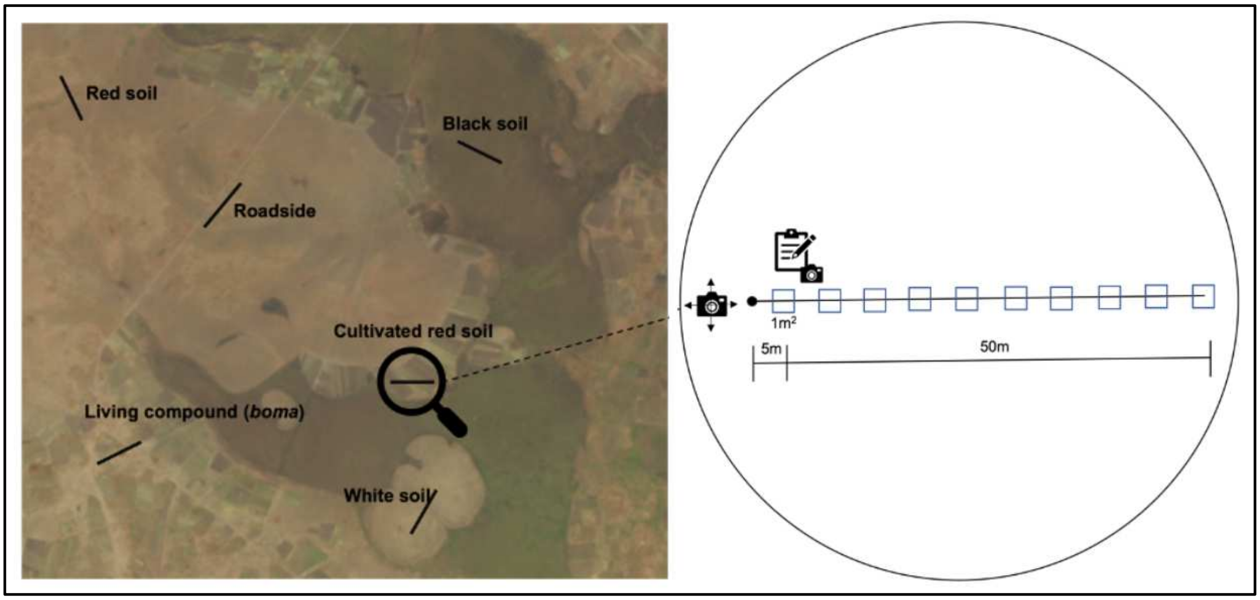


Figure 12. Diagram of a plant transect. They start at the point of each Ecological Site Description and continue for 50 meters, with 1 m2 quadrats every 5 meters measuring total biodiversity and ground cover. At least 10 transects were intended to be conducted on each of the six landscape distribution types, for a total of at least 60.

Unfortunately, geopolitical circumstances prevented us from completing all these intended methods. Tanzania has routinely and systematically relocated Maasai from their centuries-inhabited lands to create national parks, wilderness areas, and commercial hunting zones (Goldman, 2011; S. Lynn, 2010b; Nyeko & Nnoko-Mewanu, 2023). On June 9-10, 2022, less than a year prior to this study's data collection efforts, Maasai protestors were demonstrating at a contested land grab demarcation line in Loliondo, an area within Maasailand's borders less than 200 miles northeast from our research camp. The Tanzanian government's interest in this landscape and gifting of 1500 km^2 to a prince from the United Arab Emirates happened in the early 1990's and has been problematic on and off for 30 years. The turmoil in 2022 reached a climax when security forces began firing live ammunition on the crowd. This resulted in the death of one Maasai man and 31 others being injured. A police officer was also killed during the dispute, leading to 24 Maasai being arrested for murder (Bekele, 2022; International Work Group for Indigenous Affairs, 2022). These ongoing challenges, including newly intensified efforts at Maasai evictions, were highlighted in a recent Atlantic article, 'This Will Finish Us,' that revealed the environmental justice situation in northern Tanzania to the global community (McCrummen, 2024).

Tensions are extremely high in the region between the Maasai community, the government, and foreigners due to ongoing fears of land loss. While conducting our first ESD, we used a permitted process of open reel measuring tapes, plant presses, and various field notebooks to collect data. Despite gaining Free, Prior, and Informed Consent to conduct our research from the national, regional, district, and village officials, our activities elicited suspicion and reprimand from passersby. After only two points, we chose to abandon this form of data collection to avoid causing further stress and risking decades of relationship-building. Twenty years ago, most locals were agreeable to field measurements being taken near their homes. However, following recent events and insecurities, and with rumors of a government land grab for conservation looming in the Simanjiro area adjacent to Tarangire National Park, Maasai communities have become suspicious of outside interests in their landscapes and any activity related to taking landscape measurements. Any future research in this region will require even more careful and deliberate partner engagement.

Remote Sensing Layers

The Google Earth Engine (GEE) Coder is a web-based integrated development environment for writing and running JavaScript. It allows users access to publicly available layers from the GEE catalog at their most recent years at their native spatial resolution for countless geospatial analyses (Gorelick et al., 2017). Leveraging data accessibility and cloud computing efficiency within GEE, we compiled and processed 29 layers from five sources for inclusion within our HSMs (see Appendix B). These layers were chosen because of their importance in other dryland HSM research (Luizza et al., 2016; West et al., 2016; Young et al., 2020), were publicly and freely available, covered our area of interest, and were at fine enough spatial scales (≤1000m) to show potential variation within the relatively small boundaries of the Maasailand region. Further processing was applied to several layers in ArcGIS Pro to create unique indices that provide novel perspicacity to the landscape using the specific bands in the *Normalized Difference Index* tool for each layer, respectively (see Appendix B for the band equations). We also extracted and compiled political, environmental, and cultural boundaries from various sources to create an unambiguous perimeter around the ambiguously defined Maasailand region.

Data Processing and Analysis

We used the USGS VisTrails: Software for Assisted Habitat Modeling (SAHM 2.2.1 on VisTrails 2.2.2) to model plant distributions in the greater Maasailand ecosystem. VisTrails is an open-source system with a user-friendly interface habitat suitability workflow using five different algorithms: boosted regression trees (BRT), generalized linear models (GLM), multivariate adaptive regression splines (MARS), Maxent, and random forests (RF) (Morisette et al., 2013; Sofaer et al., 2019; United States Geological Survey, 2014).

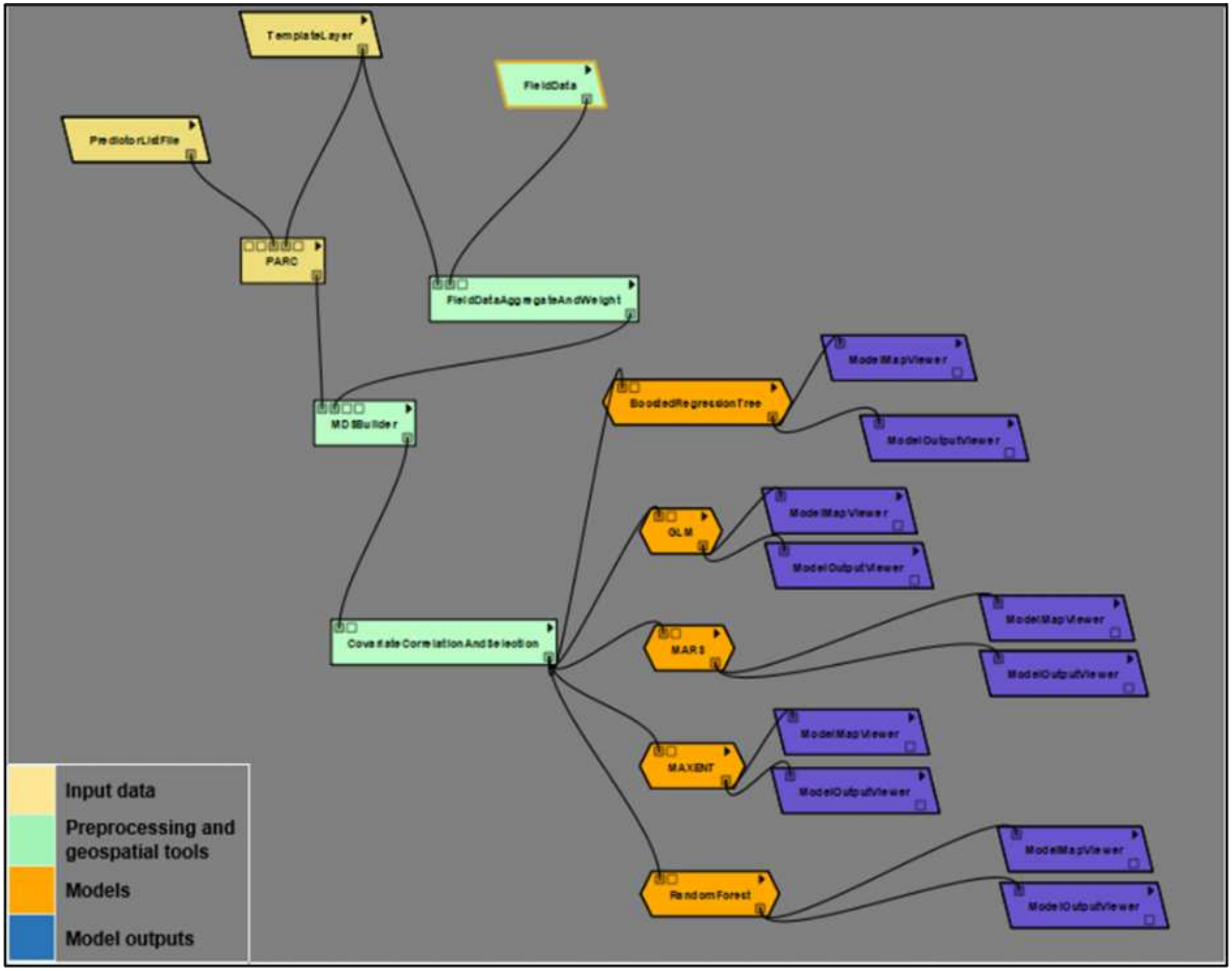


Figure 13. The user interface layout of the modules we used in SAHM. This is a common example of a habitat suitability workflow. using a five-step framework: specifying data inputs (yellow), data pre-processing and preliminary model analysis (green), model execution (orange), and viewing outputs and routines (purple).

There are numerous modules that can be applied to the data within a five-step framework: (1) specifying data inputs, (2) data pre-processing, (3) preliminary model analysis, (4) model execution, and (5) viewing outputs and routines (Talbert & Talbert, 2014). To create our HSMs, we compiled common routines outlined by Morisette et al. (2013), Luizza et al. (2016), and West et al. (2016) who are ecologists working on plant invasion in dryland systems and adapted them to our own methodologies. These methods are summarized below.

1. *Specifying data input*

    - The **FieldData** is the presence only, presence/absence, or count data that was collected by participatory science participants through CitSci and GBIF throughout the Maasailand region.
    - The **PredictorListFile** module file contained 29 environmental layers that included the most up-to-date representations of the Maasailand region (see Appendix B for a full list).
    - The **TemplateLayer** is a raster data layer with a defined coordinate system, a known cell size, and an extent that defines the study area, which the predictor rasters and field data are resampled, reprojected, clipped, and snapped to match. It has 4326 projection (WGS 1984) at a 30 m^2 spatial resolution.

2. *Data pre-processing*

    - The **ProjectionAggregationResamplingClipping** (**PARC**) module is a powerful utility that automates the preparation steps required for using raster layers in most geospatial modeling packages. Each layer must have cells of the same size that coincide, have the same coordinate system, and the same geographic extent. The PARC module ensures that all these conditions are met for the input layers by transforming and/or reprojecting each raster to match the coordinate system of the template layer.

- The **FieldDataAggregateAndWeight** tool helps aggregate field data locations so only one field data observation is represented per pixel or multiple points are down-weighted proportionately, should multiple exist in the same pixel. For example, if four field data presence points existed within a single 30 m^2 cell, then this module allows the user to either pick one of those points or make each point worth ¼ of the result for that cell.
- Absence points in niche modeling are contentious because the absence of a species does not immediately indicate that a spot is inhabitable. The species may have not physically reached that location yet, or it could be present and was overlooked by the observer (Bradley et al., 2012). The **BackgroundSurfaceGenerator** is a module that creates a continuous surface layer of background points that act as pseudo-absence points. We used the Kernel Density Estimate (KDE) function to produce background points. The KDE weights the likelihood of an environmental variable existing at a given point based on the distribution of the data. A kernel equation estimates kernel values over a given range of the distribution. The KDE then adds the kernel equations at each point across the entire distribution (Bradley et al., 2012; G. Zhang et al., 2018).
    - The distribution range is defined by a single bandwidth value, which is a smoothing parameter that defines the number and amplitude of peaks and troughs in the distribution. A low-value bandwidth produces greater variance, and a high-value bandwidth produces more smoothing.
- The **MergedDataSetBuilder** (**MDSBuilder**) extracts the value of each predictor layer at every field data point (including background points, if applicable) and produces a .csv file

exhibiting this information. This module is also where the user can establish the number of points to be generated in the background surface layer. In most scenarios, n = 10000 background points are preferred, but without ubiquitous landscape distribution, our dataset was limited to n = 7500.

3. *Preliminary model analysis and decision-making*

   - The **ModelSelectionCrossValidation** module is a tool for comparing models by their prediction accuracy. In many scenarios, there are not enough data to remove a subset to test as validation points against the model's training data. The dataset is divided into *K*-number of folds (groups) at random (Hastie et al., 2013). We used the ten-fold value (K = 10) as a default with stratification. Then K-1 (i.e., nine) folds are used to train the model, while the one remaining fold is used to test it. The average of all the prediction errors for each run is used as an estimate of the cross-validation prediction accuracy for the model overall. Evaluation metrics for each individual fold are reported in the cross-model comparison.
   - The **CovariateCorrelationAndSelection** allows the user to assess how well each variable explains the distribution of the sampled field data points and evaluates each variable against every other variable. At this point, users can remove by unchecking specified variables in the final models due to:
     - Low deviance between the predictor and response that is explained in a univariate Generalized Additive Model (GAM) or Generalized Linear Model (GLM).
     - High correlation (≥0.7) with other covariates based on the maximum of the Pearson, Spearman and Kendall coefficient.
     - Irrelevant to the specific species based on expert advice and/or literature reviews.

- Missing the extent of any percentage of field data points.

4. *Modeling*

- **BoostedRegressionTree** (**BRT**) combines two algorithms: regression trees and boosting. Regression trees divide the predictor space (i.e. environment) into grids, and the mean response for observations to the most constant predictor are plotted. It starts with a single split decision at this point and then adds a tree that best explains the errors that arose in the first tree. Each successive tree incorporates the relationship of variables in preceding branches. It continues iteratively in this fashion until the optimal number of trees (*nt*) is reached, and the data is overfitted. This optimal number is determined by the learning rate (*lr*), also known as the shrinkage parameter, and tree complexity (*tc*). *lr* determines the contribution of each tree to the growing model, and *tc* controls how interactions are fitted by determining how many terminal nodes will exist on the tree. Based on the literature (Elith et al., 2008), we used values $lr = 0.005$, $tc = 5$, $nt = 1000$. Another variable, the bagging fraction (*bf*), determines what percentage of the data is used in each iteration. We chose $bf = 0.75$, meaning that 75% of the data is used and 25% is withheld. Boosting then optimizes the model by decreasing "loss," which can be defined here as the unexplained residual from suboptimal modeling. Each successive model is iteratively fit to the training data by choosing the points with the worst fit based on previous steps. It focuses on the branches with the largest residuals, attempting to explain them in the next split.
- **GeneralizedLinearModel** (**GLM**) is an extension of linear regressions that is able to handle responses such as binary and count data. GLMs are defined by the response data distribution and the link function, which describes the linear link between an expected value and its relation to explanatory variables. Beginning with a null model, the Akaike

Information Criterion (AIC) score is calculated for each covariate. AIC is a statistical goodness-of-fit measure for each model. The lowest score has the best fit and is thus added to the model. In the first step, the covariate with the best/lowest AIC score is added, and then each of the remaining covariates' AIC is calculated again as a two-covariate model with the first that was picked. Covariates are added at each step and the one that improves the AIC most is moved forward until the model is optimized (Faraway, 2010; McCullagh & Nelder, 1989).

- **MaxEnt** is a machine learning technique that was built specifically for presence-only datasets. Maxent works on the maximum-entropy principle, which states that when we have limited information about a system, the most unbiased assumption we can make about the distribution of its possible states is the one that maximizes entropy. Based on this theory, in habitat suitability modeling the target probability distribution should be the most spread out (i.e. most normal), which is at the point that maximizes its entropy within the environmental constraints provided. Without known population sizes or densities, Maxent creates relative occurrence rates for each cell by comparing the presence points provided. The model requires presence data for the species of interest and background locations representative of the sampled environment. Features are created by transforming the covariates, and then products are created by having those features interact. MaxEnt ensures that the expected value of each environmental variable under the predicted distribution matches the observed average value at known species occurrences. It then incorporates regularization techniques to penalize complex models in favor of simpler ones less likely to overfit the data (Elith et al., 2011; S. B. Phillips et al., 2006; S. J. Phillips et al., 2017).

- **MultivariateAdaptiveRegressionSplines** (**MARS**) is a flexible, non-parametric technique that utilizes linear regressions. However, instead of a single linear model to fit the data, MARS uses many linear segments called “piecewise linear basis functions.” The full range of the model is broken into smaller sections of varying slopes connected by “knots” so that the final model appears angular compared to the smooth curves of other models. It is deliberately over-fit and then pruned back using general cross-validation statistics to make additions and deletions to each predictor’s significance based on the residual squared errors. We defaulted the variables to MarsDegree = 1 and MarsPenalty = 2.0 (Elith & Leathwick, 2007)
- **RandomForest** (**RF**) is a machine learning ensemble of many decision trees. The theory is that a single tree can have extremely different outcomes based on minute modifications, which makes them unreliable. However, numerous decision trees are computed using random subsets of the covariates, and, when all viewed together, these express a generalized pattern. Each tree takes a random sample of approximately two-thirds of the field data to produce its model using a bootstrap method (i.e., with replacement). The remaining unselected points are called out-of-bag (OOB) and are used like validation points to estimate the model’s error. Additionally, each tree uses a random subset of the predictors to de-correlate them, which reduces overfitting. Each tree in the forest gets one “vote,” and whichever class that receives the most votes produce the highest predicting model. We chose *nt* = 1000 trees. The relative importance of each covariate is assessed by the change in a fit statistic, on average, for trees that include it. All evaluation metrics for the training data are based on OOB predictions and thus should be like the results from

applying evaluation metrics to independent test data under the assumption that our observations are independent (Breiman, 2001; Valavi et al., 2021).

5. *Viewing outputs and routines*

- The **ModelMapViewer** provides a convenient means for viewing the numerous spatial outputs produced by individual model runs in an interactive Matplotlib.
- The **ModelOutputViewer** is used for viewing the textual and graphic outputs, which will be discussed in the Results section.

Once SAHM had successfully produced a complete set of models, the data were uploaded into ArcGIS Pro for further analysis. The probability maps were created using a stretch symbology running from 0-100% probability.

Results and Discussion

Research Question #1: Challenges and Possible Solutions of Participatory Science Methods

Altogether, 25 Maasai participants were signed up on the CitSci mobile phone app while the research team was in Tanzania. The majority, 23, were men; two were women, which is more demonstrative of Maasai culture than research bias. As mentioned before, participants needed to be literate and have access to a smartphone to interact with the CitSci app, which is a minority of the population in the rural Maasai villages in Simanjiro.

By the time the research team had left, fewer than 10 individuals could still access their CitSci accounts on their phones, and no additional users had joined. After several months, only three individuals were still collecting data on the CitSci app; one was our local research partner, one was a research assistant, and one was a local man signed up during a workshop. That is an

88% attrition rate. The last observations prior to this manuscript completion were collected in January 2024, a gap of nearly six months, likely due to problems we have identified.

Identified Challenges

There were many issues immediately apparent with the community's ability to utilize CitSci on a larger scale. First, although many people have cell phones, it is estimated that *<10% of people may have access to smartphones* (Isaya Rumas, personal communication, March 28, 2023). This inherent obstacle prevents the majority of the population from downloading the CitSci app and participating in data collection, minimizing the capacity for new participant recruitment.

A second limiting factor is *the low literacy rate in many rural villages.* Although the datasheet's questions and answers were translated to Swahili, literacy of the Latin-script is necessary to fully understand whether it is written in English or Swahili, since both alphabets use this same base. The initial instructions to log on to the app are in English, so without some English literacy, it is unlikely that a newcomer will be able to complete the process without the ability to read and understand English or external help.

Third, to set up a CitSci account and access the app store to download and use the mobile app, *participants must have an email address that they are able to access*. This is a security feature and deliberate choice of the CitSci team to require an account to participate so that multiple observations can be linked to individual observers. We helped all participants to create new emails or access idle accounts during initial workshop setups. However, email is a foreign concept that has almost no daily utility for many pastoralists. After downloading their desired apps, most Maasai disregarded their inboxes. Without access to their emails, they were unable to confirm their CitSci accounts. As we helped sign people up on the app, we also helped download email apps, reset passwords, and even debug phones bogged down by malware.

This transitions into the fourth issue: *lack of technological understanding*. Because many people were unfamiliar with email, the CitSci app, and even phone functionality beyond basic calls and texts, there was a tremendous learning curve. If anything went wrong, it was extremely difficult for local users to troubleshoot and fix the issue without help from the research team. If individuals had trouble in the field, it would require a phone call or WhatsApp message to the research team, which introduced additional complications. If they did not have service to contact the research team, then, in most cases, the effort to collect data was abandoned.

Fifth, *rural connectivity is limited*. Participants who signed up were given data vouchers to allow them to upload acquired points. However, that data does not last indefinitely, so after the research team left, participants needed to spend their own limited funds to purchase more data or find publicly available WiFi. Neither of these are abundant in these rural villages.

Lastly, QAQC revealed many points taken at the exact same or very proximal locations. For example, multiple observations were made as an individual walked down a road through a patch of one plant species. In fact, 240 out of the 257 data points removed from final analysis were due to replication. In addition, despite presence *and* absence being discussed during workshops, not a single absence point was collected.

Most of these issues are centered around Human-Computer Interaction for Development (HCI4D), a component of Information and Communication Technologies (Catholic Relief Review, 2010). This field focuses on designing and studying interactive computing systems – the CitSci app on cellphones in this case – typically in low-resource and underserved settings, making them accessible, usable, and relevant to the needs, skills, and contexts of the intended users. It requires understanding the social, cultural, economic, and infrastructural contexts in which technologies will be deployed, knowing that users may have varying degrees of digital literacy. Other considerations are the rights, values, and dignity of the users and communities involved including privacy, data security, and cultural sensitivity. HCI4D research and practice involves interdisciplinary (plus *cross-cultural* and *cross knowledge* in this case) collaborations among local stakeholders, programmers, scientists, and designers/engineers. The goal is to create appropriate, effective, and empowering technological solutions (Biljon, 2018; Biljon & Renaud, 2019; HCI Featured Community, 2023). Fortunately, we do have this type of collaboration to be able to improve our HCI4D approach to better serve the communities and improve model outcomes. We will return to this later in this chapter.

The combination of the six major issues we had with our participatory design resulted in significantly fewer observations than we had hoped for or anticipated. Despite these compounding issues, over 140 useful independent points were collected by community members to help create habitat suitability models, which is a commendable feat for a first attempt at an iterative process. The purpose of any pilot project, and specifically this project, however, is to identify challenges, to devise solutions to the challenges with potential to be fixed, and find workarounds for unfixable challenges (e.g., incorporate these expected issues into workshop trainings and discussions with communities).

Possible Solutions to Identified Challenges

Our team is in the early stages of writing a proposal to continue this work. We aim to (1) reduce barriers to entry by providing smartphones to motivated and literate community participants, recognizing that there are still some literacy needs that will limit participation; (2) expand our training to not only overcome the technological challenges but also improve overall technological literacy; (3) create a train-the-trainers style program that relies on village-based sentinels as liaisons between the community participants and our research team, relaying community needs to the research team while providing technical support to community members; (4) provide support to sentinels and our lead partner for their extra time investment and effort; and (5) maximize data collection for all species of interest. This final point will be accomplished by including all species in each observation point and converting basic presence/absence observations to 10x10m plots. Additionally, sentinels will be allocated at least 30 randomly located 10x10m plots per village to take observations on all species of interest with additional training and handheld GPS units. These points will help establish locations with potentially zero species of interest present, as well as observations in locations that had not been previously recorded and may be off typical travel paths.

<u>Research Question #2: Models' Statistical Accuracy</u>

Before the results, here is a brief background of the model output statistics provided by SAHM. The Confusion (Error) Matrix illustrates an algorithm's ability to accurately predict an outcome (see Table 4). The ideal outcome demonstrates high levels of agreement between model outputs (predicted data) and observed data. In the instance of habitat suitability modeling there are four potential outcomes for each model of predicted presence versus actual organism presence:

1. True Positive: An organism is predicted to exist at a location, and it does exist there.
2. True Negative: An organism is predicted not to exist at a location, and it has not been discovered there.
3. False Positive (Type I Error): An organism is predicted to exist at a location, but it does not exist there.
4. False Negative (Type II Error): An organism is predicted not to exist at a location, but it does exist there.

Table 4. A generic Confusion (Error) Matrix. "True" values exist when the Predicted and Observed values are the same. "False" values exist when the Predicted and Observed values contradict one another.

		Observed		
		Positive	**Negative**	**Total**
Predicted	**Positive**	True Positive (*tp*)	False Negative (*fn*)	Predicted Positive
	Negative	False Positive (*fp*)	True Negative (*tn*)	Predicted Negative
	Total	Observed Positive	Observed Negative	

Note: "Accuracy" is a difficult statistic to measure in this scenario. It is hard to know the true accuracy of our models without ground-truthing data to validate potential presence/absence locations for sociopolitical reasons discussed in the *Methods - Ecological Data* section. While our inability to gather these observations is disappointing and does affect the quality of our research outcomes, we want to recognize that there are many circumstances where it is not possible to collect ground data and yet ecological analyses remain valuable. This can be result from political and civil unrest (war, protests, government change), health and safety concerns (famine, disease outbreak, poor air/water quality, researcher illness or injury), environmental disasters (extreme storms, volcanic eruption, earthquakes), or inaccessibility (unusable vehicles, unmaintained roads, physical barriers). These areas may be impassable, unsafe, or even unrecognizable compared with their typical state. It is an ever-looming conundrum in research that requires habitual adaptation by the researchers.

In total, 401 points were collected between March 2023 and January 2024. Only 145 points (36% of the data) remained valid after the dataset had undergone quality assurance. We started off with 452 points for *Ipomoea hildebrandtii*, 384 from GBIF (85.0% of the data) and 68 from CitSci (15.0%). This was aggregated down to 82 points, 15 of which remained CitSci points. *Parthenium hysterophorus* had available 918 points, 875 (95.3%) from GBIF and 43 (4.7%) from CitSci. This was aggregated down to 253 points, 14 of which were CitSci points. Both data sources show high rates of spatial autocorrelation, which is likely a byproduct of convenience sampling.

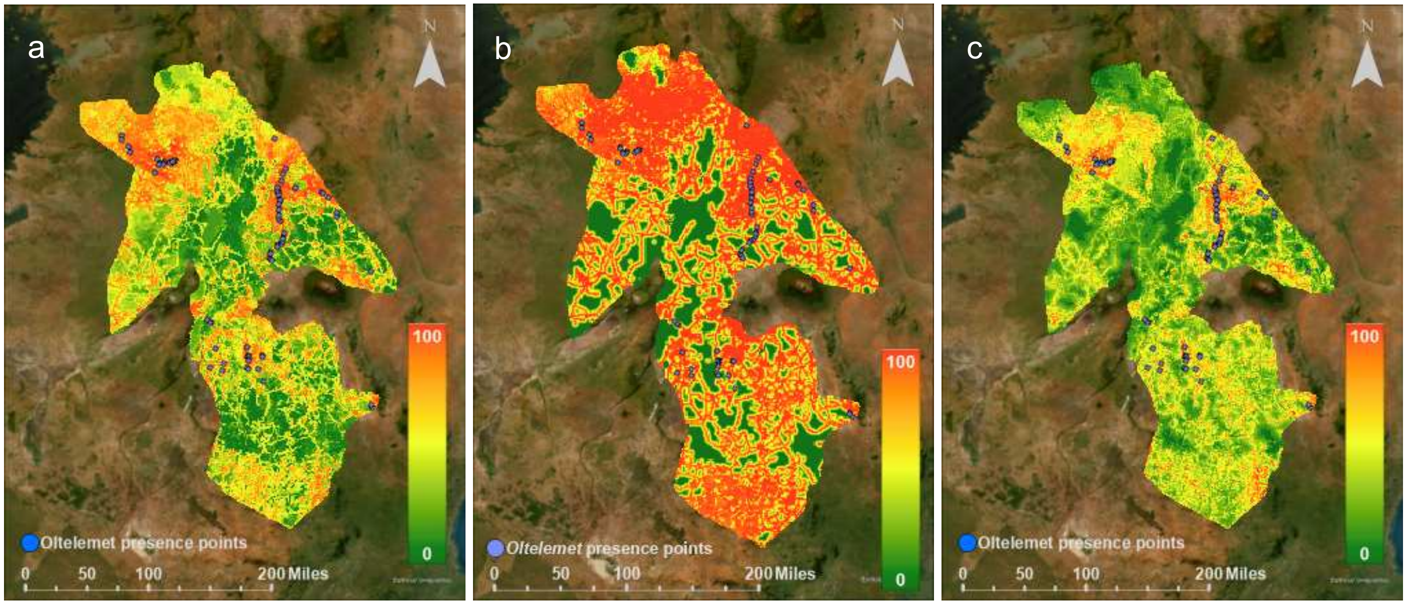
The statistical outputs from each model are provided in Table #. Of the 10 models produced, only seven are valid after three others were disqualified for overfitting: the Boosted Regression Tree models were overfit for both *I. hildebrandtii* and *P. hysterophorus* as well as the Maxent model for *I. hildebrandtii*. Had BRT not been overfit, it would have provided the most favorable statistical outputs. Instead, based on consistent output, Random Forest shows the greatest promise. For *I. hildebrandtii*, RF had the highest performance in 9/16 statistics, and 2/16 were the second-best performing statistics. For *P. hysterophorus*, this number rose to 12/16 and 2/16, respectively. All the models ranging from 74.9 - 91.1% accuracy using enhanced datasets are "reliable" (AUC $\geq$ 0.7) and one is considered to have "very good model performance" (AUC $\geq$ 0.9) (Manel et al., 2001; Pearce & Ferrier, 2000). Based on this line of evidence, while using the appropriate algorithm(s) and large enough datasets, participatory research observations can produce robust and accurate models.

Our initial intention was to use points gathered by locals through CitSci *only*, but SAHM could not generate enough background points to ensure ubiquitous distribution of data across the spatial extent because the CitSci dataset encounters less than 1% of the heterogeneous 150,000 km^2 area. In this regard our models are entirely inaccurate. Two studies (Sampaio & Cavalcante, 2023; van Proosdij et al., 2016) tested the minimum number of presence records required for Maxent – a presence-only specific software – to quantify the number of minimum records required to create accurate models for both species with (a) low and (b) high prevalence over continental ecoregion scales. They found strikingly similar results: (a) 14-17 records across the study area for the low prevalence species and (b) 25-30 for the high prevalence species (Sampaio & Cavalcante, 2023; van Proosdij et al., 2016). Based on the findings of these minimum-presence-points papers and our initial results – 68 points for *Ipomoea* and 43 for *Parthenium* – follow-up data collection efforts over a larger spatial extent should generate accurate models without too much additional effort or the need for supplementary data.

Table 5. SAHM evaluation statistics applied to the training and cross-validation splits for Ipomoea hildebrandtii (green) and Parthenium hysterophorus (blue). The darker shades indicate better statistical performance, lightening to white as they decrease in performance. The data for Boosted Regression Tree was overfit for both plants as was the Maxent model for *I. hildebrandtii*, so these models were excluded from further analysis, which is why they are crossed out.

AUC: Area Under the Curve; AUC-PR: Precision Recall Area Under the Curve; PCC: Percent Correctly Classified; K: Kappa; TSS: True Skill Statistic

		Training data							**Cross-validation data**						
		AUC	**AUC-PR**	**PCC**	**K**	**TSS**	**Sensitivity**	**Specificity**	**AUC**	**AUC-PR**	**PCC**	**K**	**TSS**	**Sensitivity**	**Specificity**
I. hildebrandtii	**GLM**	0.749	0.022	69.902	0.027	0.394	0.695	0.699	0.742	0.024	69.454	0.026	0.377	0.682	0.695
	MARS	0.850	0.038	77.539	0.050	0.556	0.780	0.775	0.803	0.038	76.035	0.042	0.483	0.722	0.761
	RF	0.911	0.161	83.606	0.081	0.677	0.841	0.836	0.911	0.233	95.226	0.166	0.449	0.492	0.957
	~~**BRT**~~	~~0.974~~	~~0.334~~	~~91.150~~	~~0.166~~	~~0.826~~	~~0.915~~	~~0.911~~	~~0.880~~	~~0.142~~	~~89.567~~	~~0.101~~	~~0.535~~	~~0.636~~	~~0.899~~
	~~**Maxent**~~	~~0.917~~	~~0.226~~	~~82.179~~	~~0.073~~	~~0.661~~	~~0.840~~	~~0.822~~	~~0.775~~	~~0.059~~	~~72.642~~	~~0.026~~	~~0.351~~	~~0.623~~	~~0.728~~
P. hysterophorus	**GLM**	0.809	0.121	72.391	0.093	0.450	0.726	0.724	0.803	0.133	72.144	0.091	0.443	0.722	0.721
	MARS	0.834	0.120	75.404	0.117	0.516	0.762	0.754	0.809	0.112	74.757	0.106	0.474	0.726	0.748
	Maxent	0.791	0.093	70.810	0.091	0.463	0.757	0.706	0.770	0.101	74.522	0.090	0.375	0.626	0.749
	RF	0.887	0.161	82.232	0.186	0.644	0.821	0.822	0.884	0.171	91.750	0.245	0.420	0.488	0.932
	~~**BRT**~~	~~0.927~~	~~0.279~~	~~85.801~~	~~0.240~~	~~0.711~~	~~0.853~~	~~0.858~~	~~0.870~~	~~0.180~~	~~84.429~~	~~0.185~~	~~0.558~~	~~0.710~~	~~0.849~~



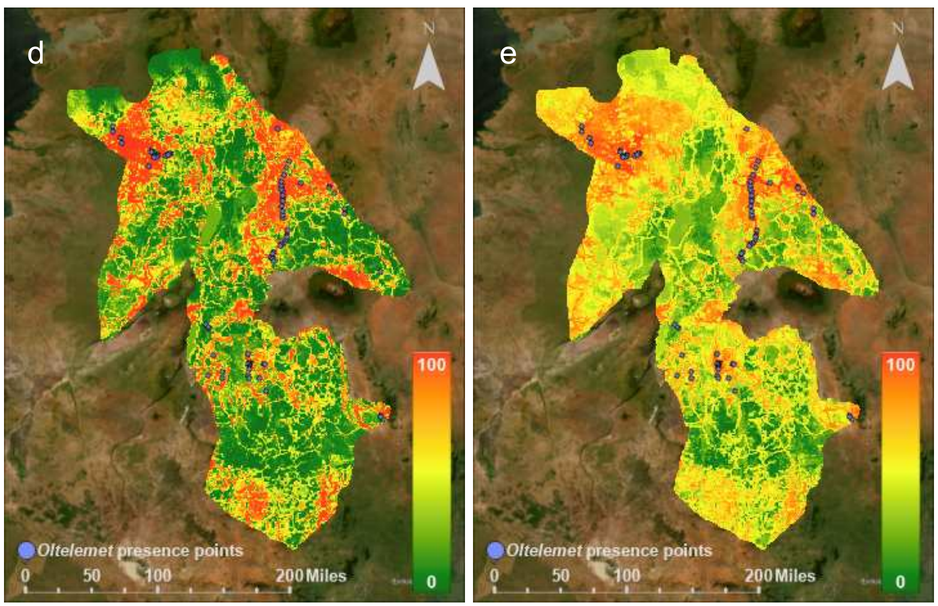
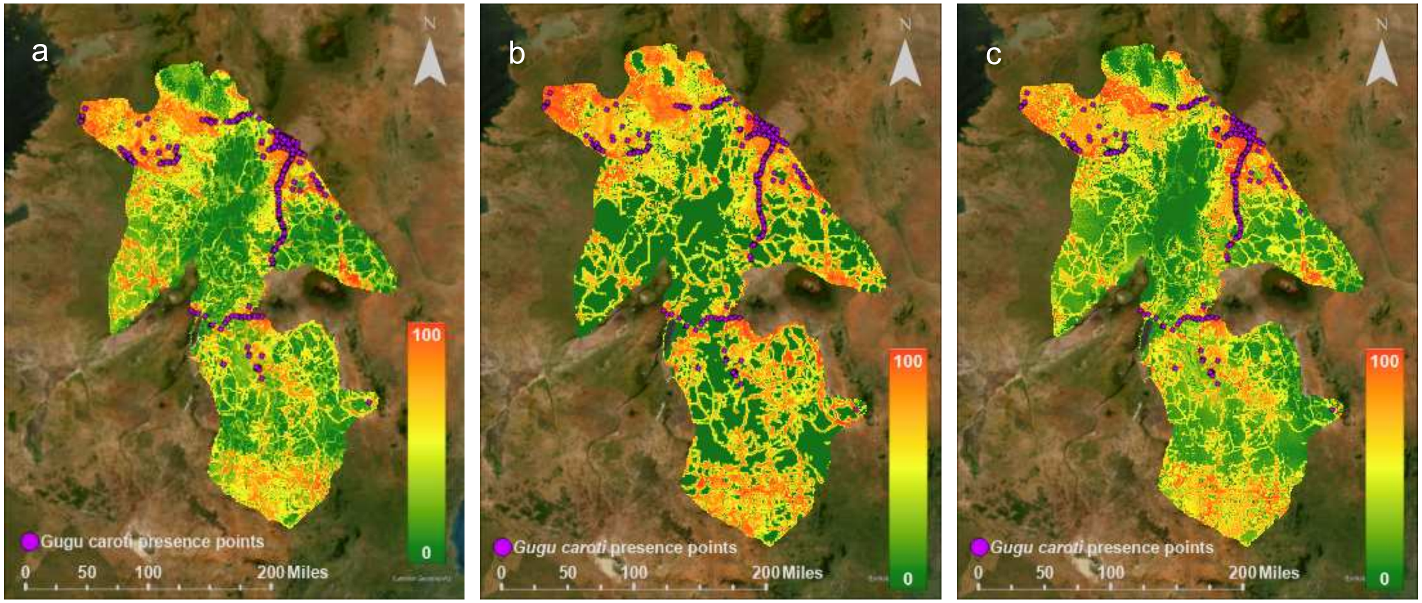


Figure 14. Results of the *Ipomoea hildebrandtii* habitat suitability models within the Maasailand boundaries - (a) Boosted Regression Tree; (b) Generalized Linear Model; (c) Maxent; (d) Multivariate Adaptive Regression Splines; and (e) Random Forest. The models for Boosted Regression Tree and Maxent are overfit. Each pixel is scaled from 0-100% on the likelihood of the habitat being suitable for the plant.



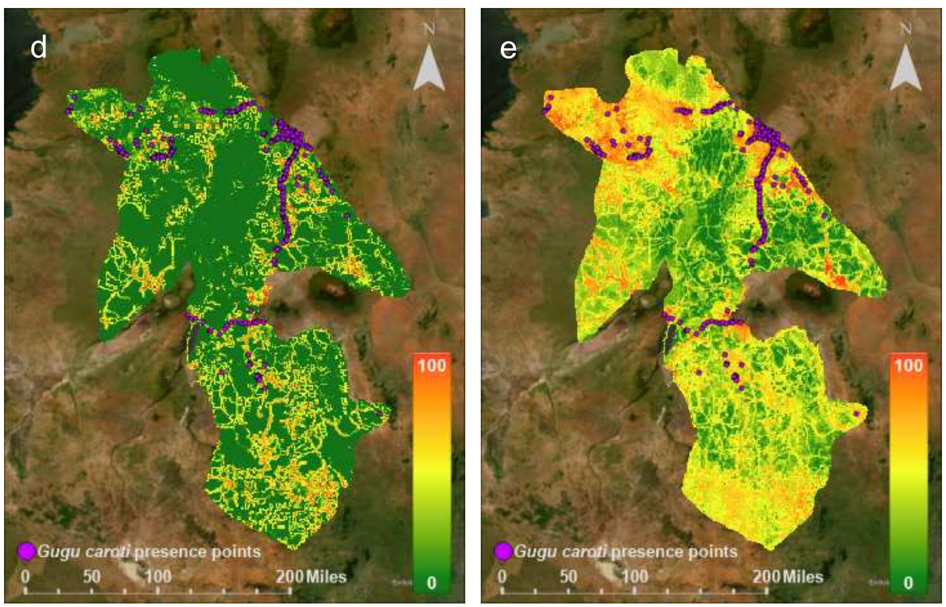


Figure 15. *Parthenium hysterophorus* (*Gugu caroti*) habitat suitability models within the Maasailand boundaries - (a) Boosted Regression Tree; (b) Generalized Linear Model; (c) Multivariate Adaptive Regression Splines; (d) Maxent; and (e) Random Forest. The Boosted Regression Tree model was excluded because it was overfit. Each pixel is scaled from 0-100% on the likelihood of the habitat being suitable for the plant. The Boosted Regression Tree model is overfit. Each pixel is scaled from 0-100% on the likelihood of the habitat being suitable for the plant.

Research Question #3: Emergent Potential Local Participatory Science Applications

Many Maasai understood the benefit that participatory science could provide for their community. During training sessions, people discussed–unprompted–the additional place-based utility of the CitSci app. Unbeknownst to us, this is what led to the addition of our third research question. Here are a few examples of CitSci utility constructed and proposed by local Maasai:

- A healer wanted to start a project regarding the locations of medicinal herbs. As he marked the plants' locations, he would be showing the community where these plants exist. In turn, the community could also let him know when they found areas where these plants existed. The process could be reciprocal in that knowledge would beget more knowledge as more people became aware of and documented these plants. Traditionally this is done through word-of-mouth, but recording and sharing this information through CitSci could greatly enhance the process.
- One of the few benefits of any problematic plant came from a traditional, non-Maasai bowhunter in regard to the concealment that *Oltelemet* offered. He realized that the presence/count data on *Oltelemet* cross-referenced with wildlife presence/count could provide him greater success. This was made apparent when he realized that this real-time information sharing could happen through the CitSci app.
- Herders thought it would be useful to note the locations of wildlife herds and predators. This way, livestock movement could be done efficiently and reduce competition (e.g., large herds of zebra), disease transfer (e.g., malignant catarrhal fever from wildebeest to cattle), and/or predation (e.g., by lions).

These are but a limited set of Indigenous ideas for where this project could expand to within the community. We recognize the importance of our team remaining engaged as guides in the construction of such projects, to hold conversations that bridge Indigenous knowledge and ways of seeing the world with Western science approaches that boost the power of observations for drawing conclusions and reducing bias.

Conclusion

This phase of the project focused on how participatory science tools could be used in Indigenous communities. Working with Simanjiro Maasai communities as a population for our case study, the questions we asked were: (1) How successfully can participatory science tools, such as CitSci, be adopted, what challenges are faced, and how can those challenges be overcome? (2) How statistically reliable can habitat suitability models be using data collected through participatory methods? (3) What other Indigenous two-eyed seeing applications could participatory data collection methods help achieve? The answers to these questions are less statistically quantitative and more qualitative in nature.

The technological barriers and learning curves can seem prohibitive. Without constant input or formal training, it is not likely that the app will easily catch on with our hopeful train-the-trainer approach. Ultimately, presence points were collected by community members using the mobile app, but this required significant trial-and-error and did not necessarily resolve any of the initial stumbling blocks. There was, however, great interest from locals in the multitude of applications that participatory science could offer, and many lessons learned on facilitating that process. This indicates that participants understood the power that participatory science approaches and documentation of observations could add to traditional oral methods of sharing observations. This portion of our project provided a means to test approaches, evaluate shortcomings, propose solutions, enhance knowledge, reflect on experiences, and expand the utility of two-eyed seeing. In that regard, it was an enormous success.

CHAPTER 3: SYNTHESIS

Summation of Project

Maasai agro-pastoralists live close to the land and are reliant on properly functioning ecosystem services in widely stochastic environments. Plants in particular play a central role in their livelihood primarily as forage for livestock, wild and cultivated foods, firewood, and structural materials for housing and fencing. However, unusable and detrimental plants can be just as important. Through participatory methods with Maasai communities in the Simanjiro Plains of Tanzania – including collective voices from different genders and age sets – we were able to identify and rank place-based problematic plant species and characteristics. We were then able to investigate multiple components of a framework focused on locally gathered and community-focused information. We evaluated the successes, (many) obstacles, statistical reliability, and emergent uses of the participatory tool, CitSci, using presence/absence points of key problematic plants for habitat suitability modeling as an initial case study. All evidence suggests the capacity for this framework to be adaptable and successful in other communities, given a few methodological improvements. This project illustrates the value of two-eyed seeing in mixed community-scientific endeavors for a holistic understanding of the social-ecological system of interest. As we conclude this project, we reflect on the journey and the outcomes. How can this information be applied in practice? What other communities might benefit from this practice, and how might their journeys differ through this process? What are the next steps to keep momentum with this approach?

Future Potential Research Avenues

First, it would be beneficial to *test how accurately our habitat suitability models can be scaled up to greater spatial and temporal extents*, or even to answering additional questions using different variables. There are inherent strengths and limitations associated with different remote sensing data sources and spatial data extraction methods that can impact the scalability. For example, if accurate HSMs can be constructed exclusively with Landsat-8 spectral information, accessibility to temporal Landsat imagery at global extents increases opportunities to include larger regions and seasonal information. On the other hand, if manual digitization of high-resolution imagery is necessary for predicting suitable habitat, there may be more restrictions, such as availability of images and the time-intensive job of digitizing. Similarly, if existing higher-level spatial products, such as publicly available LULC maps, are necessary to predict high-risk areas, there is a reliance on continued maintenance and upkeep of those products. Testing the model accuracy using various data source combinations could help determine the trade-offs between models' predictive strengths and dataset availabilities.

A second recommendation for future research would be *evaluating control, mitigation, and eradication (CME) measures for the most concerning plants*. For rural communities, it is important to find simple and cost-effective solutions to reduce the severity and/or breadth of problems caused by these species. The best example is *Parthenium hysterophorus*. Due to this plant's significant problematic characteristics, CME methods for this species have been researched extensively around the world. Manual removal and synthetic herbicides are two options commonly used in cultivation (Mao et al., 2021; Tabe Ojong et al., 2022), but these are restricted by finances and/or labor capacity. Biological controls have also been tested extensively across the globe with various levels of efficacy including, the leaf-eating beetle *Zygogramma bicolorata* (Kanagwa et al., 2020;

Shrestha et al., 2019), several species of *Puccinia* rust fungus (Dhileepan & Wilmot Senaratne, 2009), and several competitor plants such as *Cassia* spp. and *Tagetes* spp. (Patel, 2011) have shown high success rates in reducing *Parthenium*. These agents have already been introduced into natural environments in countries like India, Australia, and South Africa to prevent further invasion. Aside from each method's efficacy, a cost-benefit analysis would also help evaluate their true costs. Additional steps can be used for other plants of concern. Educational programs can be used to teach children which plants to avoid eating such as *Alauwii*, *Olorondo*, and *Oledwairai*. Veterinary practices can be taught for treating plant-borne diseases such as laminitis from *Alairahirah* (Greenough, 2016; Shearer & van Amstel, 2011) and bovine sunburn caused by ingesting the photodynamic compounds in *Orkiyapore* (Quinn et al., 2014). Future research could focus on determining which methods would be practical, legal, cost-efficient, and effective. This is one area we can contribute to by creating posters for Village offices to share species-specific information and management suggestions. Our team has collaborated with an undergraduate student group to begin some of these communication pieces that will be useful for communities.

Our third recommendation for future research relates to the ensemble model analysis (Araújo & New, 2007; Elith et al., 2005; Kotu & Deshpande, 2019) that would benefit from further exploration. For each species, the statistically relevant maps were merged using the *Merge Raster* tool, and the overlap method was set to *Mean*. This created a new map that showed the average likelihood of habitat suitability across the combined models. Next, these merged maps for both *Oltelemet* and *Gugu caroti* were merged again using the same *Merge Raster* tool. But instead of using *Mean*, the *Max* method was used to resolve overlaps. This created a final map that illustrated areas where *Oltelemet* and/or *Gugu caroti* are likely to exist based on the maximum likelihood between them (see Figure 16). Areas at greatest risk of these species being or becoming present are deemed potential *invasion hotspots* (IH) because the possibility of invasion from two or more species is high (Lyons et al., 2020). While these initial models are only cursory and not statistically robust, rerunning them with new data from future projects may produce IH sites with more realistic probabilities of invasion. Future research questions might ask: Are these areas already invaded by these, or other, species of concern? What factor(s) make these spots more susceptible to invasion? Are there any management methods that can be done to mitigate those odds? Answering any one of these questions could help improve these social-ecological systems.

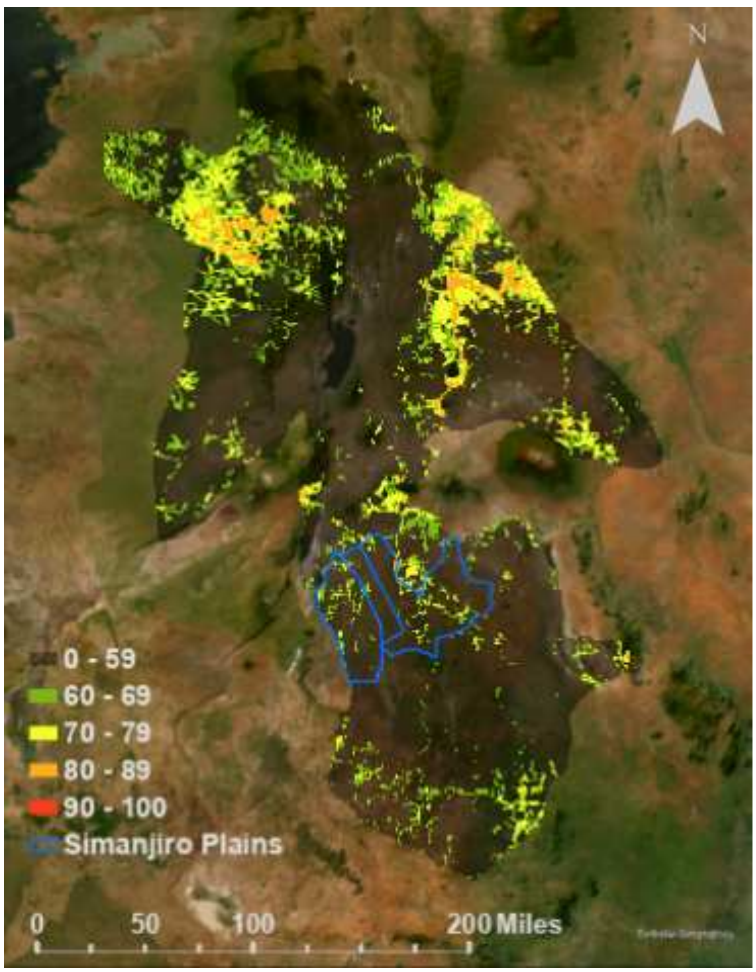


Figure 16. Example of potential invasion hotspots in Maasailand. These are areas that are at increased risk of invasion by *Oltelemet*, *Gugu caroti*, and/or other potentially problematic species.

Future Applications

The benefits gained from exploring and applying the CitSci app in a non-Western setting are two-fold. First, the CitSci team has assessed the design needs for new platform functionalities (website and mobile app) that will better serve rural, Indigenous, and non-literate populations who are interested in collecting data for their own use and planning. These need to accommodate the limitations and requirements of mobile app design that are dictated by security challenges and the broader needs of participatory science.

Second, with this experience, the team has learned a lot about how the community members approached this collaborative effort, their tendencies in making convenience-based observations, and how we can address some of these issues with an adapted data sheet design. We also learned more about the necessary local support services that could be provided by a few highly trained project facilitators, as well as the funds that it will take to provide a core set of handheld technology and to support data submission. The team has identified several ways to improve the two-eyed seeing process and how it is applied to problematic plant participatory research via approaches to study design and data collection, protocols and training, incorporation of outside data for modeling applications (e.g., GBIF), and data analysis. These approaches will improve the fit of the project for local Maasai participation, and – we hope – will provide a framework for future projects in Maasai communities, and similar participatory projects in Indigenous spaces globally. It will also improve data outcomes and rigor with both more data and more useful data and will improve the utility of the data outcomes for future local decision making and problematic species management.

Study Design and Data Collection

Due to the challenges of collecting ground data in the Simanjiro region at this time, future study designs will be based on Indigenous processes and will be achievable both quickly and without use of a field tape. In addition, the study design and associated data sheet will facilitate collection of data on multiple species at once – in this case the top six species of interest: *Oltelemet*, *Alairahirai, Gugu caroti*, *Orkiyapore*, *Almirirwaki*, and *Oltelemet* – opportunistically whenever any one of the plants of interest is observed. That observed plant will act as the centerpoint of a data plot to be measured in paces, starting with five paces (the way Maasai traditionally measure meters) toward the point where the sun rises in the east, then in the three remaining cardinal directions. The endpoints of the paces from center form the four corners of an approximately 10x10m(100m^2) plot that will become the observation space, with the center and each of the corners temporarily marked with orange flagging attached to a small stake. Observers will open the data sheet observation at the location of the initial plant (i.e., plot centerpoint). They will then make their observations for the initial species, including selecting which plant species they are observing, whether it is present or absent ("Present" for the initial species), and a count of the number of plants of that species in this 100m^2 plot to assess approximate density per 100m^2. They can choose the most representative plant of that species in the plot for their individual plant photos (whole plant, stem, thorns if exist, leaves if exist, flower if exists, fruit if exists, other). Finally, they will record whether any plants of this species are visible/detectable outside of the plot as far as they can reasonably see. This will conclude the observations of the first plant species, after which they will record the same information for the remaining species on the data sheet, starting with present/absent, with a response of "present" initiating the additional questions. In this case, observations will be taken for a total of six species. Observers will select land uses for the plot location from a selection (e.g., grazing, cultivation, road, settlement), will note soil color of the plot area (red, black, white, mixed red and black – classification of soils as Maasai talk about them and make land use decisions), and whether they can see a settlement, road, cultivated field, or livestock from where they are standing (as a "select all that apply" checklist). The final data sheet items will be to take an elevated photo holding the smartphone up of the full plot and two photos of the surrounding environment taken towards north and south from the north and south flags (to avoid sun glare to the east and west). Date, time, and geographic location will automatically be collected by the app. Additional protocol points: An effort should be made to make data sheet observations of a single species at least approximately 100m apart, represented by 100 paces. Autocorrelated points for each species will be removed during data analysis. Observations should be made during the rainy season post-emergence (approximately March through June) for the best likelihood of seeing and identifying plants.

By collecting data in this way, we 1) incorporate methods that are part of the way Maasai pastoralists already measure and observe the world around them; 2) make it possible for anyone with a smartphone to collect the data with minimal other equipment (small stakes or common nails with orange flagging that can be carried by anyone anywhere); 3) open up the opportunity to collect absence data for each species of interest; 4) improve the scientific rigor of data; 5) ensure we collect sufficient observations across each village; 6) make it possible to measure density; 7) reduce the risk of upsetting community members by the mere appearance of land measurements by foreigners; and 8) improve retention and continuity of data collection by training a core set of support sentinels, providing sentinels with smartphones, and providing resources for ongoing data upload needs of participating community members.

Study Protocol and Training

The improved study design will include two types of participants: Sentinels and Observers. All sentinels will perform the functions of observers by collecting plant observations in the CitSci mobile app but will also have additional responsibilities. 3-4 Sentinels per village, depending on village size and population, and on project budget will be identified by our CSU-Tanzanian research team (each village is composed of multiple sub-villages, and having Sentinels at the village will make them most accessible to Observers). Sentinels must have a smartphone (we will provide), must speak some English, must have some minimal technical proficiency to be able to navigate the CitSci website and mobile app, and must be willing to help observers set up email accounts, log back in if they are logged out of the system, and give other basic support. Sentinels will receive some compensation for their efforts. Anyone with a smartphone with basic Swahili literacy can be an observer and will be provided materials needed (English will not be needed since data sheets will be in Swahili). Our research partner, Isaya Rumas, will serve as a "Super Sentinel" or in-country lead to assist with sentinels' questions and bringing issues and questions to our attention.

The issue of observers being intermittently logged out and needing to log back in should be expected and incorporated into workshop trainings and protocols instead of being seen as a barrier, since this is a security feature of the CitSci mobile app. CitSci members are logged out of their accounts with each update to the system as a security precaution and this cannot be changed. In the future it may be possible to allow logins using phone numbers as an alternative to email, and the programming effort to incorporate this new feature will be included in our next proposal. However, some observers may still have difficulty logging back in; it will be the sentinels' job to assist anyone having this or other technical issues and to liaise between observers and the in-country lead and research team.

In addition, our team will create a visual protocol with minimal words in both English and Swahili that can be handed out to participants and posted on the CitSci project page for easy reference by Sentinels and participants. Finally, pending funding, we will update the CitSci data sheet creator to create capacity to add information buttons (symbolized by an icon of an "**i**" in a circle) that users can click on for each question when collecting data that can guide them in the process and making decisions. Having at-a-glance instructions in the data sheet will aid the Sentinels when assisting Observers, or ideally may include images as guides that can help observers themselves via example observations.

In addition to their support role, each Sentinel will be sent a set of random locations within their village to make observations using an identical data sheet with the title "Random Location Observations" to ensure that observations will be made in areas that people do not frequently visit in their day-to-day lives, and which may also provide an opportunity to have observation locations where none of the problematic plant species of interest are present. This will improve our absence data, and geographic representation of observations. The random locations will be selected after several months of data collection by masking areas where observations exist with a buffer of 100m and dropping 30+ random location points no closer together than 100m to any existing or new point and ensuring that no large gaps of >1km exist between points. Observations will still have some clustering because we cannot control whether multiple individuals make observations proximal to one another, but they will be made independently and autocorrelated observations will be eliminated as part of quality control prior to data analysis.

Trainings will be conducted with Sentinels at the onset of the project, including multiple practice field days to ensure that questions are addressed, and any issues or stumbling blocks fixed prior to initiating data collection. We will give sentinels three days to make observations and for the scientific team and Sentinels to address any additional emergent challenges. During this time Sentinels will each also recruit 4-6 male and female observers (approximately even male:female ratio) to collect data for their village (sentinels should also have both male and female representatives in each village, with at least one woman representing the local women's group if possible). They may collect observations anywhere, even outside of Simanjiro if they wish, but will represent their village. Following the three days of recruiting we will assemble all Sentinels and their village's observers for a half-day training session on their market day, including setting observers up with emails. In addition to owning a smartphone and attending the training, recruits must complete five unique observations that conform to protocol before being provided with data cards to support the cost of continuing observations. Village teams will work together to make practice observations with the Sentinels and the scientific team as guides and can schedule monthly meetups at the weekly market for teambuilding, to recruit new participants, and to address questions and challenges, logouts, and other issues. We will proceed through this process village by village for 5-6 Simanjiro villages, with 4-5 days total time onboarding and training per village. Before departing the country, the scientific team will follow-up with all Sentinels and create a WhatsApp group for monthly meetings and interim communications. The entire project initiation will take approximately one month, with an additional 3-4 weeks planned for meetings with village leadership and the national-level research permit process.

Data Analysis

Remote sensing and GIS methods will remain relatively the same, with two exceptions. First, layers that occur over a broader scale - climate, temperature, precipitation – will be excluded from analyses. These layers provide clarity on a larger scale (i.e., national or international) but do not provide enough differentiation on the scale of Maasailand. Therefore, more localized layers will be sought such as water and topographic features or soil type/color that can discern differences at a finer scale.

An additional LULC layer would be created based on Indigenous classification using the CitSci data, with the land use at a particular observation point providing current ground truth data for that layer. Along with plant information from each point, certain environmental characteristics will be collected in the datasheets. This qualitative geospatial data will be run through a GIS image classification software, such as *Classification Wizard* in ArcGIS Pro, to create a predictive map based on Maasai designations. Two classification systems were identified that could be used: one based on land utility, the other based on soil color. A rudimentary version of this was attempted, but there was not enough data from this pilot study to create reliable maps.

Results Interpretation

With ground-truthed data, we will be able to discern the real-world accuracy of our models. Variables can be fine-tuned, and predictive maps can be provided as additional tools in the decision-making toolboxes of stakeholders. This project can provide a conceptual framework that blends traditional ecological and Western scientific knowledge systems through two-eyed seeing methodologies, including the use of participatory science, in traditionally disenfranchised regions of the world. By placing this collaboratively developed information in the hands of *locals*, natural resources can be managed by *locals* in ways that support *local* needs, socioeconomics, and culture. It might also shine light on unique, place-based adaptation and resiliency techniques. The academic implications are great, but the information provided to the communities themselves could prove vastly more invaluable.

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APPENDICES

Appendix A: Focus group questions.

Village: S K L **Sub-location**________________________ **FG #**___ **Date**__________
Participants: M F **Translator**_________________________ **Start:**_________**End:**__________
NOTES:

Participant Information

1. What is your name?
2. What is your age?
3. Which age set did you grow up with?

ID	Name	Age	Age set
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			

Species Identification Exercise

4. Which species of plants that are found in this area do you find to be problematic for you, your animals, your crops, the environment, or anything else? [freelist]

Identify problematic plant SPECIES and TRAITS

5. What problematic traits does this species exhibit? [freelist]
6. Does the plant bring you any benefits?
7. How do you think the plant spreads?
8. Is this plant increasing, decreasing, or staying the same?
9. Are there ways that you manage this plant locally, or that you have heard about managing it?
10. Would you like to see this plant managed?

Sev. Rank	Com. Rank	Plant	Problems/Benefits, Spreading Mechanisms and Management
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:
			Problems: Benefits: Spread: Mgmt:

Species Ranking exercise (by individual participant)

(Hand out sets of 4 colored stickers to each participant, with a personal ID# attached to age/gender classes written in sharpie on each sticker. At the end, determine rank and add above. Assign numerical value to red, yellow and green stickers [1st = 3, 2nd = 2, 3rd = 1] and sum together for each species to find the top three most severe plants in each group. The top common plant will have the most blue stickers. Continue with next questions for the top 3 severity species and the top 1 common species.)

11. Place the **red** sticker next to the species you think is most problematic for you.
11. Place the **yellow** sticker next to the species you think is second most problematic for you.
12. Place the **green** sticker next to the species you think is third most problematic for you.
13. Place the **blue** sticker next to the species you think is most common in this area. This can be placed next to any one plant, including ones that you've placed another sticker next to.

Species-specific questions (top 3 highest ranked plants)

Species #1 (repeated for #2 and #3):______________________________

Phenology

14. What month or time of year does this plant:
    a. First appear?
    b. Flower or fruit?
    c. Senesce, die, or disappear?
    d. Appear to be the most problematic?

Development

16. Was this plant around when you were a child? If not, when did you first see it?

Habitat

15. On a scale from 0-3, how prevalent is this plant in each of the following habitats?
    a. Ewas (pastures)?
    b. Orkung (forests)?
    c. Engusero (black cotton soils)?
    d. Iraat
    e. Irkejek
    f. Ildonyo
    g. Bari bari ni (roadsides)?
    h. Shambas (agricultural fields)?
    i. Bomas (homes)?

18. On a scale from 0-3, how prevalent is this plant in each of the following soil types?
    j. Red?
    k. White?
    l. Black?
    m. "Islands"?
    n. Red/white?
    o. Black/white?
    p. Red/black?

Seasonality and Response to Environmental Factors

19. How is [this plant] affected by floods?

16. How is [this plant] affected by drought?

Appendix B: Remote Sensing environmental covariate layers and sociopolitical boundaries used in SAHM habitat suitability models.

Full File Path	Description	Date	Spatial Resolution (m^2)	Source/Citation
Chemistry_Harmonized_Soils	Attributes of the Harmonized World Soil Database v1.2 including Organic Carbon (% weight), Calcium Carbonate (% weight), Gypsum (% weight), Salinity (electrical conductivity), and pH	2012	1000	FAO, IIASA, ISRIC, ISSCAS, JRC
General_Harmonized_Soils	Attributes describing the basic properties of soil derived from Phase 1 and Phase 2 of the Harmonized World Soil Database v1.2.	2012	1000	FAO, IIASA, ISRIC, ISSCAS, JRC
Texture_Harmonized_Soils	Attributes of the Harmonized World Soil Database v1.2 including USDA Texture Class, Gravel (% volume), Sand (% weight), Silt (% weight), and Clay (% weight)	2012	1000	FAO, IIASA, ISRIC, ISSCAS, JRC
HOTOSM_Roads_Euclidean	Distance to the closest road for each point, shown as a gradient.	2024	10	HOT
Aspect	Aspect based on SRTM DEM	2000	90	NASA and CGIAR-CSI
Elevation	Elevation based on SRTM DEM	2000	90	NASA and CGIAR-CSI
Landforms	Landforms based on SRTM DEM	2000	90	NASA and CGIAR-CSI
Slope	Slope based on SRTM DEM	2000	90	NASA and CGIAR-CSI
Topographic_Diversity	Represents temperature and moisture conditions available to the biotic environment.	2000	270	NASA and CGIAR-CSI

Topographic_Position_Index	Distinguishes topographic features by comparing each pixel to its surrounding neighbors (AKA local relief model).	2000	90	NASA and CGIAR-CSI
Human_Influence_Index	Anthropogenic impacts using nine global data layers covering human population pressure (population density), human land use and infrastructure (built-up areas, nighttime lights, land use/land cover), and human access (coastlines, roads, railroads, navigable rivers).	1995-2004	100	WCS and CIESIN
Ecophysiographic_Lands_Units	Areas of distinct bioclimate, landform, lithology, and land cover that form the basic components of terrestrial ecosystem structure.	2015	250	USGS, ESRI, Metzger et al., ESA, GEO
Landsat8_Brightness_Tasseled_Cap	Transformation of spectral bands to focus on bare soil, partially covered soil, concrete, asphalt, gravel, rock outcrops, and other bare areas.	2020-2023	30	USGS and Baig et al.
Landsat8_Greenness_Tasseled_Cap	Transformation of spectral bands to focus on green vegetation.	2020-2023	30	USGS and Baig et al.
Landsat8_Wetness_Tasseled_Cap	Transformation of spectral bands to focus on soil moisture, water, and other moist features.	2020-2023	30	USGS and Baig et al.
Landsat8_BSI	Bare Soil Index: ((B6 + B4) – (B5 + B2)) / ((B6 + B4) + (B5 + B2))	2020-2023	30	USGS Landsat-8
Landsat8_EVI	Enhanced Vegetation Index = 2.5 * ((B5 – B4) / (B5 + B6 * B4 – 7.5 * B2 + 1))	2020-2023	30	USGS Landsat-8
Landsat8_NDMI	Normalized Difference Moisture Index: (B5 - B6) / (B5 + B6)	2020-2023	30	USGS Landsat-8
Landsat8_NDVI	Normalized Difference Vegetation Index: (B5 - B4) / (B5 + B4)	2020-2023	30	USGS Landsat-8
Landsat8_SAVI	Soil Adjusted Vegetation Index = ((B5 - B4) / (B5 + B4)) + 0.5	2020-2023	30	USGS Landsat-8
Local_Climate_Zones	Classifies natural and urban landscapes into categories based on climate-relevant surface properties.	2018-2019	100	Demuzere et al.

World_Terrestrial_Ecosystem	World classified into areas of similar climate, landform, and land cover, which form the basic components of any terrestrial ecosystem structure	2023	250	USGS, ESRI, TNC
Rivers_Euclidean_Distance	Distance to the nearest surface water for each point, shown as a gradient.	2021	90	WWF-CSP
Annual_Mean_Temperature	Annual mean temperature from 1970-2000	2019-2020	1000	WorldClim
Annual_Precipitation	Annual precipitation from 1970-2000	2019-2020	1000	WorldClim
Max_Temperature_of_Warmest_Month	Annual average of the maximum temperature from the historically warmest month for 1970-2000	2019-2020	1000	WorldClim
Min_Temperature_of_Coldest_Month	Annual average of the minimum temperature from the historically coldest month for 1970-2000	2019-202	1000	WorldClim
Precipitation_of_Driest_Month	Annual average of the precipitation amounts from the historically driest month for 1970-2000	2019-2020	1000	WorldClim
Precipitation_of_Wettest_Month	Annual average of the precipitation amounts from the historically wettest month for 1970-2000	2019-2020	1000	WorldClim

File Path	**Description**	**Date**	**Spatial Resolution (m^2)**	**Source/Citation**
Administrative_Boundaries	Levels 0 (country), 1 (region), 2 (district), and 3 (ward)	2018	-	UN OCHA
Tanzania_Protected_Areas	Protected areas and other effective area-based conservation measures in	2023	-	UNEP-WCMC
Ethnography	Geopolitical, ethnic, and cultural boundaries	2014	-	East View Geospatial

Appendix C: CitSci datasheet

To Mimea ya Simanjiro

Uchunguzi wa mimea

Observation Date * 2024/03/02 02:34 PM

Observer * Connor McCarty

Location *

Name * Location name

Latitude * Latitude

Longitude * Longitude

Address, City, Landmark SEARCH

Piga picha ya mmea mzima. (Take a photo of the entire plant) *

PRESS HERE TO CHOOSE IMAGE FILE

Chukua picha ya majani machache. (Take a photo of a few leaves)

PRESS HERE TO CHOOSE IMAGE FILE

Chukua picha ya gome na miiba yoyote. (Take a photo of the bark and any thorns)

PRESS HERE TO CHOOSE IMAGE FILE

Chukua picha ya maua yoyote. (Take a photo of any flowers)

PRESS HERE TO CHOOSE IMAGE FILE

Picha za ziada. (Additional photos)

PRESS HERE TO CHOOSE IMAGE FILE

Je ni majani gani ya mmea huu unayojua? (What are the names you call this plant?)

Cama hijui sema "sijui". (If you do not know say "I don't know".)

Kiasi gani cha mmea huu kiko ndani ya mita 5 kutoka kwako? (How much of this plant is there within 5 meters of you?) *

- Kidogo (A little)
- Kiasi (A moderate amount)
- Nyingi (A lot)
- Hakuna (None)

Rangi ya udongo ni nini? (What is the color of the soil?) *

- Nyekundu (Red)
- Nyeupe (White)
- Nyeusi (Black)
- Nyekundu na nyeupe (Red/White)
- Nyeusi na nyeupe (Black/White)
- Nyekundu na Nyeusi (Red and Black)
- ? Kitu kingine (Something else)

Mfumo wa ikolojia nini? (What type of land are you in?) *

- Ewas (Plains)
- Orkung (Forests)
- Engusero (Cotton soils)
- Iraat (Depressions)
- Irkejek (Rivers)
- Ildonyo (Mountains)
- Oloigeiruno ("Islands")
- Engarkash
- Kitu kingine (Something else)

Je, uko ndani ya mojawapo ya mabadiliko haya ya ardhi? (Are you within one of these land changes?) *

- Kando ya barabara (Roadsides)
- Mashamba yaliyolimwa (Cultivated fields)
- Bomas (Houses)
- Kuchunga kupita kiasi (Overgrazing)
- ? Kitu kingine (Something else)
- Hakuna mabadiliko ya ardhi (No land changes)

Maelezo ya ziada. (Additional notes)

Acha hii ikiwa huna chochote kingine unachotaka kushiriki kuhusu mmea huu. (Leave this blank if you have nothing else you want to share about this plant.)

SUBMIT

Questions (*required answers)

1. *Observation date (autofilled)
2. *Observer (autofilled)
3. *Location (autofilled)
    a. *Name (autofilled)
    b. *Latitude (autofilled)
    c. *Longitude (autofilled)
4. *Take a photo of the entire plant.
5. Take a photo of a few leaves.
6. Take a photo of the bark and any thorns.
7. Take a photo of any flowers.
8. *What are the names you call this plant?
9. How much of this plant is there within 5 meters of you?
10. What is the color of the soil?
11. What type of land are you in?
12. Are you within one of these land changes?
13. Additional notes