DISSERTATION

SOCIAL-ECOLOGICAL MODELS FOR KNOWLEDGE CO-PRODUCTION AND LEARNING IN COLLABORATIVE ENVIRONMENTAL MANAGEMENT

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ABSTRACT

SOCIAL-ECOLOGICAL MODELS FOR KNOWLEDGE CO-PRODUCTION AND LEARNING IN COLLABORATIVE ENVIRONMENTAL MANAGEMENT

In a rapidly changing world, human communities struggle to address complex environmental problems that are multidimensional, without clear definitions or solutions, and that require collaboration among actors with potentially conflicting objectives. Collaborative approaches to environmental management engage diverse actors who work together to produce shared understanding and novel solutions to these challenging problems. Collaborative approaches encourage participants to learn from each other and reflect on that learning, which can improve their collective ability to cope with variability brought on by global environmental change. Modeling is increasingly used by academics and development practitioners to encourage and inform collaborative environmental management, yet there has been insufficient attention paid to how collaborative modeling processes interact with the social and cultural factors that shape environmental outcomes.

This dissertation engages at the intersection of science and culture to examine the use of social-ecological models in the context of collaborative environmental management. First, I present a snapshot of current barriers and best practices in collaborative or transdisciplinary environmental work, using a global survey to inform a conceptual model of knowledge co-production and learning. I then apply this conceptual model in a case study of a community-managed Afroalpine grassland in the Ethiopian highlands known as Guassa, using a combination of cognitive, geospatial, and simulation modeling. Specifically, I bring together insights from local knowledge and remote sensing analyses to present a more holistic understanding of social and biophysical change in this area and to situate the environmental consequences in relation to locally-defined ecosystem services. I then use individual and small group mental modeling to compare how different types of people involved in managing Guassa conceptualize the key components of this social-ecological system. I describe a co-designed agent-based model of shrub encroachment into the Guassa grassland, using it to improve our understanding of the system and to explore potential management interventions. I assess the learning experienced by participants in these mental modeling and agent-based modeling exercises to advance our understanding of the kinds of learning that occur throughout a collaborative modeling process. This work informs the design and application of social-ecological models to contribute to more equitable and sustainable collaborative environmental management.

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CHAPTER 1

INTRODUCING THE DISSERTATION

1.1 Theoretical Foundations

Global environmental change encompasses a wide range of human-driven activities that alter the structure and function of ecosystems (Turner et al. 2007). Changing lifestyles and technological advances around the world have increased demand for goods and services, leading humans to environmentally harmful activities such as burning fossil fuels, expanding agriculture to marginal lands, cutting forests, and polluting chemicals. Climate change (Parmesan and Yohe 2003), biological invasions (Vitousek et al. 1996ca), and unsustainable natural resource use (Persha et al. 2011) are among the most pressing examples of global environmental change around the world. Understanding and responding to these changes is a central challenge for the management of sustainable ecosystems, with far-reaching consequences for human well-being (Lambin et al. 2001, Carpenter et al. 2009, Rockström et al. 2009, DeFries et al. 2012).

Understanding global environmental change within integrated social-ecological systems is critical for developing effective responses due to the complexity of these systems (Ostrom 2007, Turner et al. 2007, Lambin & Meyfroidt 2010). Social-ecological systems are complex, adaptive systems that often exhibit nonlinear dynamics, indirect effects and feedbacks, emergent properties, and heterogeneous links across space and time (Liu et al. 2007; Lambin & Meyfroidt 2010). These characteristics can cause unanticipated outcomes that make environmental management extremely difficult, particularly as decisions are often made in the context of limited data and high uncertainty (Polasky et al. 2011).

As global environmental change continues to accelerate and intensify (Cleland et al. 2007, Steffen et al. 2011, Pepin et al. 2015), science and society are turning to transdisciplinary work

(TDW) to facilitate transitions to sustainability (Lang et al. 2012; Brandt et al. 2013). In the context of environmental sustainability, TDW is a reflexive research approach that brings together actors from multiple academic fields and diverse sectors of society to engage in mutual learning, with the intent to collaboratively produce solutions to social-ecological problems (Klein et al. 2001; Lang et al. 2012; Jahn et al. 2012; Cundill et al. 2015). From a theoretical perspective, TDW overlaps with a wide range of scientific domains, including participatory action research (Lewin 1948; Freire 1970), citizen science (Bonney et al. 2014) or public participation in science (Shirk et al. 2012), and common pool or common property resources (Ostrom 1990; Agrawal 2001; Cox et al. 2010). A common theme throughout these bodies of literature is the idea that collaborative approaches, especially those that bridge science and society, can lead to improved solutions to the challenges of global environmental change (Knapp et al. 2019).

Effective TDW draws on multiple types of knowledge to understand problems more holistically. Many times, the challenges facing social-ecological systems are multidimensional "wicked problems" that lack clear definitions or solutions (Rittel and Webber 1973; Chapin et al. 2008). These problems are "wicked" not in an ethical sense, but due to their resistance to simple explanations or objective resolution. Managing these complex systems and challenges increasingly requires collaboration among diverse teams with a range of knowledge types and worldviews so that the boundaries of the problem can be understood from multiple perspectives, and the scope of potential solutions can be expanded (Polasky et al. 2011; Tengö et al. 2014; Bernstein 2015; Hoffman et al. 2017). This diversity also contributes to the perceived credibility, salience, and legitimacy of TDW results (Cash et al. 2003; Cundill et al. 2015), which can empower participants to take ownership of TDW products and increase people's ability to apply new knowledge and products to sustainability problems on the ground (Lang et al. 2012; Balvanera et al. 2017).

However, it is not sufficient to bring diverse people together for effective TDW to occur – there must be collaboration and mutual learning among TDW participants, so that trusting relationships and open channels of communication can develop (Dietz et al. 2003). These conditions support the development of adaptive capacity, which is critical for decision-making under the high uncertainty facing social-ecological systems (Kates et al. 2001; Fazey et al. 2014; Fujitani et al. 2017). Social learning, which derives largely from theories of organizational management (Argyris & Schön 1978), is an increasingly useful concept for understanding how people learn within particular social and cultural contexts (Lave & Wenger 1991; Keen et al. 2005; Fernández-Giménez et al. 2019). Social learning has been shown to improve understanding of social-ecological systems (Walters & Holling 1990), to foster adaptation and collective action (Pahl-Wostl et al. 2007), and to build trust among diverse individuals (Reed et al. 2010) – all of which contribute to improved TDW process and outcomes (Lang et al. 2012; Jahn et al. 2012; Cundill et al. 2015).

Modeling increasingly is used by academics and development experts to encourage collaboration and learning among resource users, policy makers, researchers, and conservation practitioners (Bousquet & Le Page 2004; Barnaud et al. 2008; Verburg et al. 2016; Voinov et al. 2018). This doctoral dissertation advances understanding of the benefits of cognitive, geospatial , and simulation modeling by examining the kinds of learning that occur when social-ecological models are used to support collaborative environmental decision making.

1.2 Dissertation Structure

The following dissertation is comprised of four main chapters, with an introduction and conclusion to frame the research. The main chapters were written to be stand-alone peer-reviewed journal articles, which introduces some repetition throughout.

In Chapter 2, I present a seven-step conceptual model to guide learning and knowledge co-production through environmental TDW. This model has similarities to other frameworks and guides present in the literature (Carew & Wickson 2010; Jahn et al. 2012; Lang et al. 2012; Brandt et al. 2013; Mauser et al. 2013; Scholz & Steiner 2015b), though it distinguishes itself through the inclusion of very specific activities that are largely absent from these other examples (but see Lang et al. 2012), and which provide practical guidance for best practices in environmental TDW that are inclusive of the diversity of people and places where it occurs. I used this conceptual model to guide the development of a survey, which I administered to scientists, practitioners, and stakeholders involved in environmental TDW projects worldwide. Results from 168 responses inform the identification of 23 activities to include in a 'toolbox' of TDW best practices for overcoming barriers to effective collaboration and increasing the societal and scientific impacts of TDW projects.

In Chapter 3, I describe a case study that illustrates the benefits of drawing on diverse knowledge to understand global environmental change, following the early exploratory steps in the conceptual model from Chapter 2. I used a multiple-evidence based approach (Tengö et al. 2014) to investigate the causes and consequences of environmental change in a community-protected grassland known as "Guassa" and its surrounding landscape in the Ethiopian highlands, drawing on remote sensing and ethnographic approaches to explore the interaction of biophysical and social change, and to understand potential impacts for ecosystem service provisioning. The knowledge co-production process revealed both complementary and contradictory findings across knowledge systems, which led to new system understanding.

In Chapter 4, I present an iterative process of constructing and revising mental models of the same community-protected grassland in Ethiopia. I analyzed these mental models to understand how knowledge of this social-ecological system compares across the different groups involved in managing Guassa, and I assessed the kinds of social learning experienced by participants in the mental modeling process. Similarities across group mental models pointed to key drivers and sensitivities in the social-ecological system, Differences across mental models illustrated that system understanding and uncertainty varied according to the gender and occupation of participants, demonstrating the need for diverse perspectives in a collaborative process (Paulus & Nijstad 2003; Bernstein 2015; Hoffman et al. 2017).

In Chapter 5, I describe a process of collaboratively designing an agent-based model (ABM) of shrub encroachment in the Guassa area. Collaborative ABM is an effective tool for exploring systems in a prospective rather than a purely predictive way (Anselme et al. 2010), which can aid environmental managers in formulating new ideas about how to anticipate and manage systems under future uncertainty. This model enabled people involved in managing Guassa to explore the individual and combined effects, as well as the tradeoffs, of social and ecological factors controlling the spread of native shrubs, and to evaluate the efficiency of different management strategies to control their expansion. Results from the modeling process contribute to our understanding of the level of model complexity that is most useful for learning and decision-making (Grimm et al. 2005; Le Page & Perrotton 2018).

In Chapter 6, I synthesize my findings across chapters 2-5 and discuss the ability of social-ecological systems models to support knowledge co-production and learning for collaborative environmental management. This work provides new insights and information regarding the ways in which local and scientific knowledge can jointly improve the capacity of managers to understand and respond to global environmental change.

1.3 Author Positionality

The positionality of a researcher is influenced by their background, including their values, beliefs, and personal experiences with a topic. This positionality in turn shapes what a researcher chooses to investigate, the approach and methods they select, their relationship to the people involved in the research, and their interpretation or framing of the research (Finlay 2002; Mauthner & Doucet 2003; Khagram et al. 2010).

Growing up next door to the last functioning dairy farm in the suburbs of Chicago gave me a deep appreciation for the value of public participation in conservation. The farm was repeatedly threatened by developers throughout my childhood, leading my parents to help form the organization Citizens Organized for Wagner's Farm (C.O.W.S.). After years of meetings, protests, poetry contests, and several embarrassing stints as our mascot – Bart the Bull – I was thrilled to be part of the celebration when the Park District purchased the farm for conversion to an interactive museum on local farming history. This experience taught me the important lesson that tangible personal and community gains must be present if we want to catalyze public engagement and commitment to conservation. Without a doubt, this early passion for the protection of a natural and cultural resource has shaped my current work.

Throughout my career in conservation, I have found the greatest personal and professional satisfaction working at the intersection of research and practice. As an undergraduate at the University of Illinois, I worked with the Forestry Extension office on several projects that opened my eyes to the difficulty we face in reconciling ecological and economic objectives in U.S. conservation. This motivated me to serve as an environmental education volunteer with the Peace Corps, where I could learn how other cultures perceive and address conservation challenges. My work in Kolda, one of the least developed regions in Senegal, revealed the power of working on community-identified problems with joint ecological and economic benefits – in this case, community gardens that used permaculture techniques to improve household food security and soil health, and to increase income generation. These experiences inspired a career dedicated to merging the goals of conservation and development in the U.S. and abroad.

As a transdisciplinary conservation scientist, I do not perceive myself as an outside observer of some process, but rather as an integrated member of a research team composed of scientists and non-scientists seeking to understand and solve social-ecological problems. My epistemological approach to this type of research is thus understandably eclectic. On the one hand, I subscribe to a realist philosophy that says there is an objective world out there that is separate from me. I believe it is the same physical entity for all of us, and we can use empirical observations and measurements to produce new knowledge about the world to improve our management of the environment. On the other hand, I am also a constructivist that believes social-ecological systems exist as cognitive constructs in the minds of the people living in them. I believe we must pursue a more nuanced understanding of the internal states (i.e., attitudes, values, and beliefs) of people in order to design environmental management strategies that fit particular socio-cultural contexts. I am a critical realist in the sense that I believe we cannot fully know any one "truth", but only approximate truth under different contexts through the collection and analysis of data, both qualitative and quantitative.

My objective as a conservation scientist is to improve the equitable and sustainable management of natural resources by studying the process of collaborative conservation. I believe that collaborative decision-making – when diverse groups of people work and learn together on an issue – can help us overcome significant social and cultural barriers in conservation by promoting trust and respect among people with sometimes very different worldviews. A guiding principle in my research is to do relevant and practical research that improves our ability to build effective teams that can support conservation science and practice. The lengthy time I spent exploring and learning about the people and the environment of the Guassa area helped ensure my dissertation work fit the needs of this area. For example, one local farmer told me, "no one has asked us what we want them to research before. We have many ideas – we know what needs to be researched." Another farmer commented that he remembered me because "…you pay us when we participate. Other scientists don't pay us when they ask us questions." Because of my ethic of collaboration, I work to treat my partners with respect, generosity, and kindness.

My positionality makes me particularly sensitive to issues of power within conservation teams, and I work to ensure that different perspectives are valued and respected in collaborative processes – even when this contradicts my own research objectives. For example, the second modeling workshop of my dissertation started off with low motivation and low participation among local farmers. It emerged that there was another meeting organized at the same time as our workshop, and they were expected to attend both. I negotiated with them to reduce our workshop to a single day so that they could fulfill both obligations at least partially. This reduced the time I had to present and discuss the agent-based model in Chapter 5 with them, but it further strengthened our ability to communicate when things weren't working for certain members of the team. I believe this kind of transparency and power sharing is essential to effective collaborative conservation.

CHAPTER 2

BARRIERS AND BEST PRACTICES IN ENVIRONMENTAL TRANSDISCIPLINARY WORK[1]

2.1 Introduction

As global environmental change increasingly threatens environmental systems and human well-being, science and society are turning to transdisciplinary work (TDW) to facilitate transitions to sustainability (Lang et al. 2012; Brandt et al. 2013). In the context of environmental sustainability, TDW is characterized by a reflexive research approach that brings together actors from multiple academic fields and diverse sectors of society to engage in mutual learning with the intent to co-produce knowledge and solutions to social-ecological problems (Klein et al. 2001; Lang et al. 2012; Jahn et al. 2012; Cundill et al. 2015). Actor diversity is the foundation of TDW; scientists from multiple disciplines are needed (interdisciplinarity) as well as practitioners from different work sectors and/or stakeholders from diverse social worlds (Gibbons et al. 1994; Tress et al. 2005; Lang et al. 2012; Cundill et al. 2015). Transdisciplinary work is reflexive in that it encourages actors to clarify values, assumptions, and understandings, and to think critically about how these impact the framing of the problem, the process of the research, and the communication and implementation of the results (Popa et al. 2015; Cockburn & Cundill 2018). Mutual learning, sometimes referred to as multiple-loop social learning (Keen et al. 2005; Fazey et al. 2014; Fernández-Giménez et al. 2019), is related to reflexivity as it requires TDW participants to collectively explore the limits of current knowledge, exchange and generate new knowledge, and understand how this knowledge is situated in a particular social and cultural context (Lave &

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Wenger 1991; Scholz & Marks 2001; Westberg & Polk 2016). Finally, TDW is problem-oriented, seeking solutions that advance scientific and societal objectives in parallel (Scholz & Steiner 2015a; Delorme et al. 2016).

Each of these aspects is essential for a fully transdisciplinary approach, and together produce the benefits of TDW. Heterogeneity among TDW participants ensures that multiple perspectives are represented and the full complexity of both problems and solutions are realized (Bernstein 2015; Hoffman et al. 2017). This diversity also contributes to the perceived credibility, salience, and legitimacy of TDW results (Cash et al. 2003; Cundill et al. 2015), which can empower participants to take ownership of TDW products and increase people's ability to apply new knowledge and products to sustainability problems on the ground (Lang et al. 2012; Balvanera et al. 2017). Reflexivity in the TDW process can help reduce conflict arising from power asymmetries among TDW participants or from differences in values, preferences, and behaviors (Mobjörk 2010; Cundill et al. 2018). Reflexivity and mutual learning can also support the development of adaptive capacity in TDW participants (Fazey et al. 2014; Fujitani et al. 2017), which is critical for managing social-ecological systems in the face of high uncertainty, ambiguity, and risk (Kates et al. 2001). For example, participatory and formative evaluations that occur periodically throughout the TDW process allow participants to share perspectives, challenge dominant knowledge types, and flatten hierarchies that impede co-production and mutual learning (Fazey et al. 2014). When learning moves beyond cause and effect processes (single-loop learning) to expand system understanding or question underlying assumptions (double-loop learning) or change the institutions, norms, or beliefs guiding behavior (triple-loop learning), it can facilitate transitions to sustainability by motivating change towards adaptive strategies (Berkes & Jolly 2002) and building trusting relationships and systems thinking capacity among TDW participants (Pahl-Wostl & Hare 2004; Reed et al. 2010).

Efforts to describe an ideal TDW process to achieve these potential benefits have produced a series of conceptual frameworks, models, and guides (Carew & Wickson 2010; Jahn et al. 2012; Lang et al. 2012; Brandt et al. 2013; Mauser et al. 2013; Scholz & Steiner 2015b). Yet, the need for evidence-based "best practices" in TDW remains unfulfilled (Tress 2003; Huber & Rigling 2014). Best practices are the methods and techniques that have been shown to produce optimal results for a given objective; the term arose from agricultural and animal husbandry literature in the 1800s (Malcolm 1805; Dickson 1824) and has permeated to other fields, including business administration (O'dell & Grayson 1998) and statistics (Osborne et al. 2008). The pursuit of best practices in TDW implies that consistent approaches should be identified and widely adopted; yet, we recognize the need for flexibility and adaptation given the highly context-specific nature of TDW. We do not consider a one-size-fits all approach desirable or even feasible for TDW, but we believe the development of guiding principles can help ensure the quality and reproducibility of TDW and prevent the approach from becoming shallowly understood and applied (Jahn et al. 2012). Standardization has been shown to streamline communication across diverse groups, allowing information to travel without losing its meaning (Star & Griesemer 1989; Steger et al. 2018). However, when standards are enforced too inflexibly, conflict and miscommunication can occur (Turnhout 2009). Therefore, efforts to create guidelines for TDW should focus on providing a 'toolbox' of best practices that can be selected by participants according to their needs and desires without being overly prescriptive.

The purpose of this paper is to leverage the experiences and opinions of the international researcher and practitioner communities to better understand how TDW is applied in environmental projects and processes. We seek to examine how different aspects of respondent diversity influence perceptions and preferences in the TDW process, which can help clarify why actor diversity has been shown to promote innovation in collaborative projects (Paulus & Nijstad 2003), and how this actor diversity relates to the types of activities and desired outcomes observed in TDW projects. Our research questions ask: How does the gender, geography, and positionality (i.e., researcher or non-researcher) of respondents influence their perceptions of TDW best practices and barriers to TDW success? What best practices and characteristics of TDW case studies are associated with desired outcomes such as perceived project success, policy impact, and learning? We use these insights to refine a seven-step conceptual model to provide practical, evidence-based guidance for best practices in environmental TDW that are inclusive of the diversity of people and places where it occurs.

2.1.1 A Conceptual Model for Co-Production and Learning Through TDW

Drawing on peer-reviewed literature and personal experiences from the Mountain Sentinels Collaborative Network (mountainsentinels.org), we describe a conceptual model to guide learning and knowledge co-production through TDW (Figure 2.1). This model has similarities to other frameworks and guides present in the literature (Carew & Wickson 2010; Jahn et al. 2012; Lang et al. 2012; Brandt et al. 2013; Mauser et al. 2013; Scholz & Steiner 2015b), though it distinguishes itself through the inclusion of very specific activities (Table 2.1) that are largely absent from these other examples (but see Lang et al. 2012), and which provide concrete and practical advice for future TDW efforts. The model also differs from previous synthesis efforts by removing the focus on distinct "scientific" and "societal" domains that come together in TDW (cf. Lang et al. 2012; Jahn et al. 2012; Cockburn & Cundill 2018). We argue that a 'left loop' and 'right loop' approach to TDW (Jahn et al. 2012), which proposes a spectrum of TDW where some projects can be focused almost entirely on practical solutions while other projects can focus instead on scientific insights, propagates confusion over the role of non-researcher participants in TDW. There is evidence that some projects that only engage non-researcher participants on a superficial ('informative' or 'consultative') level still consider their approach transdisciplinary (Miller et al. 2008; Brandt et al. 2013). The model presented here emphasizes that diverse actors are necessary throughout the entire TDW process at a fully collaborative level, and that neither societal nor scientific needs should take precedence over the other.

The general structure of this conceptual model mirrors the 'TD Wheel' (Carew & Wickson 2010), a useful heuristic that emphasizes the cyclical and iterative nature of TDW as participants move through different phases of the process. We emphasize the need to draw on multiple knowledge systems and bring them into conversation with one another throughout the TDW process; in this regard, our model reflects the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services' five-step process for conducting valuation studies for ecosystem services (Pascual et al. 2018) and the five core tasks for successful collaboration across diverse knowledge systems (Tengö et al. 2017). However, these previous models provide guidance to projects that are already in existence, whereas our model seeks to clarify that preliminary exploration of the system and partnership formation are integral parts of the TDW process and can sometimes be the most challenging aspects of TDW. Common across all these models is the expectation of continuity over time – typically, a "finished" TDW project is ideally just the beginning of another turn of the TD wheel.

In our model, Step 1 is an introductory and exploratory phase where participants exchange knowledge about the history and context surrounding the place and problem being addressed, and when pre-existing and potential partnerships are considered. Collaborative projects may be initiated by researchers, practitioners, or concerned citizens/other stakeholders. Step 1 is an exploratory phase similar to the 'Phase 0' described by Cockburn et al. (2016) or the 'problem history' phase of Enengel et al. (2012). Step 2 involves a team-building process, where researchers, practitioners, and stakeholders co-design their partnership to ensure it addresses everyone's concerns and interests. Step 3 requires explicitly incorporating diverse perspectives and worldviews through the partners involved in the collaboration so that the project can benefit from multiple types of knowledge. At Step 3, it is essential to evaluate the team composition and revisit partnership formation, if necessary. Step 4 is an iterative process of co-design, where partners develop the appropriate processes to achieve their desired outcomes. Again, depending on the goals and outcomes identified it may be necessary to revisit partnership formation and design to ensure all relevant perspectives are included. Step 5 involves the co-production of both research and societally-relevant action, where partners conduct the co-designed research and analyze the results of different methods or activities. If at this point it becomes clear that some project objectives will not be met by the methods or activities taken in Step 5, it may be necessary to revisit the co-design process or begin back at partnership formation and design. Step 6 occurs when project outcomes and outputs are distributed and discussed outside of project partners, and when action is taken based on these results. Step 7 requires partners to reflect on past experiences and prepare for the next set of co-learning and collaborative opportunities. We present steps, and the activities we identified within them, in Table 2.1.

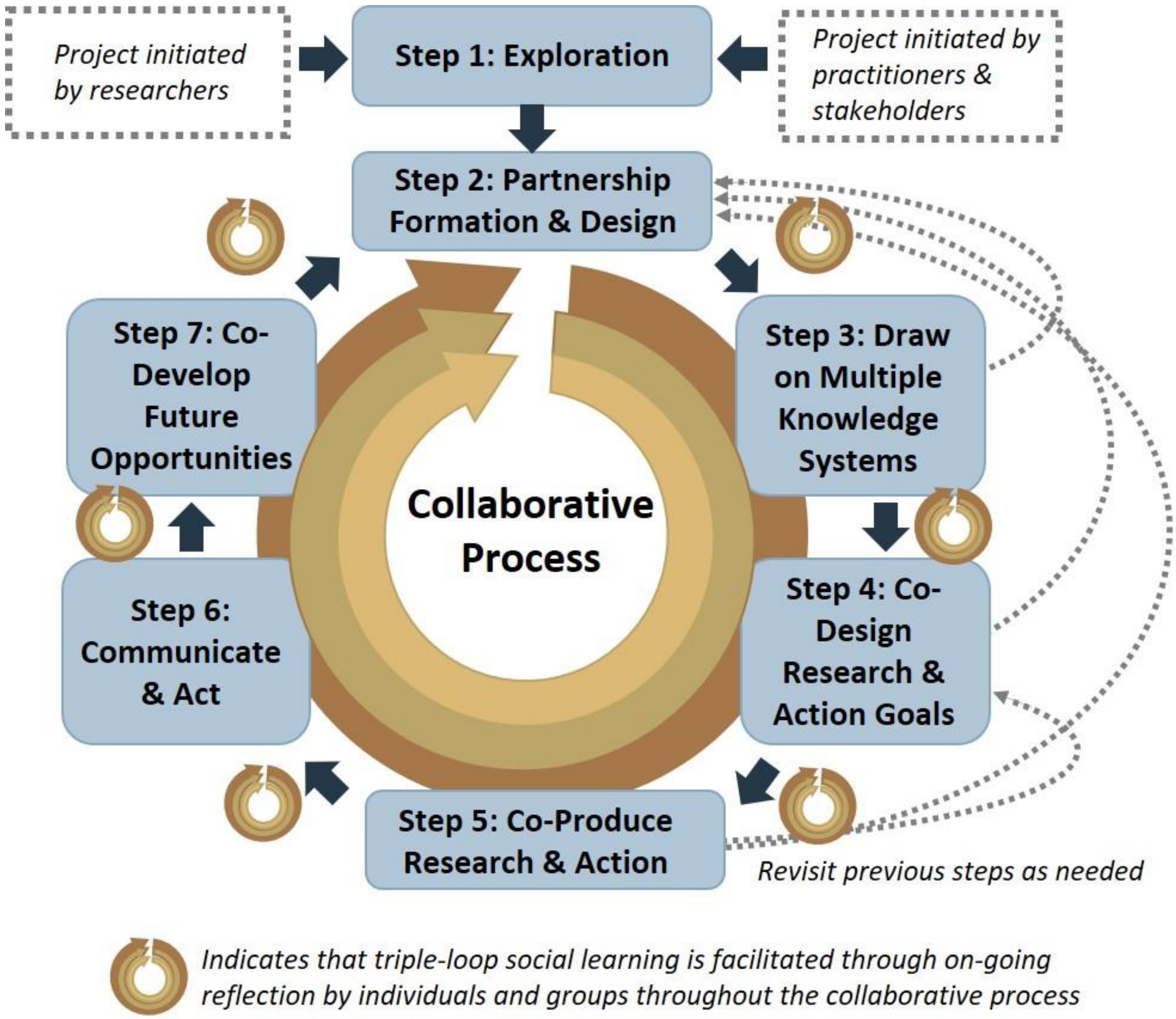

Figure 2.1. A seven-step process for facilitating learning and knowledge co-production through a TDW process. Steps 2-4 correspond to ‘Phase A’, Step 5 corresponds to ‘Phase B’ and Steps 6 and 7 correspond to ‘Phase C’ in other popular TDW conceptual models (Lang et al. 2012; Jahn et al. 2012; Cockburn & Cundill 2018). Step 1 relates to the proposed ‘Phase 0’ of Cockburn et al. (2016).

2.2 Methods

2.2.1 Survey Design

We used the seven-step conceptual model described above to guide the development of a survey (Appendix A). We began by screening respondents to ensure they conducted transdisciplinary research that fits our definition of: "sustained engagement between researchers (professional scientists or scholars) and practitioners (e.g., resource users, natural resource managers, policy makers)". We then asked survey respondents to draw on their overall experience with TDW to rank the top three most important activities in each step, even if they had not personally used them in their work. These activities emerged from a review of the literature as well as the experiences of members of the Mountain Sentinels Collaborative Network. We asked respondents which of these seven steps they considered to be the most difficult to implement.

We also asked respondents to rank the most significant barriers in TDW from a list of fifteen specific barriers synthesized from the literature and expert experience, which we then aggregated into nine general barriers during the analysis. We asked respondents whether they had any open-ended recommendations for how to overcome these barriers. We also asked respondents to select the three most important non-traditional skills and characteristics for successful TDW from a list of nine we had synthesized from the literature and personal experiences among our network. We then asked respondents to identify their most successful TDW project, and to report which of the 42 activities in our conceptual model they conducted during that project. We asked respondents to describe the context and outcomes of their most successful TDW project, including for example: how successful it was on a scale of 1 "not at all" – 10 "perfect, just as planned or better", who initiated the project, how long they worked in the area before the project started, and how long it lasted. Finally, we requested their response to a few questions about themselves (e.g., gender, research location, length of time conducting TDW).

2.2.2 Survey Administration

We administered the survey to researchers, practitioners, and other stakeholders involved in environmental TDW projects worldwide. The survey was offered in four languages: English, Spanish, French, and Chinese. The survey link was shared widely via targeted emails, list servs, and Twitter. We sent two to three reminder emails to each list serv and email group to maximize responses and requested TDW project leaders encourage practitioner and other stakeholder partners to complete the survey. This research was reviewed and approved by Colorado State University's Institutional Review Board (264-18H), and was conducted with free, prior and informed consent of all participants.

2.2.3 Analysis

We analyzed quantitative survey responses using common statistical tests such as chi-square or Fisher's exact tests, t-tests, and ANOVA, as relevant for sample size and the mix of data types (categorical, ordinal, and continuous). When using Fisher's exact tests for contingency tables greater than 2 x 2 variables, we approximated the p-value using Monte Carlo simulations with 10 million replicates. When using ANOVA, we conducted post-hoc Tukey pairwise comparisons to understand which variables had significant relationships.

For ranked activities and barriers, we first calculated a weighted mean, assigning a rank of "4" when the activity or barrier was not listed in the top three. We used these values to provide a single, weighted importance score for each activity and barrier (Dietsch et al. 2018). We then tested for differences in how respondents rank individual activities and barriers using Wilcoxon rank sum tests, again assigning a rank of "4" when the activity or barrier was not listed in the top three. All analyses were conducted in R (R Core Development Team 2019). We used a Bonferroni adjustment to correct for multiple comparisons, resulting in stricter thresholds for significance depending on the number of tests used for different combinations of variables (i.e., p-values < 0.05). All tests, results, and adjusted significance thresholds can be found in Appendix B. For textual responses, such as solutions to TDW barriers, we used in vivo coding (Corbin & Strauss 2015) and inductive thematic analysis to analyze the results (Boyatzis 1998).

We considered each respondent's most successful TDW project to be a case study in successful TDW. We assessed case study success using three variables: stated project success (on a scale of 1 – 10), level of policy impact (none, low, medium, or high), and levels of participant learning (none, single and/or double loop, triple loop, or all three loops). Single-loop learning entails participants changing their ideas about what actions to take regarding the problem (Pahl-Wostl 2009); double-loop learning involves participants realizing the problem was more complicated than they thought or expanding the way they think about the system ("systems thinking", cf. Dyball et al. 2007; Keen & Mahanty 2006); and in triple-loop learning, participants change the institutions, norms, and beliefs surrounding the problem of interest (Keen et al. 2005; Fernández-Giménez et al. 2019).

In our analyses, we consider respondents as researcher only (n=100) or non-researcher (n=34), women (n=68) or men (n=61), and internal (n=82) or external (n=50) to assess whether these groups differ on particular aspects of the TDW process. Non-researchers include some researchers who also identify as practitioners or stakeholders. We regret that our sample size prevents including in our gender-based analysis the four respondents who identify as other than a woman or a man; however, they were included in the positionality and geographic analyses. Respondents who are considered 'internal' conduct research on the same continent where they are primarily located and nowhere else (see Section 3.2). Chi-squared tests revealed no significant associations between respondent gender, geography, or positionality – for example, there are not significantly larger numbers of men researchers or internal women respondents.

We used three metrics to assess whether each activity from our conceptual model could be considered a best practice in TDW: their perceived importance across respondent types, the frequency with which they were applied in respondents' most successful TDW projects, and their impact on project success, learning, and policy outcomes.

2.3 Results

The survey was available online from April 4 – October 22, 2018, and yielded 139 complete responses (many non-viable responses appeared bot-generated and did not make it past our initial screening question). An additional 29 responses were partially complete and used in our analysis where applicable (total n = 168). The number of responses per question varies as responses were voluntary throughout the survey.

2.3.1 Respondent Demographics and Experience

Of the 139 complete responses, respondents identified as women (n=68, 48.6%), men (n=61, 43.6%), and other (n=4, 2.9%). The majority of responses were in English (n = 117, 84.2%), followed by French (n=11), Spanish (n=9), and Chinese (n=2). Most respondents identified as researchers only (n=100, 71.9%), 17 identified as practitioners only (12.2%), and one identified as a stakeholder only. A group of 16 respondents (11.5%) identified as some combination of these three categories, and five respondents declined to respond to this question. Our results revealed that offering the survey in a language other than English may have improved the response rate from non-researchers in non-English speaking countries, as a larger proportion of non-English respondents identified as practitioners (36%) compared to English respondents (19%).

Generally, the number of projects each respondent has been involved in increases with the number of years they have spent conducting TDW. The majority of respondents conducted fewer than six projects in less than a decade of collaborative work (n=80, 56.7%). Yet, a substantial proportion of respondents seem committed to long-term, place-based research: 27 respondents

(19.1%) have been conducting environmental TDW research for over a decade, but have been involved in fewer than six projects.

2.3.2 Geographic Patterns of Environmental TDW

We received 132 responses with answers for both the continent where the respondent is primarily located and the continent(s) where they do the majority of their research. The largest group of respondents were located primarily in North America (n=59, 44.7%), and nearly all of them (n=51) conducted part of their research in North America (Figure 2.2a). The next largest group of respondents was based in Europe (n=39, 29.5%), and again most of them (n=33) conducted part of their research in Europe. All 18 Africa-based respondents conducted part of their research in Africa, as did all 11 respondents based in South America. Eight of the nine Asia-based respondents conducted part of their work in Asia, and one of the two Oceania-based respondents conducted their work in Oceania. No respondents were based in Central America. The two most frequent cross-continental links were Europeans working in Africa (n=15) and North Americans working in Asia (n=11) (Figure 2.2a).

Respondents reported working on TDW projects in 70 countries around the world (Figure 2.2b). Of the 135 respondents that answered this question, the largest proportion worked in the United States during their most successful research project (n=50, 37%). While it was most common for projects to occur in a single country (n=102, 75.6%), other projects ranged from two to 52 countries (n=33, 24.4%). A notable subset of projects (n=19, 14.1%) took place across multiple continents. However, the majority of projects occurred on the same continent where the respondent was primarily located (n=83, 61.5%). Critical gaps in project locations are observed in North and West Africa, Central Asia, the Middle East, Eastern Europe, the Caribbean, and the Pacific Islands.

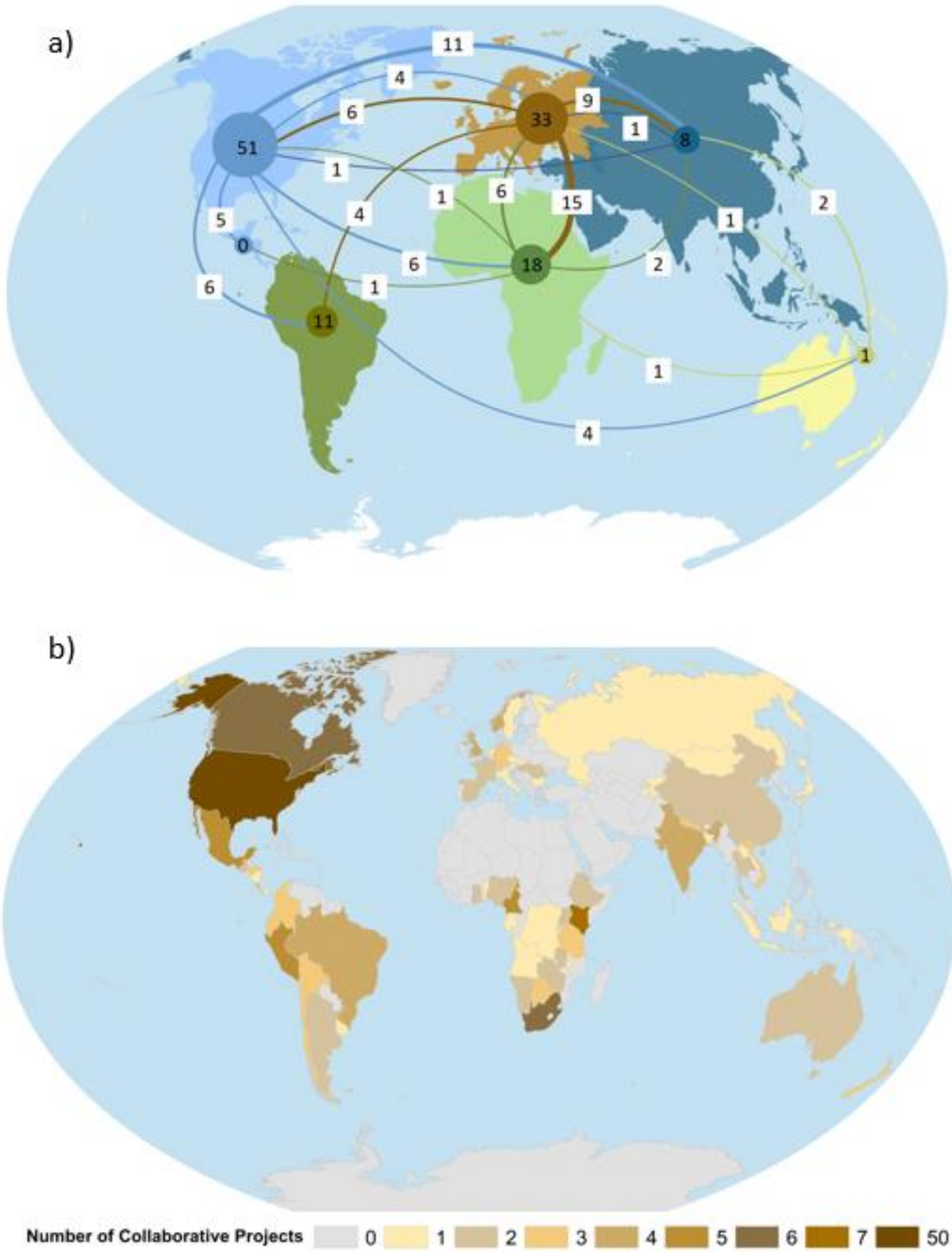

Figure 2.2. a) Circles are colored according to continent and reflect the number of internal linkages (i.e., when respondents worked on the same continent where they are primarily located). Lines are colored by the primary locations of respondents, signifying when those respondents work on another continent. The number of cross-continental links are given in white boxes. b) Number of most successful collaborative projects per country.

2.3.3 Skills and Characteristics for Successful Collaboration

Respondents selected three of the nine most important skills or characteristics that enhance the success of environmental TDW endeavors, resulting in 474 total selections (Figure 2.3). Overall, the most frequently selected characteristic was flexibility (n=81, 17.8%), followed by mutual respect (n=77, 16.9%), collaborative spirit (n=72, 15.8%), humility (n=56, 12.3%), trust (n=53, 11.6%), patience (n=43, 9.1%), persistence (n=30, 6.6%), interdisciplinary training (n=25, 5.5%), and generosity (n=19, 4.2%). Researchers were more likely than non-researchers to consider flexibility an important characteristic for successful collaboration ($p<0.01$).

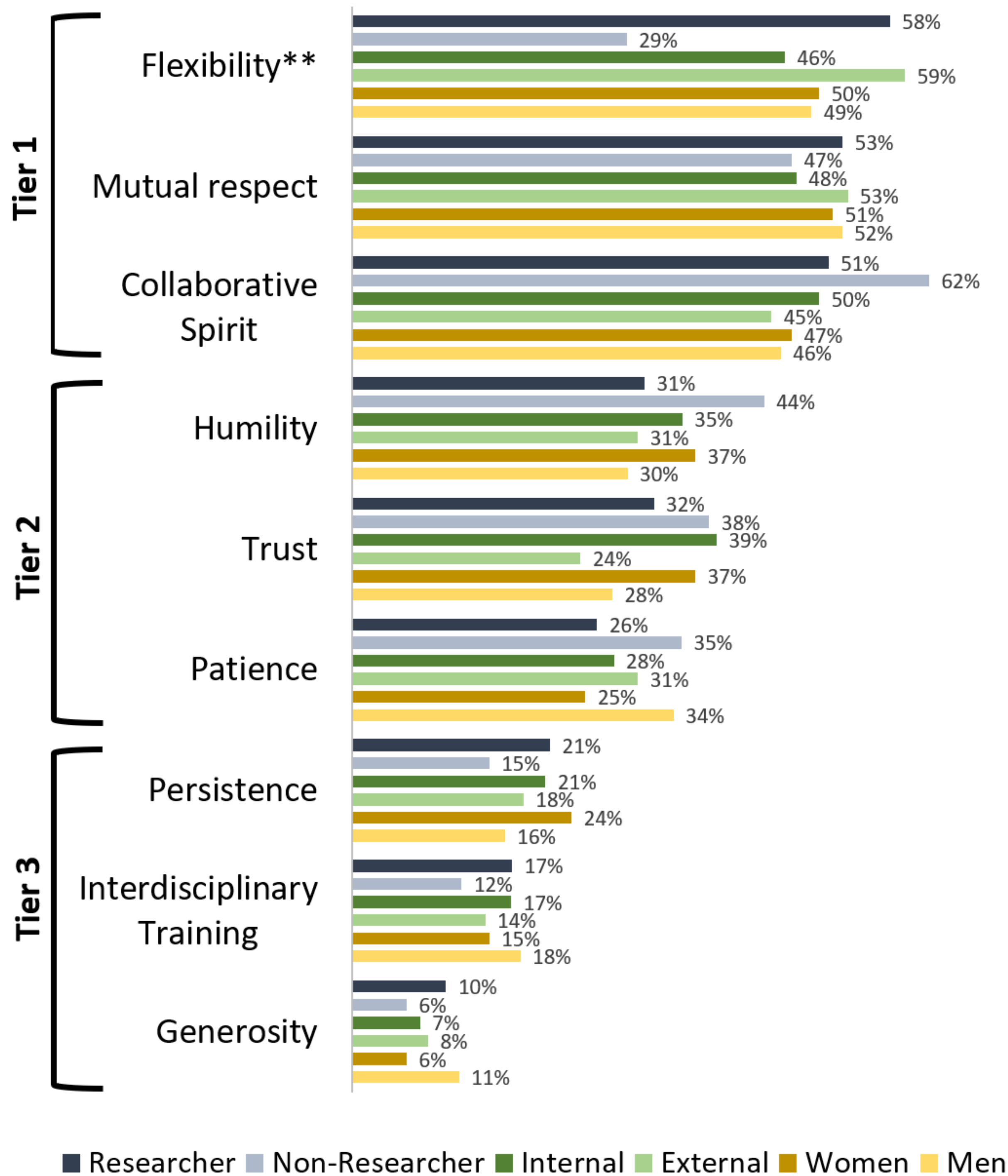

Figure 2.3. Respondents selected three out of the nine proposed skills or characteristics that enhance the success of environmental TDW endeavors, resulting in roughly three tiers of relative importance. Researchers and non-researchers differ significantly in the way they value flexibility (**).

2.3.4 Barriers to Successful Collaboration

Respondents (n=165) selected the top three most significant barriers to TDW, according to their knowledge and experience. All respondent types considered insufficient time and unequal power dynamics the two most important barriers (Figure 2.4). The least important barriers included disagreements over the approach taken, knowledge barriers (e.g., when certain participants rejected the validity of other forms of knowledge), the inability to take action based on results, and using the wrong method for the project purpose. In the barriers of medium importance (ranks 3-5), clear groupings emerge among respondent types. Women, non-researchers, and internal respondents (Group 1) considered ineffective communication to be the third most important barrier, while men, researchers, and external respondents (Group 2) considered this the fifth most important barrier. Group 2 also considered a lack of shared interests or motivation and insufficient funding to be more important barriers than ineffective communication. Men ranked knowledge barriers higher than women did. Overall, it appears non-researchers and men were the respondent types that deviated from the other responses most frequently.

A subset of respondents (n= 65) provided advice for overcoming these barriers. The most common themes presented by respondents involved time (n=23, 35.3%), shared goals (n=20, 30.8%), communication (n=21, 32.3%), and strong leadership (n=21, 32.3%). Roughly even proportions of respondent types provided advice for overcoming barriers (e.g., 46% of researchers and 41% of non-researchers). Recommendations differed slightly by respondent types, though due to the small sample sizes we hesitate to over-interpret these findings. There were more women than men recommending strong leadership (W=41%, M=17%) and communication (W=39%, M=17%). Larger proportions of external respondents also recommended strong leadership compared to internal respondents (E=50%, I=25%). Finally, non-researchers appeared more likely than researchers to recommend finding common goals as a strategy for overcoming obstacles (NR=50%, R=26%).

TDW projects require time commitments from many people over many years, and respondents emphasized that they should not be rushed. Several respondents proposed that adjusting expectations from participants early on can help ensure people set aside enough time to contribute meaningfully to the collaboration and can facilitate the emergence of trusting relationships. Another key to overcoming TDW barriers is the establishment of shared goals early in the project. Respondents stressed these goals should be clearly articulated and revised to ensure all participants agree on them, which can help sustain motivation for the project over the long term. Constant and equitable communication was emphasized as a way to overcome many conflict-related barriers like power asymmetry and historical injustices. Ensuring all participants' voices are encouraged, heard, and respected can prevent miscommunication and reduce elite capture by certain groups. Respondents suggested that professional training or facilitation in conflict resolution is often beneficial for this kind of communication. Finally, strong leadership was a widely recognized theme in overcoming TDW barriers, involving organizing meetings, assigning roles and responsibilities, monitoring and ensuring people are held accountable for their contributions to the project. Strong leadership is in many ways the foundation that supports long-term, equitable, and actionable TDW projects.

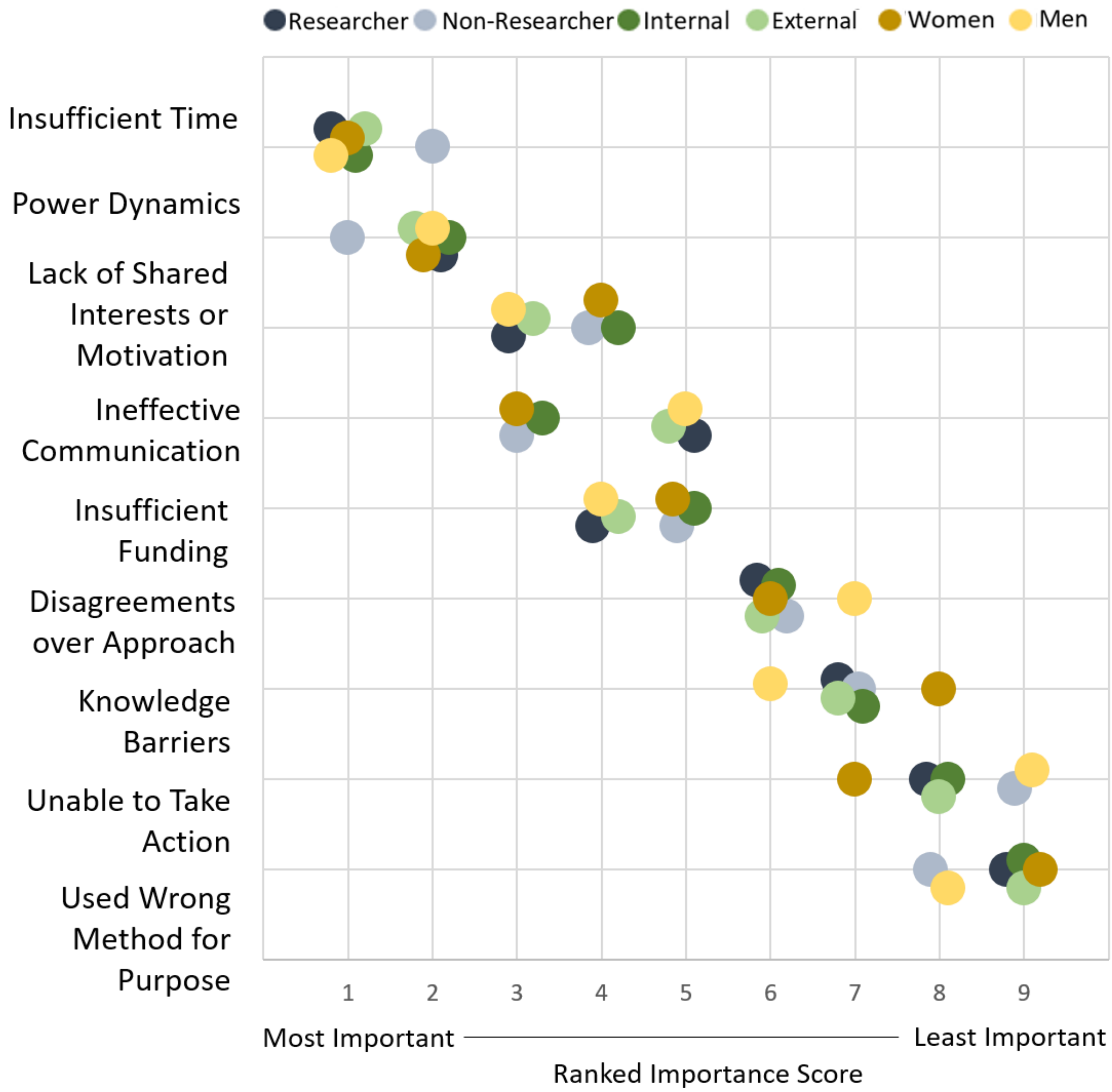

Figure 2.4. Nine barriers to successful TDW are listed on the vertical axis, and their weighted importance score is given on the horizontal axis, with one being the most important barrier. Dots are colored according to respondent gender (women or men), geography (internal or external), and positionality (researcher and non-researcher). Groupings emerge in ranks 3 – 5 between women, non-researchers, and internal respondents (Group 1) and men, researchers, and external respondents (Group 2).

2.3.5 Perceived Importance of Activities

We found good agreement across respondent types for the most important activities in all steps except for Steps 5 and 7 (Table C1, Appendix C). All respondent types considered partnership formation and design (Step 2) to be the most difficult step in the TDW process, and there was good agreement regarding the most important activities in this step. All respondent types agreed that identifying shared interests (A.2.8) was the most important activity and identifying a diverse core leadership team (A.2.6) was the second most important activity. With the exception of non-researchers, all respondent types considered including individuals with experience (A.2.9) to be the third most important activity; non-researchers thought the identification of mutually appropriate spaces (A.2.7) was more important. While it was ranked relatively low across respondent types, men respondents considered conducting a smaller, preliminary project (A.2.2) more important than women respondents (p=0.01).

Within the exploration stage (Step 1), the top three activities were connecting with individuals who are well-informed, helpful, or who have extensive networks (Activity 1.3), identifying the concerns of the different groups (A.1.6), and assessing the context, history, or on-going initiatives surrounding the place or problem (A.1.1). All respondent types agreed that expressing mutual respect (A.3.3) was the most important activity when drawing on multiple knowledge systems (Step 3), and that the second most important activity was trying to accommodate different processes for learning, understanding, and decision-making (A.3.5). Researchers considered sharing experiences with each other (A.3.4) significantly more important than non-researchers (p=0.01), who ranked it lowest. There was almost perfect agreement among respondent types on the importance of all four activities in co-designing research and action (Step 4). The only difference was that most respondents considered collaboratively defining the issue (A.4.1) to be the most important activity, while women respondents considered collaboratively developing project goals (A.4.3) the most important. Finally, all respondent types agreed that holding feedback workshops with decision-makers (A.6.6) was the most important activity in communicating and acting on relevant learning (Step 6), followed by communicating results to practitioners outside the immediate project (A.6.1) and discussing how to expand upon learning (A.6.5).

We found inconsistent results across respondent types regarding the most important activities in the co-production of research and action (Step 5) and the co-development of future opportunities (Step 7). In Step 5, researcher, internal, and men respondents considered collaboratively developing outputs and outcomes (A.5.2) to be the most important activity; in fact, researchers considered this activity significantly more important than non-researchers ($p<0.01$). Instead, non-researchers and external respondents considered fostering capacity to conduct the methods (A.5.5) to be the most important activity, while women respondents considered collaboratively interpreting results (A.5.3) to be the most important – and they considered this significantly more important than did men ($p<0.01$). In Step 7, most respondent types agreed that reflecting on strengths and weaknesses (A.7.4) was the most important activity; however, women respondents considered this significantly more important than did men ($p<0.01$) respondents. Rather, external respondents considered reflecting on the quality of outcomes and outputs (A.7.3) the most important activity; researchers also considered this a significantly more important activity than non-researchers ($p<0.01$). Men respondents considered reflecting on the usefulness of outcomes/outputs (A.7.5) to be the most important activity in Step 7, and they ranked it significantly higher than did women ($p<0.01$). While it was ranked relatively low across respondent types, non-researchers considered assessing participants' learning (A.7.1) to be significantly more important than did researchers ($p=0.02$).

2.3.6 Elements of Successful TDW Projects

Case studies (n=139) of respondents' most successful TDW project occurred in 70 countries (Figure 2.2b), primarily in forest (n=42, 30.2%), mountain (n=36, 25.9%), urban (n=28, 20.1%), and/or grassland (n=24, 17.3%) systems. Respondents generally worked in the study area for less than 3 years before beginning their most successful project (n=64, 46.0%), though it was also common to work in the area for 4-9 years (n=37, 26.6%) or over 10 years (n=30, 21.6%) before beginning the project. Projects were initiated by either researchers (n=70, 50.4%), practitioners/stakeholders (n=46, 33.1%), or a mix of the two, and typically lasted less than three years (n= 81, 58.3%), with projects over 10 years uncommon (n=8, 5.8%). Aside from researchers, participants often came from government (n=88, 63.3%) and non-profits/NGOs (n=83, 59.7%), but farmers (n=57, 41.0%) were also common TDW collaborators. Most projects (n=96, 69.1%) produced at least one peer-reviewed publication, and feedback workshops with decision makers (n=82, 59.0%), maps (n=70, 50.4%), and news media products (n=64, 46.0%) were other frequent outputs. Most projects (n=86, 61.9%) used some form of qualitative or quantitative modeling.

Perceived project success was generally high, with a mean of 7.25 (SD = 1.62) across all projects. Most projects also reported at least one type of participant learning (n=104, 74.8%) and medium (n=53, 38.1%) or high (n=20, 14.4%) policy impact. Mean project success was marginally higher in projects where some level of learning occurred, and project success was significantly higher in projects with medium to high policy impact (Figure 2.5a). Specifically, there were significant differences between no or low policy impact and medium and high policy impact ($p<0.01$ for all comparisons). All projects jointly initiated by a mix of researchers, practitioners, and/or stakeholders had some level of policy impact, and projects initiated by practitioners and/or stakeholders had a larger proportion of high policy impact compared to projects initiated by researchers only ($p=0.01$, Figure 2.5b). Notably, projects that produced policy briefs did not appear to achieve higher policy outcomes.

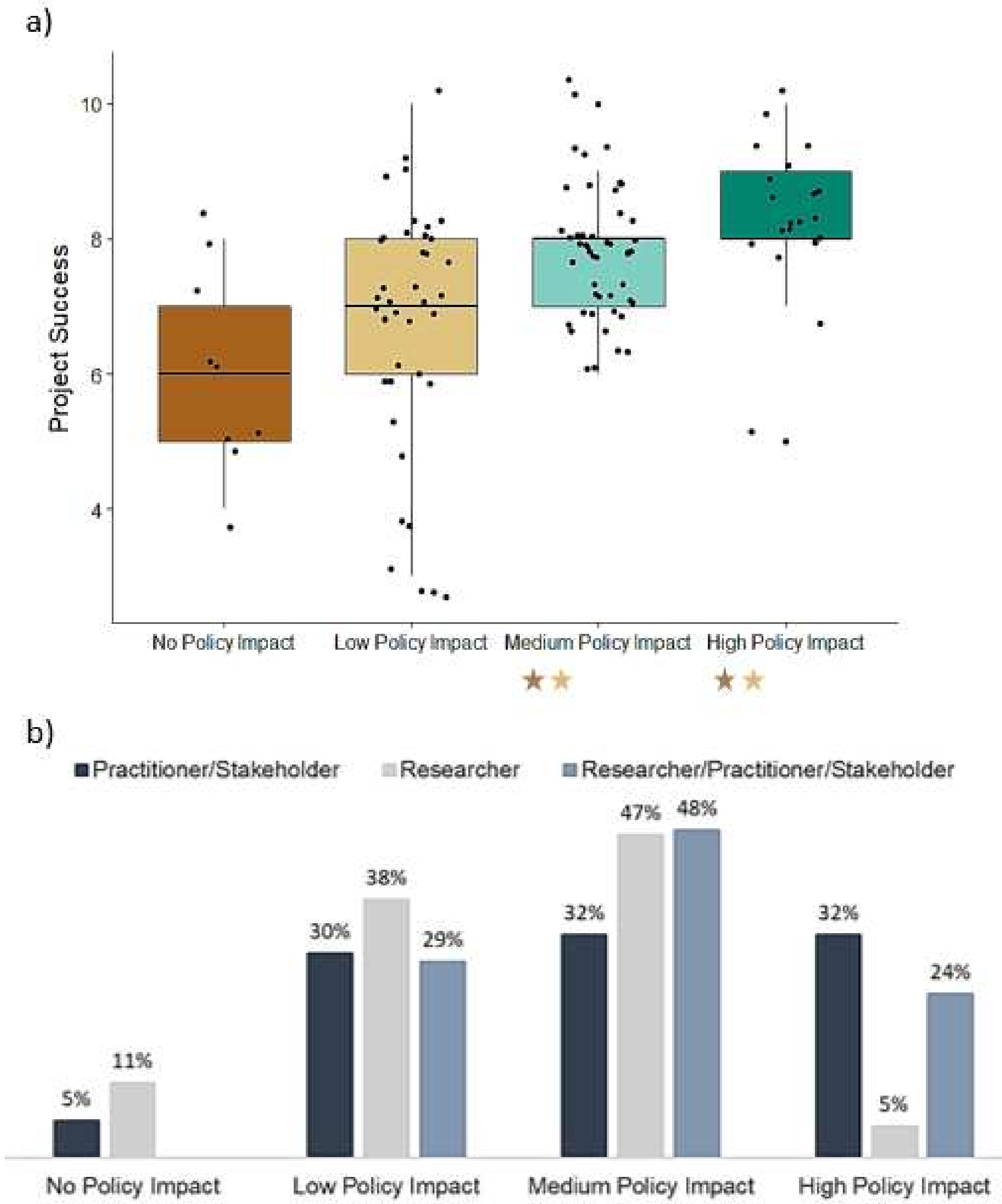

Figure 2.5. a) Perceived project success increases with perceived policy impact. Stars indicate that projects with no and low level policy impacts had significantly lower project success compared to projects with medium and high policy impacts. B) Projects initiated by practitioners and/or stakeholders had the largest proportion of perceived high policy impact.

2.3.7 Activities of Successful TDW Projects

The activities most frequently conducted in respondents' projects were often the same activities that respondents perceived to be important for successful TDW, but not always (Table C2, Appendix C). The three most important activities from Step 1 were also frequently implemented (75-76% of projects), including identifying group concerns (A.1.6), connecting with helpful individuals (A.1.3), and assessing the context of the place (A.1.1). The most important activity in Step 2 was identifying shared interests (A.2.8), which was also the only frequently implemented activity in that step (77% of projects). Meanwhile, the second most important activity in Step 2 (identifying a core leadership team, A.2.6) was only implemented in 47% of projects. Expressing mutual respect (A.3.3) was the most frequently implemented activity across all steps (83% of projects) and was also the most important activity in Step 3. Collaboratively defining the issue (A.4.1) was the most important activity in Step 4 and also the only frequently implemented activity in that step (78% of projects). Holding workshops with decision makers (A.6.6) was the most important and most frequently implemented activity in Step 6 (75% of projects). Interestingly, communicating results to the academic community was another frequently implemented activity in Step 6 (72% of projects) even though it received the lowest importance rank across all respondent types (Table C1, Appendix C). In fact, communicating results to academic audiences occurred more often (72% of projects) than communicating results to practitioners (68%) and the public (57%). There was no agreement regarding the most important activities in Step 5 and Step 7, and none of these activities were frequently implemented across projects (35-68% of projects). The implementation of activities sometimes differed according to respondent type. When forming and designing partnerships (Step 2), men were more likely than women to include researchers who are interdisciplinary (A.2.10, $p<0.01$). Unsurprisingly, researchers were more likely than non-researchers to extend the results of their TDW project to academic audiences (A.6.2, $p<0.01$).

Some of the activities associated with high impact were among those considered important and frequently implemented. Collaboratively developing project goals (A.4.3) was associated with higher project success ($p<0.01$) and learning outcomes ($p<0.01$), and was also an important and frequently implemented activity. Reflecting on the quality (A.7.3) of outcomes and outputs were also associated with higher learning outcomes ($p<0.00$), and was one of the most frequently implemented activities in Step 7 (67% of projects). However, other activities with high impact were not considered very important and were not frequently implemented. Collaborative development of research questions (A.4.4) was associated with higher project success ($p<0.01$) but was implemented in only 54% of projects. Assessing participant learning (A.7.1) was associated with higher learning outcomes ($p<0.00$), yet was only conducted in 35% of projects. Notably, none of the activities were associated with high policy impacts.

2.3.8 Best Practices for Environmental TDW

We identified 23 priority activities for environmental TDW using the three metrics described above – their perceived importance across respondent types, the frequency with which they were applied in respondents' most successful TDW projects, and their impact on project success, learning, and policy outcomes (Table 2.1). We do not claim that the remaining 19 activities are not useful, but based on our survey we do not currently have sufficient evidence to call them best practices. In particular, ten activities stood out as meeting our criteria across multiple metrics, and we propose that projects with limited resources might target these activities when implementing the seven-step collaborative process.

Table 2.1. Of the 42 proposed activities in our conceptual model, 23 emerged as best practices in environmental TDW based on their perceived importance, frequency of use, and impact on project success, learning, and policy outcomes. The ten activities which met our criteria across multiple metrics are highlighted in bold. As none of our proposed activities resulted in high policy impact, we do not include this category in the table.

	Activities	Most Important	Most Frequent	Learning Impact	Project Success
A.1.1	**Assess the context, history, or on-going initiatives surrounding this place or problem**	X	X		
A.1.2	Attend meetings of the different groups involved				
A.1.3	**Connect with individuals who are well-informed, helpful, or who have extensive networks**	X	X		
A.1.4	Connect with stakeholders who are often marginalized				
A.1.5	Identify activities to build credibility across participants				
A.1.6	**Identify concerns of the different groups involved**	X	X		
A.1.7	Learn a locally-spoken language				
A.2.1	Check the credentials or history of key participants				
A.2.2	Conduct a smaller, preliminary project				
A.2.3	Define the roles and duties of everyone involved				
A.2.4	Engage face-to-face outside of project meetings				
A.2.5	Hold regular meetings with diverse participant groups				
A.2.6	Identify a diverse core leadership team	X			
A.2.7	Identify mutually appropriate spaces for interactions	X			
A.2.8	**Identify shared interests among participant groups**	X	X		
A.2.9	Include individuals with experience working with these participant groups or in this location	X			
A.2.10	Include researchers who are interdisciplinary				
A.3.1	Attend each other's meetings and events				
A.3.2	Explore how you will use different types of knowledge				
A.3.3	**Express mutual respect for one another's knowledge, experiences, or worldviews**	X	X		
A.3.4	Share experiences with each other				
A.3.5	**Try to accommodate different processes for learning, understanding, or decision-making**	X			
A.4.1	**Collaboratively define the specific issue(s) being addressed**	X	X		
A.4.2	Collaboratively develop data collection methods				
A.4.3	**Collaboratively develop project goals for both research and action**	X		X	X
A.4.4	Collaboratively develop research questions or hypotheses				X
A.5.1	Collaboratively analyze data collected				
A.5.2	Collaboratively develop outputs or outcomes	X			
A.5.3	Collaboratively interpret results	X			
A.5.4	Distribute responsibilities among participants				
A.5.5	Foster capacity to conduct agreed upon methods	X			
A.6.1	Communicate results to practitioners outside the project	X			
A.6.2	Communicate results to the academic community		X		
A.6.3	Communicate results to the broader public				
A.6.4	Create a group of high-profile individuals with power to impact the issue of interest				
A.6.5	Discuss how to expand upon learning from project	X			
A.6.6	**Hold workshops or meetings to exchange feedback with decision makers**	X	X		
A.7.1	Assess participants' learning			X	
A.7.2	Discuss opportunities for the next collaboration				
A.7.3	**Reflect on the quality of outcomes and outputs**	X		X	
A.7.4	Reflect on the strengths and weaknesses of the collaborative process	X			
A.7.5	Reflect on the usefulness of outcomes and outputs	X			

2.4 Discussion

In this paper, we present a conceptual model to guide the implementation of environmental transdisciplinary work (TDW), providing suggested activities to conduct throughout a seven-step process. We used a survey with 168 respondents worldwide to evaluate the relative importance of these activities and the non-traditional skills and characteristics required to implement them successfully. We also explored the relative importance of barriers to successful TDW and offer suggestions for how to overcome them. Together with case studies of respondents' most successful TDW projects, these results point to a toolbox of TDW best practices that can be used to overcome barriers and increase the societal and scientific impacts of TDW projects. Our study highlights the benefits of diversity in TDW, supporting previous research into the importance of methodological diversity (Balvanera et al. 2017) as well as actor diversity (Hoffman et al. 2017).

2.4.1 Balancing Diverse Perspectives through Careful Partnership Design and Formation

Our conceptual model stresses the need to bring together diverse actors throughout the entire TDW process without prioritizing scientific or societal objectives over the other. Yet, survey respondents highlighted partnership formation and design as the most difficult step in the TDW process. The effective functioning of diverse teams is a considerable challenge in environmental TDW, which requires trusting and respectful relationships (Dietz et al. 2003) and shared vision and goals among team members (Balvanera et al. 2017; Hoffmann et al. 2017). Building trusting relationships is typically a time-intensive process (Enengel et al. 2012), requiring interpersonal skills and characteristics that are often not included in academic training (Wiek et al. 2011). Our results emphasize the importance of flexibility, mutual respect, and collaborative spirit, though non-researchers are more likely than researchers to consider collaborative spirit a key characteristic, and to consider Tier 2 characteristics (humility, trust, and patience) more important than flexibility (Figure 2.3). While our survey had considerably more researcher respondents, we believe these differences highlight important rifts between scientific and societally-focused actors that must be considered in the formation of TDW teams. For example, one key aspect of collaborative spirit is the sharing of control and equal credit among participants, which is often difficult for academics who are used to the siloed and highly individualized structure of the university (Bernstein 2015). Indeed, very few TDW projects have yielded decision-making power and project control to non-researchers (Brandt et al. 2013). It is therefore understandable that non-researchers might value collaborative spirit more than researchers. Our results indicate that the formation of a diverse core leadership team (A.2.6) that clearly defines the roles and responsibilities of each member (A.2.3) could be one of the most important and effective ways to create collaborative spirit on a team, which is supported by other observations in the literature (Lang et al. 2012; DeLorme et al. 2016; Hoffmann et al. 2017; Balvanera et al. 2017).

Additionally, we stress the importance of the exploratory Step 1 in our conceptual model, which is largely absent from other conceptual models and guides for TDW (but see Cockburn et al. 2016). Other approaches typically begin with problem definition, skipping over what we believe is a necessary, somewhat amorphous period where individuals and groups learn about each other and the context of the social-ecological system. Step 1 can be a lengthy process, as seen from almost a quarter of survey respondents working in an area for a decade before initiating a TDW project. In our survey, identifying the concerns of different social groups (A.1.6) emerged as a best practice in Step 1, as was the identification of activities that build credibility among these groups (A.1.5). There are many ways to elicit this kind of information, including through methods in participatory action research such as transect walks and photo-voice (Chambers 1994; Catalani & Minkler 2010) and ethnographic approaches like participant observation and life histories (Atkinson et al. 2001). Note that we do not consider detailed problem identification to occur until Step 4, so that a foundation of place-based understanding is established and diverse forms of knowledge have been brought to bear on the issue before it is collectively defined. Problem definition can be a laborious process, especially when disagreements emerge across knowledge types and need to be more thoroughly examined (Klein et al. 2014; Steger et al. in press). In fact, one Swiss TDW project found that collaboratively defining the problem unexpectedly became the primary project result (Lang et al. 2012). This emphasis on preliminary stages of TDW is intended to ease the barriers to partnership formation and design so that a more equitable and sustainable TDW process can be achieved.

2.4.2 Selecting TDW Activities to Overcome Barriers

Our results indicate that while there are no universally appropriate activities for all TDW projects, there is general agreement as to the most significant barriers for successful TDW. We draw on our survey results, conceptual model, and the broader TDW literature to present a set of recommendations for overcoming these barriers.

Barrier 1: Insufficient Time

TDW is a time-consuming process, and our survey respondents repeatedly stressed that it cannot and should not be rushed. Most projects highlight the time required for building trusting relationships and effective partnerships as we described above, but the integration of research methods across diverse academic disciplines and social worlds is also not a quick process (Brandt et al. 2013, Hering et al. 2012). Yet, our survey results revealed that very few TDW projects continue for longer than a decade, which reflects other findings in collaborative research (Balvanera et al. 2017) and may be related to a lack of shared interests (Barrier 3) and insufficient funding (Barrier 5). Alternatively, this could be a reflection of another turn of the 'TD wheel' (Carew & Wickson 2010), where relatively short, individual TDW projects flow into one another over time. As TDW is still a relatively new approach in environmental sustainability research, many projects are still 'learning by doing' with the result that many participants may consider their time wasted if efforts lead to failures. We propose that the 24 best practices identified from our survey results may help overcome this important barrier in TDW by helping new collaboratives target limited resources to activities with demonstrated evidence of success across TDW projects.

Barrier 2: Power Asymmetries

Power asymmetries are a widely acknowledged challenge in environmental TDW (Jahn et al. 2012; Mauser et al. 2013; Scholz and Steiner 2015a), as they can enable certain groups or individuals to achieve their objectives at the cost of others (Mobjörk 2010; Cundill et al. 2015). Some of the most important activities for overcoming power asymmetries are concentrated in Steps 1-3 of our conceptual model, which stresses the development of diverse teams with good communication and mutual respect for all kinds of knowledge and experience. We also emphasize the importance of fostering capacity to conduct the agreed-upon methods (A.5.5), so that all team members have the tools to engage in the research if they choose and are not relegated to the sideline during critical parts of the collaborative process. Other projects suggest that leveraging the expertise of different leaders throughout the life cycle of a TDW project can help mitigate power imbalances (Cundill et al. 2015), while others emphasize the ability of internal researchers to understand and respond to complex power dynamics in their home region (Schmitt et al. 2010). Our conceptual model encourages on-going reflexivity in TDW participants, both as individuals and collectively, so that these power asymmetries can be identified and bridged through discussion and compromise (Fazey et al. 2014).

Barrier 3: Lack of Shared Interests or Motivation

Participants in a TDW project must have shared interests and the ability to sustain their motivation over an often lengthy collaborative process (Eigenbrode et al. 2007; Lang et al. 2012). Again, we stress the importance of the early steps in our conceptual model, which include best practices like identifying the concerns of different groups (A.1.6) and identifying shared interests among team participants (A.2.8). The development of a shared vision at the outset of a TDW project has been shown to positively impact project outcomes (Pohl et al. 2015; Hoffmann et al. 2017). Additionally, well-designed TDW outputs and outcomes can also motivate continued interest in a project, especially when they are collaboratively developed (A.5.2) and target a range of audiences and user groups (Kueffer et al. 2012). Reflecting on the quality (A.7.3) and usefulness (A.7.5) of these products at the end of a TDW project is also critical for inspiring learning, which can help leaders refine their approach for future iterations. Lessons from other TDW projects indicate that when participant interest exceeds leadership capacity, motivation for the project can falter (Lang et al. 2012). Therefore, it is important to clearly define participant expectations early in the project so that leaders have the ability to follow through on promised outcomes and outputs.

Barrier 4: Ineffective Communication

Clear and effective communication becomes a top priority when groups of people with divergent backgrounds, experiences, and values are brought together. In fact, some scholars have cautioned TDW to actively avoid the academic trend of highly specialized language and jargon (Tress 2003; Brandt et al. 2013). Primary barriers to communication were not emphasized in our survey results; for example, learning a new language (A.1.7) was considered the least important activity in Step 1 and engaging face-to-face outside of project meetings (A.2.4) was also considered a low priority activity. Rather, respondents emphasized the importance of equitable communication (e.g., making sure every voice is heard and respected) at regular intervals, which supports findings in the broader TDW literature (DeLorme et al. 2016). Professional facilitation appears to be one of the best ways to ensure that communication remains effective and equitable (Lang et al. 2012; Kragt et al. 2013; DeLorme et al. 2016).

Barrier 5: Insufficient Funding

Funding for research is highly competitive and often follows a 3-5 year cycle, which necessitates near-continuous grant writing to support on-going initiatives and detracts from the actual implementation of research. This is true for conventional research as well as TDW, which has the added burden of requiring substantial time investments in relationship building and continuous collaboration throughout the project. Furthermore, funding agencies often require clear goals and outcomes to be defined at the beginning of a project, which contradicts the iterative and collaborative TDW process. We therefore join others (e.g., Balvanera et al. 2017) in calling for innovative funding opportunities for TDW, which we are beginning to see with large-scale initiatives like Future Earth and the Belmont Forum (Mauser et al. 2013; Suni et al. 2016). Lessons from the international *Collaborative Adaptation Research Initiative in Africa and Asia (*CARIAA) project suggest that smaller amounts of flexible funding are also important, as they enable TDW projects to adapt and evolve more quickly, facilitating more successful outcomes (Cundill et al. 2019). A significant concern for TDW is the funding of Step 1 exploratory efforts, which are often quite time consuming and yield few immediate products – but which are essential to long-term TDW success.

Barrier 6: Disagreements over Approach

Disagreement and conflicts among TDW participants are common (Lang et al. 2012; Cundill et al. 2019), and not always avoidable given the diversity of values, worldviews, and organizational structures involved (Jahn et al. 2012). Most TDW projects focus on mitigating conflict among participants, relying on strong leadership to anticipate and resolve disputes (Hoffmann et al. 2017). The most frequently employed activity in our survey was expressing mutual respect for one another's knowledge, experiences, and worldviews (A.3.3). This respect for difference is a core tenet of TDW and may help avoid negative feelings despite occasional conflicts and disagreements throughout a project. In fact, there is some evidence that conflict is necessary for learning to occur; a disorienting dilemma (Pennington et al. 2013) or cognitive struggle (Bransford et al. 2006) can challenge TDW participants' understandings and pave the way for meaningful learning (Fernández-Giménez et al. 2019).

Barrier 7: Knowledge Barriers

The integration or co-production of multiple types of knowledge is often a goal in TDW, yet it can be a significant challenge given the prevalence of power imbalances – particularly across scientific and indigenous or local knowledges (Bohensky & Maru 2011, Hering et al. 2012, Brandt et al. 2013, Tengö et al. 2014, Tengö et al. 2017). Knowledge integration has often resulted in attempts to scientifically validate other forms of knowledge (Agrawal 1995; Turnbull 2003), which disrespects the unique epistemology of traditional knowledge (Nadasdy 1999; Knapp et al. 2019). Knowledge co-production focuses more on the socio-cultural context of collaboration, encouraging equitable processes for generating holistic understanding of some issue (Armitage et al. 2011; Tengö et al. 2014). Though all activities in Step 3 are helpful, our results stress that exploring how to use different kinds of knowledge (A.3.2) and working to accommodate different processes for learning and decision-making (A.3.5) are critical for overcoming knowledge barriers. For people working outside their home region, we emphasize the importance of connecting diverse individuals with strong place-based understanding and experience working in the study area (A.1.3 and A.2.9). We also point readers to the USYS TdLab at ETH Zurich (tdlab.usys.ethz.ch), which provides a toolbox of methods designed to promote knowledge co-production. TDW is sometimes criticized for drawing on a broad and ill-defined set of methods for knowledge production (Brandt et al. 2013), but we believe this diversity is valuable and necessary given the highly context-specific nature of local knowledge (Berkes 2012).

Barrier 8: Inability to Take Action

There are times when it is not politically feasible to take action based on the results of a TDW process, despite participant intentions (Brandt et al. 2013). For example, a TDW project in northern Switzerland failed to implement their results because local collaborators did not have the political mandate to affect regional development plans (van Zeijl-Rozema & Martens 2011). This barrier might be mitigated by careful partnership design that includes high profile individuals with the power to impact the issue of interest (A.6.4), though this did not emerge as a best practice in our survey results. Other findings show that policy makers on the periphery of projects, but who engage regularly with the core team, are more likely to use TDW results in their decision-making compared to policy makers to only see the final products (Crona & Parker 2011). Additionally, our results indicate that certain groups in TDW may be more likely to experience this barrier, as women ranked it significantly more important than did men. Men were also more likely to report participating in TDW projects with high policy impact. These results reflect broader trends in gender discrimination, as women are often excluded from leadership positions throughout the world. In U.S. conservation organizations, women are more likely to occupy junior positions (Taylor 2015) and are routinely denied opportunities to participate in decision-making (Jones & Solomon 2019). We encourage environmental TDW participants to recognize and resolve these imbalances, particularly when communicating and acting on relevant learning (Step 6).

Barrier 9: Wrong Methods for Project Purpose

Social-ecological systems are complex systems that exhibit nonlinear dynamics, indirect effects and feedbacks, emergent properties, and heterogeneous links across space and time (Liu et al. 2007; Lambin & Meyfroidt 2010). These interactions among social and biophysical processes can lead to unexpected outcomes (Ostrom 2007, Turner et al. 2007) that make environmental management extremely difficult, especially considering the rapid rate of global environmental change occurring in these systems around the world (Cleland et al. 2007; Pepin et al. 2015; Steffen et al. 2011). Our conceptual model highlights the iterative nature of the TDW collaborative process, suggesting places where participants may evaluate their progress toward goals and decide to return to earlier steps if necessary. Due to the complex and evolving nature of social-ecological systems, participants may find midway through a project that their methods no longer answer the questions they are asking, or no longer fit the needs of decision-makers. We encourage an adaptive approach to TDW, similar to collaborative adaptive management (Fernández-Giménez et al. 2019) or adaptive co-management (Plummer et al. 2012), where projects are subject to regular evaluation so that projects may alter their approach as needed to meet project goals.

2.4.3 Increasing TDW Impact for Science and Society

Environmental TDW seeks solutions for multidimensional "wicked" problems that threaten the structure and functioning of social-ecological systems (Kates & Parris 2003; Rockström et al. 2009), and which require immediate action. Though small-scale TDW can also be highly impactful (Balvanera et al. 2017), policy change is needed to shift the behaviors of large organizations and institutions – particularly when addressing problems that cross region to global scales (Cundill et al. 2019). Yet significant social barriers exist between scientists and policy makers that prevent the use of scientific information in policy development and decision-making (Gano et al. 2007; Landry et al. 2003). Research shows that boundary organizations, which are formal institutions and organizations that work across the science-policy divide (Guston 2001), can overcome many of these barriers through the facilitation of stronger social networks (Crona & Parker 2011). Communities of practice, which are typically more informal groups of people with a shared interest or passion (Wenger et al. 2002), are another promising institution for increasing our understanding of social learning (Cundill et al. 2015). Greater attention to the role of formal and informal social networks like boundary organizations and communities of practice in TDW holds potential for increasing the impact of TDW projects.

More research is also needed to understand the social relationships that facilitate higher TDW impact, including how information flows within and across social networks (Borgatti & Foster 2003) and how people learn – both individually and as groups (Keen et al. 2005; Reed et al. 2010). Our survey responses indicate that TDW participants view projects as more successful when they perceive them to have medium to high policy impacts as compared to projects where participants experience learning. This is perhaps not surprising, as policy impacts are tangible and so more easily observed and celebrated than learning outcomes. Yet, learning is an integral element of TDW that is severely under-researched in the context of environmental TDW (Armitage et al. 2008; Baird et al. 2014; Fernández-Giménez et al. 2019). In our survey, we attempted to assess the impact of different activities on different levels of multiple-loop social learning but found very few clear or statistically significant patterns. For example, we found that feedback workshops with decision-makers were associated with higher learning outcomes for all types of learning, yet only a small proportion of projects assessed participant learning. We encourage additional research into the conceptualization, measurement, and evaluation of social learning so that we can better understand the role of socially-embedded learning in TDW outcomes.

While we support the pursuit of policy impacts from TDW projects, we urge TDW participants not to lose sight of the balance between academic and non-academic outcomes. For example, our survey results revealed that communicating results to academic audiences outside the immediate TDW project partners (A.6.2) was ranked as the least important activity in Step 6 across all respondent types, yet it was more frequently conducted than communicating results to other practitioners and stakeholders. Further, we found that projects with peer-reviewed publications were associated with higher perceived policy impacts than those without publications. Together these results indicate that communicating TDW results to academic audiences remains valuable for advancing both societal and scientific impact of TDW projects. Though we appreciate that academics are increasingly recognizing the importance of science communication (Weingart et al. 2016), we caution not to let the pendulum swing too far and reiterate that a balance between scientific and societal outcomes holds the greatest promise for the future of TDW.

2.4.4 Limitations of the survey

Our survey results are not without limitations. For example, we did not find many differences between internal and external respondents, which may be due to our coarse geographic scale (projects on the same or different continent as respondents' primary location). We were also unable to compare case studies of most successful projects based on funding, which might be related to their overall project success or outcomes. We saw low response rates from practitioners and other stakeholders, which may be related to 'research fatigue' among these groups. In fact, one researcher responded that they would not be sending the survey to their practitioner partners because they were waiting for their response to another survey and did not want to overwhelm them. Other barriers to non-researcher responses may have been that we offered no paper option, and only administered the survey in four languages. Finally, our results are biased heavily towards respondents from North America and Europe, which may have overshadowed insights from more remote parts of the world. We were particularly surprised at the lack of responses from Oceania and Central America, which implies our distribution was perhaps not as strong in those locations.

2.5 Conclusions

TDW has emerged as an important research paradigm in environmental sustainability, with benefits for both science and society. Our conceptual model seeks to expand upon existing models to encourage deep, place-based understanding as a foundation for effective TDW. We present 23 activities that can be considered TDW best practices for a wide range of social-ecological contexts, though some caution is needed due to the limitations of our survey responses. We demonstrate how these activities can help overcome the key barriers in environmental TDW, with additional lessons from the broader literature. Further research is needed into the social aspects of TDW – specifically, social networks and social learning – so that we can better facilitate TDW that fosters transitions to sustainability.

CHAPTER 3

KNOWLEDGE CO-PRODUCTION IMPROVES UNDERSTANDING OF ENVIRONMENTAL CHANGE IN THE ETHIOPIAN HIGHLANDS [2]

3.1 Introduction

Responding to changes in the structure and functioning of landscapes is a central challenge for the management of sustainable ecosystems, with far-reaching consequences for human well-being and local adaptation to global environmental change (Lambin et al. 2001; Carpenter et al. 2009; Rockström et al. 2009; DeFries et al. 2012). Biological invasions (Vitousek et al. 1996), phenological shifts (Buitenwerf et al. 2015), and unsustainable natural resource use (Persha et al. 2011) are among the most pressing drivers of change impacting ecosystems around the world. Understanding these changes within integrated social-ecological systems is critical for developing effective responses, as drivers, impacts, and feedbacks among social and biophysical processes can lead to unexpected outcomes (Ostrom 2007; Turner et al. 2007; Lambin & Meyfroidt 2010).

As global environmental change continues to accelerate and intensify (Cleland et al. 2007; Steffen et al. 2011; Pepin et al. 2015), new approaches are required to build bottom-up understanding and place-based responses that connect across multiple knowledge systems and evidence streams (Tengö et al. 2014). Drawing on multiple knowledge systems (e.g., local or indigenous knowledge, different academic disciplines or work sectors) is increasingly necessary for improved understanding and management of adaptive social-ecological systems (McLain & Lee 1996; Dietz et al. 2003; Folke 2004). For example, Klein et al. (2014) demonstrate that local knowledge of climate change on the Tibetan Plateau contributed to scientific understanding of

[2] This chapter has been accepted for publication in *Ecology and Society*, with co-authors Girma Nigussie, Mike Alonzo, Bikila Warkineh, Jamon Van Den Hoek, Mekbib Fekadu, Paul Evangelista, and Julia A. Klein

delayed summer onset and raised awareness of the link between increasing temperature and rangeland impacts among Tibetan pastoralists. The multiple benefits of these cross-knowledge collaborative approaches have been observed in other social-ecological contexts, including whale conservation (Huntington 2000; Fernández-Giménez et al. 2006); forest change (Chalmers & Fabricius 2007); sea ice change (Nichols et al. 2004; Laidler 2006); rangeland management (Fernández-Giménez 2000; Reed et al. 2013; Jamsranjav et al. 2019); and fish and wildlife monitoring (Moller et al. 2004; Prado et al. 2013).

One key challenge when bringing multiple knowledge systems together is the critical need to address power dynamics. Knowledge integration has traditionally relied on scientific validation of other forms of knowledge (Agrawal 1995; Turnbull 2003), with the result that local knowledge has been overly simplified or ignored, and local communities divorced from their own knowledge and subsequent self-efficacy (Nadasdy 1999; Latulippe 2015). Knowledge co-production differs from knowledge integration in material and philosophical ways. It is typically an iterative, ongoing collaborative process that respects and acknowledges socio-cultural contexts, resulting in a more inclusive and equitable process for generating holistic understanding about an issue (Jasanoff 2004; Berkes et al. 2008; Armitage et al. 2011; Shirk et al. 2012). A multiple evidence based (MEB) approach (Tengö et al. 2014) is gaining attention as a particularly effective framework for knowledge co-production, as it emphasizes the importance of maintaining the internal validity of knowledge systems so that final products are salient, credible, and legitimate to the diverse stakeholders involved (Cash et al. 2003; Reid et al. 2006).

Community-based conservation areas present particularly valuable case studies for knowledge co-production, as there are often a mix of formal and informal institutions that support working across multiple groups of people and their respective knowledge systems (Dudley 2008; Ruiz-Mallen & Corbera 2013). When considered as a multilevel commons problem, community-based conservation areas can be simultaneously a local commons that produces ecosystem services for local consumption and well-being, and a regional commons that supports cross-scale activities like ecotourism and economic development (Berkes 2007). As such, the land tenure and management institutions that control access to these areas are often necessarily complex and highly influential on conservation outcomes (Dietz et al. 2003; Persha et al. 2011). Examining landscape-scale environmental change over time in community-based conservation areas can enable clearer understanding of the interactions and feedbacks between biophysical and social drivers of change in these systems, and guide the development of actionable responses that are targeted to the particular strengths and vulnerabilities of that place.

Remote sensing approaches offer tools for examining the causes and consequences of environmental change at a landscape scale, and recent advances have made these tools more accessible and more appropriate for addressing different kinds of problems. Historically, the high cost of satellite imagery and lengthy processing time limited applications to using two or three images to assess change over some period of time (Coppin et al. 2002; Kennedy et al. 2014). With the full and growing global archive of NASA/USGS Landsat imagery being made freely available in 2008 (Woodcock et al. 2008), alongside the development of open-source algorithms for multi-date image compositing, automated cloud-masking (Zhu & Woodcock 2012) and surface reflection correction (Masek et al. 2006), the spectral and spatial continuity between successive Landsat program satellites now more closely approximates a continuous representation of change (Wulder et al. 2019). These advancements enable a more direct engagement between remote sensing products and ethnographic narratives of change because the availability of cloud-free images no longer constrains the temporal and spatial bounds of the study.

An MEB approach, where people with local knowledge and knowledge derived from remote sensing are equal partners in an iterative process of knowledge co-production, can lead to more consistent and high-quality results for both academic and non-academic participants (Robbins & Maddock 2000; Naidoo and Hill 2006; Isager & Broge 2007; Herrmann et al. 2014). Local knowledge is increasingly viewed as necessary for remote sensing projects, particularly when validating and interpreting results (e.g., Smith et al. 2019), and is valued for its engagement at extremely fine spatial and temporal scales (Berkes 2007) and ability to address high levels of complexity and multiple variables (Berkes & Berkes 2009). Thus, the spatial breadth of remote sensing coupled with the depth of local knowledge can support detailed system understanding at a landscape scale, and the MEB process can produce culturally appropriate and actionable results for sustainable ecosystem management and adaptation to environmental change (Isager & Broge 2007).

In this study, we use an MEB approach to investigate the causes and consequences of environmental change over five political and management periods, with the aim of producing a more holistic understanding of change in a community-protected grassland and its surrounding landscape in the Ethiopian highlands. We draw on multiple knowledge systems to describe the interaction of biophysical change (precipitation and vegetation) and social change (political and management institutions), and explore potential impacts for ecosystem service provisioning. The ecosystem services concept was developed to clarify how ecosystem structures and functions work to benefit human societies (Ehrlich & Erlich 1981), and thus ecosystem services are often described as “the benefits people obtain from ecosystems” (MEA 2005) or conversely as “nature’s benefits to people” (Diaz et al. 2015). Work on ecosystem services valuation and integration into policy is often criticized for a lack of attention to local needs, values, and knowledge (Turnhout et al. 2012; Pandeya et al. 2016). Our work, which uses the terms “ecosystem services” and “benefits” interchangeably, presents a highly local case study of integrating diverse knowledge types to better understand and manage ecosystem services.

We formalized results as maps and narratives that were edited and validated by community members, conservation managers, and local policy makers, resulting in tangible “boundary objects” for management (Star & Griesemer 1989; Steger et al. 2018). Boundary objects emerge from collaborative processes and address a societal information need, and are characterized by their interpretive flexibility and ability to apply to both specific and general contexts (Star 2010). The boundary objects produced through this research effectively combined observations and products across multiple knowledge systems to lay a foundation for future knowledge co-production and application in this area.

3.2 Methods

3.2.1 Study Site

The Guassa Community Conservation Area (Guassa) is located in the Menz Gera woreda (similar to a county or district) of the Amhara Region of Ethiopia (Figure 3.1). Ranging from 2,600 – 3,560 m.a.s.l., this area is historically characterized by two rainy seasons known as the 'belg' (~Feb 1 – April 30) and 'kiremt' (~July 1 – September 30). However, recent research from 2007-2012 indicates that rainfall patterns may be shifting, with more than half of the average annual 1650 mm (± 243 mm SD) of rainfall occurring in a unimodal peak in July and August (Fashing et al. 2014). During that same period, the average monthly temperature at Guassa was 11.0 ºC (± 1.2 SD) (Fashing et al. 2014). Guassa supports several endemic and threatened species, including the critically endangered Ethiopian wolf (*Canis simensis*) and charismatic gelada monkey (*Theropithecus gelada*) (Ashenafi et al. 2005).

Guassa is named after the guassa grasses (*Festuca* spp.) that are valuable to the local communities for their use as thatch, rope, construction material, and forage. Guassa is 78 km^2, and the nine communities ('kebeles', the smallest administrative unit in Ethiopia) that manage and use the area occupy another 370 km^2 (Figure 3.1). These nine kebeles are the only communities in the region with ancestral and modern rights to Guassa, and therefore we focused our fieldwork in these areas. There are approximately 42,000 people living in these nine kebeles (CSA 2017), nearly all of whom belong to the Amhara ethnic group and the Ethiopian Orthodox Church. Increasing food insecurity in the area has resulted in roughly half the population relying on food aid programs (MGWA 2016).

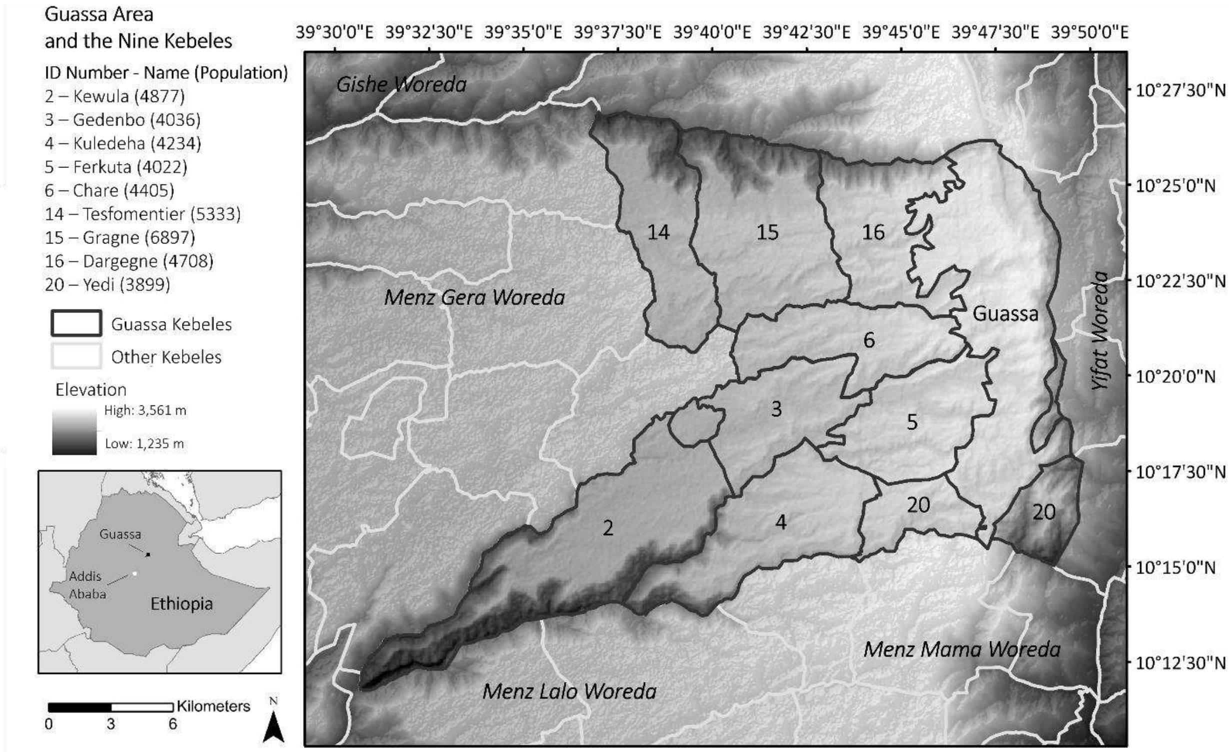

Figure 3.1. The identifying numbers, names, population, and administrative boundaries of the nine kebeles (in black) with ancestral rights to Guassa. These kebeles are all part of the Menz Gera woreda, and their numbered identifiers are used interchangeably with their local names (note: kebele 20, "Yedi", is located in two separate areas). Guassa has no human population and is administered separately as a community conservation area.

Guassa has undergone significant political and land management changes throughout its history, beginning with the overthrow of the Imperial regime of Emperor Haile Selassie (pre-1974), through a period of land reform during the military regime known as the Derg (1974 – 1991), a transitional period of mixed government and community management (1991 – 2003), followed by increased NGO leadership (2003 – 2012) and finally the current co-management regime (2012 – present) (Figure 3.2). These five political-management periods were identified as key drivers of environmental change in the area during preliminary fieldwork and literature reviews (Admassie 2000; Ashenafi & Leader-Williams 2005) and we use them to structure our subsequent analysis.

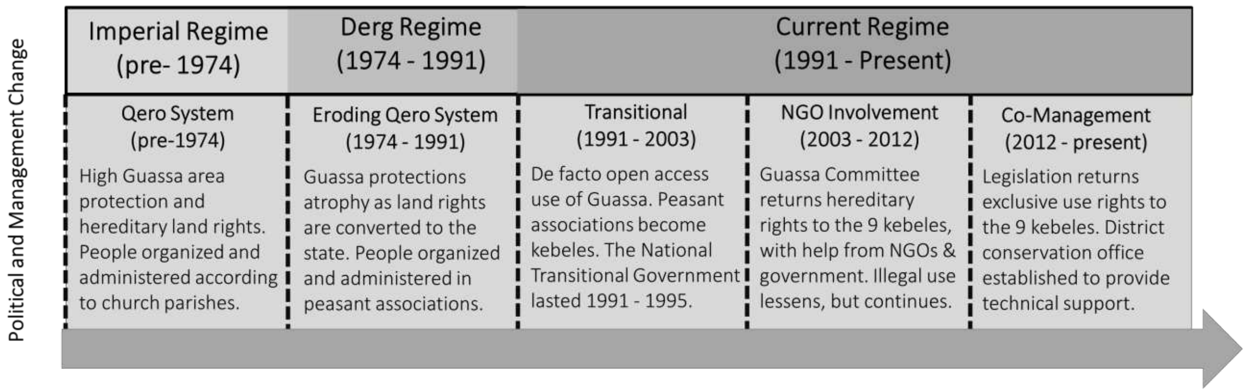

Figure 3.2. A timeline of political and management change in Guassa.

The community conservation area was managed for hundreds of years (c. 1600 – 1974) according to the locally unique and highly effective Qero system of communal management that restricted access to the grasses through 2-3 month open seasons every 3-5 years (Ashenafi & Leader-Williams 2005). That system was undermined when the Socialist military Derg regime took over, and the 1975 Agrarian Reform transferred land ownership to the state - propagating decades of confusion over responsibility for Guassa's management (Admassie 2000; Ashenafi & Leader-Williams 2005). Throughout the 17-year Derg regime, the Qero system was slowly eroded in favor of *de facto* open access use rights, which continued into the current political regime despite community efforts to re-establish their exclusive rights (Fischer et al. 2014).

As a source of water and a refuge for wildlife, the Guassa area has been attracting increasing attention from tourists, the Ethiopian government, researchers, and international conservation organizations since about 2000 (Welch 2017). Initially, NGOs were met with skepticism from the local kebeles, but this subsided with the development of an eco-tourism project that returned profits directly to the communities. Eventually a new co-management regime was established that restored daily management responsibilities to nine kebeles with ancestral rights to Guassa. International research interests in the area expanded to include long-term studies on the Guassa population of endemic gelada monkeys in 2006 (Fashing et al. 2014), and Ethiopian and international researchers arrive to study new aspects of the system each year. Exclusive use rights to the area were formally restored to the kebeles by Amhara Regional Regulation No. 97 in 2012. Currently the management team is composed of five representatives from each of the nine kebeles (the "Guassa Committee"), of which ten form an executive committee (the "Tourism Board"), and about twenty other individuals spread across two government offices – one administrative office at the local county ('woreda') level, and the Guassa Conservation Office that is sponsored by the Amhara Regional State. They manage the area collaboratively, with final decision-making power in the hands of the Guassa Committee, which meets monthly on their own and quarterly with the government offices.

3.2.2 Data Collection and Analysis

3.2.2.1 Ethnographic Data

We used semi-structured group interviews to identify the locally-defined land classes, their associated ecosystem services, and overarching perceptions of environmental change in this area over time. Semi-structured interviews are a conversational interview form that allows participants to influence the breadth and depth of topics covered (Clifford et al. 2003). We elected to conduct group interviews because they facilitated a rich, dynamic conversation among diverse members of a community (Arthur et al. 2012). Previous research has also shown that people in the Ethiopian highlands tend to state collective perceptions rather than personal experiences (Nyssen et al. 2006), which strengthened our ability to make generalizations from the relatively small number of participants. We convened a series of group interviews in March 2017, one in each of the nine kebeles, and invited an equal number of men and women with knowledge of the conservation area to attend. We reached out to kebele administrators and asked them to identify a diverse group of people with good understanding of the Guassa area and interest in participating in a 4-6 hour workshop. Ten men and ten women attended the first interview, and we determined that was too many for a productive conversation. We limited the remaining interviews to 10-12 people for a total of 106 participants across nine kebeles, with equal gender representation. The average age of participants was 42 years old, ranging from 18 – 88 years.

In each group interview, we requested that participants discuss and describe the categories they use to think about and organize their land, both in the kebele lands and in the Guassa area. After establishing this list of land classes, we then asked how those land classes have been changing over the five political-management periods of Guassa. For each land class, we requested that the group free list all the ecosystem services (translated as "benefits") they receive from that land class, and a research assistant wrote them on a chalkboard. We then collectively grouped the ecosystem services into a smaller set of distinct services (e.g., "making tools" and "making bowls" were determined to be essentially the same service of "household items"). As a group, participants ranked the services in each land class to identify which were most important to their community. This entailed group discussions and voting to achieve consensus, which took no longer than two hours. Throughout the discussions, we facilitated participation to prevent certain individuals or groups from dominating the conversation. Finally, participants were supplied with markers, blank paper, and high-resolution Google Earth images of their kebele and asked to identify the general distribution of these land classes following a standard "participatory mapping" protocol (Klain & Chan 2012; Luizza et al. 2016; Wakie et al. 2016). An example of the kebele-level maps produced is given in Appendix D (Figure D1). All participants were offered modest financial compensation for their time.

We used the software package ANTHROPAC (Borgatti 1996) to analyze the ecosystem service data and calculate the relative importance of each service across the nine kebeles based on their ranked positions. The software calculates Smith's salience value (S) from zero to one for each item in a list, considering both the frequency of the item across lists and its position within each of those lists (Borgatti 1996; Levine et al. 2017). Salience values closer to one indicate good agreement across the nine kebeles regarding the importance of a particular ecosystem service. This research was reviewed and approved by Colorado State University's Institutional Review Board (361-18H), and was conducted with free, prior and informed consent of all participants.

3.2.2.2 Remote Sensing and Precipitation Data

Following the group interviews, we conducted a supervised classification of Landsat 8 optical imagery using a random forest classifier implemented in the randomForest package in R (Breiman 2001; R Core Development Team 2019). Random forest is a machine learning technique that uses bagging (i.e., random resampling with replacement) to average across large numbers of decision trees and thus produces more accurate classifications than single trees alone (Breiman 2001; Rodriguez-Galiano et al. 2012). A random forest classifier provides flexibility by allowing for nonlinear relationships between predictor and response variables and is robust to missing predictor data and (multi)collinearity (De'ath & Fabricius 2000). Random forest classifiers have been used in Ethiopia for a variety of objectives, including the identification of wetlands (Dubeau et al. 2017), mapping irrigated agriculture (Vogels et al. 2017), and predicting soil functional properties (Vagen et al. 2013).

We used the land classes defined by participants in the interviews to conduct this supervised classification. We selected a cloud-free image taken on December 10, 2016 as it aligned most closely with the dates of the workshops and the most current high-resolution imagery available in Google Earth Pro. We collected 184 ground truth points immediately following the group interviews under the direction of participants, and used these ground truth points and the results of the group interview mapping exercises to guide the collection of 3,060 additional data points from Google Earth (where high-resolution imagery was available for December 2016 across the study area). A total of 27 environmental variables (Table 3.1) were used to predict the land classes: the seven bands from Landsat 8 comprising surface reflectance in the visible, near infrared and shortwave infrared spectral regions, three tasseled cap composites (Kauth & Thomas 1976) of those bands (brightness, greenness, wetness), fourteen metric images from remote-sensing based phenological models (described below), as well as elevation, aspect, and slope variables derived from a 30m ASTER Global Digital Elevation Model (2009). See Appendix D for a map of training points (Figure D2). Because there are no available aerial photographs or ground truth datasets for this area, we were not able to conduct a supervised classification for past time periods.

Table 3.1. Description of 27 predictor variables used in the supervised classification.

Variable	Description
aspect	downslope direction
elevation	meters above sea level
slope	degree of tilt
Band 1	Landsat 8 OLI coastal aerosol band
Band 2	Landsat 8 OLI blue band
Band 3	Landsat 8 OLI green band
Band 4	Landsat 8 OLI red band
Band 5	Landsat 8 OLI near infrared band
Band 6	Landsat 8 OLI short-wave infrared band 1
Band 7	Landsat 8 OLI short-wave infrared band 2
wetness	weighted linear combination of Landsat 8 OLI bands to produce a measure of soil or surface moisture
greenness	weighted linear combination of Landsat 8 OLI bands to produce a measure of photosynthetically-active vegetation
brightness	weighted linear combination of Landsat 8 OLI bands to produce an albedo-like measure of surface reflectance
CoMgmt_DOY253	Spline interpolated NBR values during the Co-management period for the wet season (September 10)
CoMgmt_DOY40	Spline interpolated NBR values during the Co-management period for the dry season (February 9)
CoMgmt_NGO_DOY253	Difference of spline interpolated NBR values between the Co-management and NGO periods for the wet season (September 10)
CoMgmt_NGO_DOY40	Difference of spline interpolated NBR values between the Co-management and NGO periods for the dry season (February 9)
NGO_DOY253	Spline interpolated NBR values during the NGO period for the wet season (September 10)
NGO_DOY40	Spline interpolated NBR values during the NGO period for the dry season (February 9)
NGO_Trans_DOY253	Difference of spline interpolated NBR values between the NGO and Transitional periods for the wet season (September 10)
NGO_Trans_DOY40	Difference of spline interpolated NBR values between the NGO and Transitional periods for the dry season (February 9)

Transition_DOY253	Spline interpolated NBR values during the Transitional period for the wet season (September 10)
Transition_DOY40	Spline interpolated NBR values during the Transitional period for the dry season (February 9)
Trans_Derg_DOY253	Difference of spline interpolated NBR values between the Transitional and Derg periods for the wet season (September 10)
Trans_Derg_DOY40	Difference of spline interpolated NBR values between the Transitional and Derg periods for the dry season (February 9)
Derg_DOY253	Spline interpolated NBR values during the Derg period for the wet season (September 10)
Derg_DOY40	Spline interpolated NBR values during the Derg period for the dry season (February 9)

We used spline interpolation to explore general changes in phenology and vegetation productivity in the area using all available Landsat data from 1985 to the present (n = 597 image dates). We performed standard cloud-masking on each image (Zhu & Woodcock 2012), and extracted Normalized Burn Ratio (NBR) values (Key & Benson 2006). NBR is similar to other vegetation indices like the more commonly employed Normalized Difference Vegetation Index (NDVI; Tucker 1979), except that it is calculated using the near-infrared and shortwave-infrared wavelengths, making it more resistant to atmospheric contamination. While NBR has traditionally been used to detect the magnitude and direction of vegetation change pre- and post-fire events (Key & Benson 2006), we found its resistance to atmospheric contamination and sensitivity to changes in both vegetation structure and moisture content to be useful in our cloudy study area.

The image stack was divided temporally into four date ranges corresponding to the duration of each political-management period for which satellite data were available. This resulted in 70 images in the Derg period (44 with <50% cloud cover), 148 images in the Transition period (87 with <50% cloud cover), 147 images in the NGO period (86 with <50% cloud cover), and 232 in the Co-management period (135 with <50% cloud cover). The total number of cloud-free images for each pixel ranges from 31 – 454 with a mean of 322 images. A map is provided in the Appendix D to illustrate that the Guassa area and kebeles immediately adjacent (Ferkuta, Yedi, and Dergagne) suffer from the highest cloud cover, yet still have 200-300 cloud-free images on average (Figure D3).

To assess vegetation changes over these political-management periods, we used spline interpolation to model NBR values and estimate phenological curves at each pixel within each political-management period (Figure D4). Spline interpolation allows for estimation of vegetation index values at every day of year (DOY) regardless of the timing of image acquisition (Clinton et al. 2010). This allowed us to select the best dates for comparison with local knowledge of the area rather than remaining restricted to the availability of particular satellite images. We derived maps of NBR values for wet (DOY 253, September 10) and dry (DOY 40, February 9) seasons for each period. We then subtracted maps of the earlier time period from the later time period to assess the magnitude and extent of changes in NBR, which we interpret as a measure of vegetation productivity. NBR can take values ranging from -1 to 1, though values between -0.5 and 0.5 are more common in Guassa. Therefore, using a conservative approach based on a histogram analysis, we consider a significant decline in vegetation to be values < -0.2, and a significant increase in vegetation to be > 0.2. Anything between -0.05 and 0.05 is considered to be negligible change. These outputs are analyzed individually as a measure of vegetation change, and served as inputs to the supervised classification described above.

We employed another time series dataset to explore changes in precipitation for the study area over the same time period, which we then compared to the changes in vegetation and narratives of change from group interviews. We used the Climate Hazards group Infrared Precipitation with Stations data (CHIRPS; Funk et al. 2015), processed through the Climate Engine Application (climateengine.org), to look at past precipitation patterns over the study area, stretching from 1981 – 2018 (Figure D5). CHIRPS data integrates 0.05° resolution satellite imagery with available in-situ station data on precipitation to produce a gridded time series product that estimates precipitation every five days. We conducted a nonparametric Mann-Kendall test on the total annual precipitation in the belg and kiremt rainy seasons to assess trends in precipitation patterns over the past 37 years. We then used another non-parametric test (Kruskall-Wallis) to determine whether significant differences in precipitation occurred across the historical periods of interest, again with attention to the short belg and long kiremt rainy seasons. Statistical tests were conducted in R (R Core Development Team 2019). For all of these statistical tests, we consider $p \leq 0.05$ to be statistically significant.

3.2.2.3 Co-interpretation of Results

In August 2018, 41 participants (12 women and 29 men) were invited to attend a workshop in the town of Mehal Meda. Participants were invited from the Guassa Committee and the Tourism Board (n=27, three from each community), the Guassa Conservation office (n=3), scientists and NGO workers (n= 6), and the local woreda administration office (n=5). The workshop sought to bring together results from the ethnographic and remote sensing analyses, and to request feedback to help scientists validate and interpret the results. A second workshop was held in February 2019 to refine the results and analysis further, with mostly the same participants (n = 38). For example, we requested feedback on the accuracy of the supervised classification maps and vegetation change analyses, and whether they had ideas about the causes of the changes observed. We sought to ensure the remote sensing products were useful to local participants, so we incorporated suggestions like changing the colors used to represent different land classes and editing the location and extent of administrative boundaries.

3.3 Results

3.3.1 Locally-defined Land Classes and their Spatial Distributions

Across the nine kebeles, participants identified ten land classes with local relevance, which we describe below. Using 27 environmental predictors (Table 3.1) and 3,244 training points, we conducted a supervised classification of these locally-defined land classes (Figure 3.3). We fit 5,000 trees with a random forest classifier, using cross-validation to assess model performance. The classifier had an overall accuracy of 87.1% and a kappa value of 0.85, indicating a high quality performance. Across all land classes, the variables with the strongest influence on predictions (i.e., the largest mean decrease in accuracy) were elevation, wet season NBR values from the Co-management period, dry season NBR values from the Derg period, and tasseled cap greenness. Yet, more nuanced patterns emerge at the level of individual land classes, where more densely vegetated classes (forest and shrublands) were better predicted by dry season NBR in the Derg and Co-management periods, while less densely vegetated classes (stone and grazing lands) were better predicted by wet season NBR values in the Co-management and Transitional periods. We present additional results in the Appendix D, including the confusion matrix (Table D1), a table of square kilometers per land class and percent area (Table D2), and a table of the relative importance of each predictor variable per land class (Table D5). Below, we present the land classes and their relative distributions in decreasing order of land area.

Farmland: The main crops of this region are barley, wheat, and beans. Different crop cultivars are planted depending on the season. Weeding and harvesting are often done through communal 'Debo' groups, though farmland is privately owned. Farmland is the largest land class in the study area, occupying 161 km^2 (36.1%) of the total land area, and between 29 – 59% of each kebele's land area. Averaging user's and producer's accuracies (Alonzo et al. 2014) revealed that farmland had a classification error of 15.1%. Tasseled cap greenness and dry season NBR values during the Co-management period were the best predictors of this land class.

Shrublands: Shrublands are composed of mainly short, dense species like asta (*Erica arborea*), amijah (*Hypericum revolutum*), and cheranfi (*Euryops pinifolius*) – all of which are economically valuable species, though people are no longer allowed to harvest them inside Guassa due to potential impacts to wildlife. Shrubland occupies 69 km^2 (15.5%) of the total land area, and is found mostly in Guassa (21.8 km^2) – though there are some concentrated areas primarily in Gragne, Kewula, and Yedi kebeles. Shrubland had the second largest error in classification (17%), primarily due to its spectral similarity with native forest. Band 4, slope, and dry season NBR during the Derg period were the best predictors of this land class.

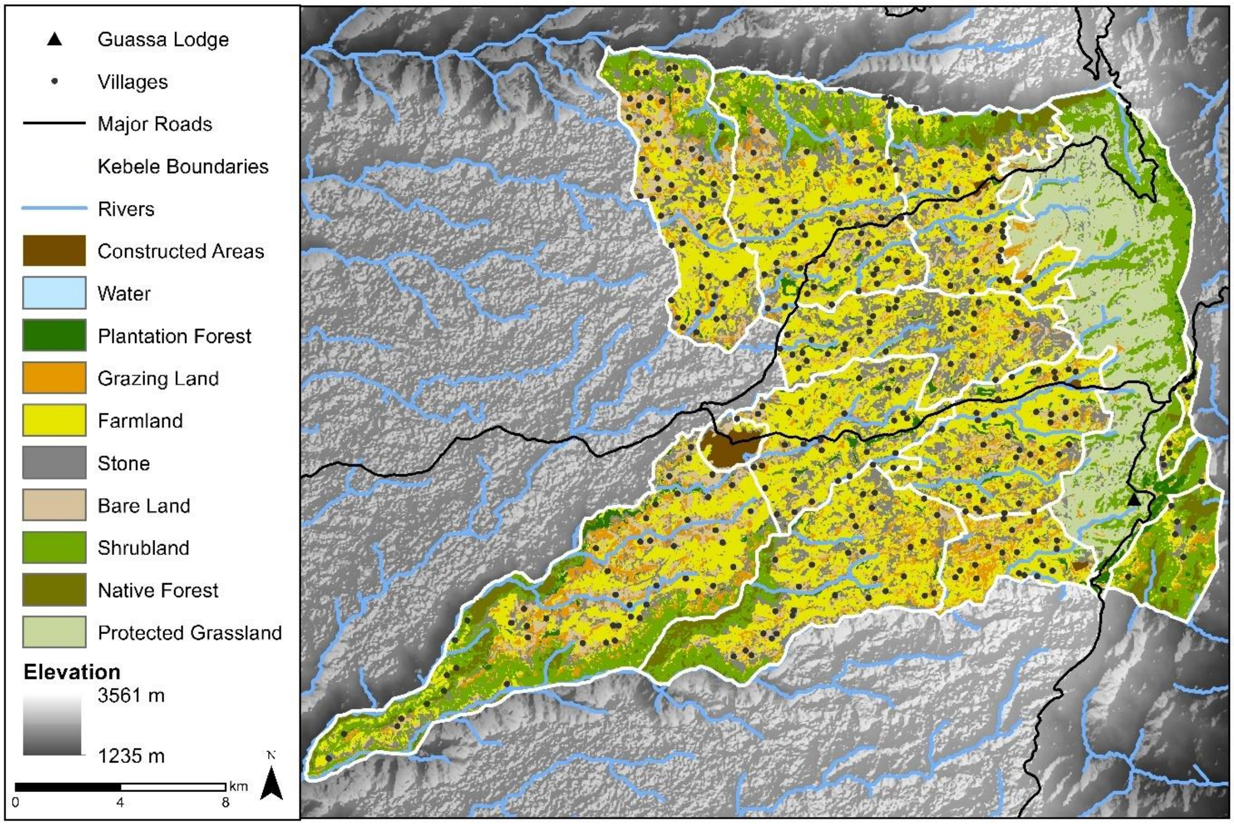

Figure 3.3. Classification of the study area using locally-defined land classes.

Stone: This land class was described as a mix of exposed, rocky outcrops and the presence of large amounts of stone in the soil – to the point that it prevents using the land as farmland. While stone occupies a large amount of total land area (69 km^2, 15.5%), it is largely concentrated inside the kebele lands (mostly in Gragne, Kewula, and Chare kebeles) and is quite limited inside Guassa (3.2 km^2). Stone had the largest errors in classification (18.6%) and was often misclassified as farmland or bare land. Wet season NBR values from the Co-management period and tasseled cap greenness were the best predictors of this land class.

Protected grasslands: Most of the land classes were used exactly as described by participants. However, when asking about the land classes within the Guassa area, people started listing individual species names rather than broader types of vegetation cover. There was then a consolidation process that resulted in the "protected grassland" class, which is made up of multiple grass and forb species. This is the only land class that contains the guassa grasses. Due to persistent confusion over the Guassa border, some of the protected grasslands fall into the administrative areas of the kebeles. The protected grasslands occupy 45.5 km^2 (58.2%) of Guassa, with scattered patches in the adjacent kebele lands. Protected grasslands had a low classification error (8.7%). Elevation and tasseled cap greenness were the best predictors of this land class.

Grazing lands: Grazing lands are communal lands, but are managed differently than the Guassa area as they do not have the same restrictions on access. One man explained that "if one man owns 50 sheep and another man owns one, the grazing area is still shared. But if he is enterprising enough, the man with one sheep can cut the grass and sell it to the rich man." Grazing lands are dominated by gaya grass (*Andropogon abyssinicus*). Grazing land occupies 39.7 km^2 (8.9%) of the total land area, and between 6.1 – 15.3% of each kebele's land area. Grazing lands had a classification error of 13.6%, and were most frequently confused with bare land. Band 6, Band 5, and wet season NBR values from the Co-management and Transitional periods were the best predictors of this land class.

Bare lands: Bare lands are characterized by the absence of vegetation on land that should be able to support vegetation; it was also described as "old" or "tired" land that has potential to recover. Bare land occupies 33 km^2 (7.4%) of the total area, most of which is found in Gragne, Kewula, and Tesfomentier kebeles. Bare lands had a classification error of 15.8%. Band 4, Band 3, and Band 2 were the best predictors of this land class.

Native forest: Besides plantation forests, native forests are the only other type of forest in this area. However, it was difficult for participants to explain the difference between native forest and shrublands - many of the same species occur in both land classes, but native forest contains larger plants with different use values. Some of the larger species that occur in both land classes are kosso (*Hagenia abyssinica*), bisana (*Croton macrostachyus*), and juniper (*Juniperus procera*). Native forest occupies 15.9 km^2 (3.6%) of the total land area, and is concentrated in Kewula, Kuledeha, Yedi, and Dargegne kebeles. There was no detectable amount of native forest in Chare kebele. Native forest had a classification error of 14.7%. Dry season NBR values from the Derg period and Band 4 were the best predictors of this land class.

Plantation forest: Plantation forests range in size depending on whether they were established as public erosion control projects or as private woodlots. There are two dominant plantation species in the area – eucalyptus (*Eucalyptus globulus*) and cypress (*Cupressus lusitanica*). Plantation forest occupies only 9.1 km^2 (2%) of the total land area, which is distributed relatively evenly throughout the kebeles with a larger concentration in Guassa. Plantation forest had a low classification error (3.6%). Dry season NBR values from the Co-management and Derg periods and the difference in dry season NBR values between the NGO and Transitional periods were the best predictors of this land class.

Water: Open water was only present in one location in the study area, a small reservoir between Gedenbo and Chare kebeles. The two training points we used for this reservoir were both correctly classified. Streams were too small to be captured by this classification. Band 3, band 4, and dry season NBR values from the Co-management period were the best predictors of this land class.

Constructed areas: Constructed areas are the areas where humans live and construct their houses and other buildings. Constructed areas had such an initially high class error that we removed it from the model and digitized the four cities, 50 churches, 22 schools, and approximately 380 villages by hand. The difficulty of accurately predicting constructed areas was partially due to the small size of individual homesteads, the brightness of tin roofs, and the presence of forest patches close to most residences – all of which led to confusion among constructed areas, farmland, plantation forest, stone, and bare land classes. Constructed areas and water reservoirs together comprise less than 1% of the landscape.

3.3.2 Ranked Preferences for Ecosystem Services by Land Class

Participants ranked the importance of ecosystem services in each class except for bare land, which they perceived as having no ecosystem services, and constructed areas, which have so many benefits that they considered it unrealistic to name them all. Participants in the first group interview chose to list benefits of Guassa ("Guassa Area" in Figure 3.4) separately from those of the protected grasslands, and so we asked participants in subsequent interviews to continue with this distinction. For example, Guassa is a source for guassa grasses ("harvest guassa grass", Figure 3.4), which then have their own set of associated ecosystem services (e.g., "roof thatch"). Salience values are used to rank ecosystem services across kebeles; values closer to one indicate good agreement across the nine kebeles regarding the importance of a particular ecosystem service.

Of these nine classes, seven had perfect agreement across the kebeles regarding the most important ecosystem service for that class. These were crops (farmland), forage (grazing land), roof thatch (guassa grass), guassa grass provisioning (Guassa area), firewood (shrubland), house construction (stone), and house construction (plantation forest). There was nearly unanimous agreement that drinking water is the most important service from the water class. Native forest services were not as uniformly valued, with the top four ecosystem services sharing similar salience values: income, household items, firewood, and house construction. This was also the only land class with income as the most important benefit, perhaps reflecting the subsistence orientation of people in this region. Indeed, the majority of ecosystem services described by participants would be considered "provisioning services", or products obtained directly from ecosystems, indicating the importance of these materials for the livelihoods of the participants.

Figure 3.4. Locally-defined land classes and their respective ecosystem services, ranked and aggregated across the nine kebeles. Colored squares indicate overlap of services with other land classes.

While there are several shared ecosystem services across the grazing land and protected grassland classes, clear distinctions arise under the particular socio-cultural and ecological context of this area. One difference is due to the types of grass found in these grasslands. Grazing lands produce grasses that are valued mainly as forage, while guassa grasses are considered valuable primarily for non-forage uses. Grazing is only allowed in the grazing areas, as it has been banned inside Guassa since 2010. Even before the ban, it was only allowed every 3–5 years or under conditions of severe drought (Ashenafi & Leader-Williams 2005). The strength and height of the guassa grass makes it particularly desirable for rope making and other local materials such as ponchos, which are not valuable uses for the gaya grasses found in the grazing lands. Five shared services exist across these classes: brick and wall plaster construction materials, fodder, income, roof thatch, and floor covering. However, differences in the relative ranks of these shared ecosystem services further demonstrate the value of guassa grasses compared to other grass species. Roof thatch is unanimously considered the single most valuable service provided by the guassa grasses, and it is only the fourth most important for gaya grasses. Similarly, gaya grasses will be used for brick and wall plaster construction only when guassa grasses are unavailable. The relative position of income in these classes is illuminating because it indicates that people may tend to sell gaya grasses (S = 0.27) before using them for construction materials (S = 0.04). Likewise, people may tend to sell guassa grasses (S = 0.44) before using them for fodder (S = 0.22). These differences in ecosystem services demonstrate a complementary relationship between the different types of grasslands in the area.

There are noteworthy similarities and differences in the ecosystem services received from shrubland, native forest, and plantation forest classes that illustrate how these classes interact to support local livelihoods. All three classes provide six shared ecosystem services: firewood, household items, house construction materials, forage, soil protection, and shelter for wild animals. However, the relative importance of these benefits varies among the land classes. For example, the most important benefit received from plantation forest is timber for house construction, while this is the ninth most important benefit from shrublands. The second most highly valued benefit of shrublands is the shelter they provide for wild animals, while this is valued much less in native and plantation forests. The second most highly valued benefit from native forest is household items, while this is valued fifth for both plantation forest and shrublands. Despite having similar species compositions, there are no further similarities in services between shrublands and native forest. However, there are two additional shared services between shrublands and plantation forest and three additional shared services between plantation forest and native forest. Shrublands and plantation forest are both valued for bee-keeping (honey production) and for their beauty, whereas plantation forest and native forest are both valued for the income opportunities they bring and for their role in climate regulation and the perceived ability to attract rain. Shrublands have one unique service apart from native or plantation forest (broom construction). Plantation forest has four unique ecosystem services: fence construction, shade, charcoal production, and the ability to increase groundwater (though this last is restricted to cypress and not eucalyptus). Native forest has three unique ecosystem services: traditional medicine, local fruits, and the ability to improve soil fertility.

3.3.3 Local Narratives of Change

We constructed timelines of change for each of these land classes by looking for consistent patterns and narratives across the group interviews. When explanations diverged, we sought additional explanations and clarity during the co-interpretation workshops. We present the classes in order of decreasing consensus, first highlighting classes where participants reported similar perceptions of change.

Bare lands: All participants agreed that bare land has been increasing in the kebele lands since the Derg period due to declines in soil fertility and precipitation, combined with intensive grazing and increased soil erosion. However, bare land has been decreasing inside Guassa since the NGO period due to improved management activities and decreased human activity.

Constructed areas: All participants agreed that human-constructed areas have been increasing since the Derg period due to an increasing local population (from births, not immigration). In addition to new villages and individual farmsteads, small cities are emerging in three communities nearest to Guassa as good farmland becomes increasingly scarce and as people in the area desire better access to urban resources and lifestyles.

Grazing lands: All participants agreed that grazing land area has been decreasing since the Derg period due to conversion to farmland. During the Imperial period, the lands immediately west of Guassa were communal grazing lands, but are now predominantly farmland and constructed areas. Participants reported that large communal grazing lands are becoming less common, and farmers are increasingly setting aside marginal farmland to use as private grazing areas. Grazing near streams and rivers has also increased.

Plantation forest: All participants agreed that plantation forests have been increasing since the Derg period. Plantations were rare during the Imperial period, and communities would travel 100km for construction-quality timber. The Derg government planted large plantations early in the regime, primarily as a soil and water conservation strategy. By the fall of the Derg 17 years later, plantation forests were well established. Smaller community and private plantations have been increasing in number and extent since the Transition period, and most participants want this expansion to continue due to the variety of novel ecosystem services they bring to the region.

Stone: All participants agreed that rocky areas have increased as soil erosion has exposed more stones, particularly since the Transition period.

Protected grasslands: All participants agreed that both the quality and extent of the protected grasslands have varied in direct response to changes in management regimes over the last 40 years. During the Imperial period, access to the area was heavily regulated and the species composition was less diverse as guassa grasses dominated. During the Derg and Transitional periods, the nine kebeles no longer had the legal right to exclude people from using the area. This resulted in a large increase in grazing as well as grass and firewood harvesting inside Guassa from people within and outside the nine kebeles. Some people from the kebeles nearest Guassa converted areas of Guassa to farmland. During the NGO period, as communities struggled to regain land tenure rights to Guassa, farmers who had moved into Guassa were evicted and grassland quality slowly improved. The area was last opened for the traditional grass harvest, grazing, and firewood collection for two months in 2006, followed by nine years of closure to "let the area recover" from heavy use in the 1980s and 90s. In 2010, people in charge of Guassa management decided to stop allowing grazing and firewood collection entirely. The area has since been opened exclusively for guassa grass harvest for a period of 10-15 days in the spring of 2015 and again in 2018. Overall, participants celebrated the re-greening of the Guassa area as an important conservation victory.

Water: Most participants (eight kebeles) reported a decrease in the surface water quantity available on the landscape since the Derg period, as smaller, ephemeral streams are filling with sediment and limiting their ability to hand-irrigate nearby farmland. Some perceived the establishment of borehole wells to have made up for those losses. One kebele (Chare) reported increasing water due to the creation of a reservoir.

Farmland: Some changes to farmland had good agreement among the participants. For example, people did not farm near Guassa during the Imperial period. However, an increasing population coupled with villagization programs (i.e., the creation of new villages) during the Derg period (Ashenafi and Leader-Williams 2005) led to increased agricultural land use in areas close to Guassa. However, different narratives arise over changes in extent of farmland since the Transition period: most participants (seven kebeles) said farmland area is decreasing due to higher rates of erosion and loss of soil fertility, leading people to leave the land fallow, convert it to grazing land, build houses on it, or plant eucalyptus plantations. One kebele (Gedenbo) maintained that farmland area has not changed, while another kebele (Kewla) said farmland area is increasing as grazing lands are converted to row crops. Despite these different narratives of change to farmland area, all kebeles were unified in the belief that farmland quality has declined since the Derg period, citing loss of soil fertility and a disappearing belg rainy season that stopped coming reliably in the early 1990s. One participant explained "we used to harvest twice a year, so the yields used to be higher…but the belg rains have reduced, and sometimes we only harvest once a year now." Declines in soil fertility and precipitation have required various adaptations in farming practices, including increased fertilizer use, new irrigation infrastructures, and new preferred cultivars of wheat and barley.

Native forest:. The majority of participants (seven kebeles) reported that native forest was common during the Imperial period, but that it has since declined in both quality and extent. Participants said much of the area that is now shrublands in the northern ravines used to be dense native forest, but intensive harvesting of larger species like kosso, bisana, and juniper over the past few decades has turned it into shrublands similar to those found within Guassa and along the eastern escarpment. One kebele (Dargegne) reported that native forest has increased in their region due to improved local conservation. Chare reported there was never any significant areas of native forest in their region, which was supported by our classification and vegetation analysis.

Shrublands: Participants made a distinction between shrublands located in the kebele lands and those located inside Guassa. Four kebeles (Kewla, Gedenbo, Kuledeha, and Tesfomentir) reported that their kebele shrublands have been declining due to overuse by local people, including illegal charcoal producers from the nearby Yifat woreda. Three kebeles (Ferkuta, Dergegne, and Yedi) reported that kebele shrublands have been increasing due to improved local conservation, and two kebeles (Chare and Gragne) reported there were never any significant areas of shrublands in their kebeles. However, all participants agreed that Guassa shrublands have been expanding since the NGO period. One nuisance shrub in particular - nachillo (*Helichrysum splendidum*) - has been expanding rapidly, with no value for either people or wildlife.

3.3.4 Vegetation Changes

Results indicate that while there are differences in NBR change across wet and dry seasons in the same time period (Figure 3.5), general trends emerge that can be brought into conversation with the local narratives of change presented above to produce a more holistic understanding of change (Figure 3.6). Between the Derg and Transition period, NBR generally increased across the study area (11.8% dry season, 62% wet season). In fact, NBR decrease occurred over an extremely small area of the total landscape (1.8% dry season, 0.93% wet season). Guassa experienced NBR increase in 30.4% of its area in the dry season and 69.3% of its area in the wet season, which contradicted local narratives of increased resource use and extraction during this period. NBR decrease was concentrated in Ferkuta (4.1% of kebele area) and Yedi (9.7% of kebele area) during the dry season.

From the Transition to the NGO period, NBR generally decreased across the total landscape (8.2% dry season, 27.5% wet season). These decreases were widespread across the landscape in the wet season, but disproportionately impacted the ravines in Dargegne (12.7% of kebele area), Kewula (14.6% of kebele area), and Yedi (18.4% of kebele area) in the dry season. NBR increases were small across the entire landscape (2.3% dry season, 6.3% wet season) and located primarily in Gedenbo (11.5% of kebele area), Gragne (16.1% of kebele area), and Tesfomentir (15.2% of kebele area) in the wet season.

From the NGO to the Co-management period, NBR generally decreased across the landscape (6.5% dry season, 10.1% wet season), though NBR increases were also widespread in the wet season (2.2% dry season, 10.6% wet season). NBR decreases were most pronounced in the southern ravines and in Guassa, which contradicted local narratives of conservation success during this period. NBR increases were concentrated mostly in Dargegne (19.8% of kebele area) and Gragne (18.4% of kebele area) in the wet season.

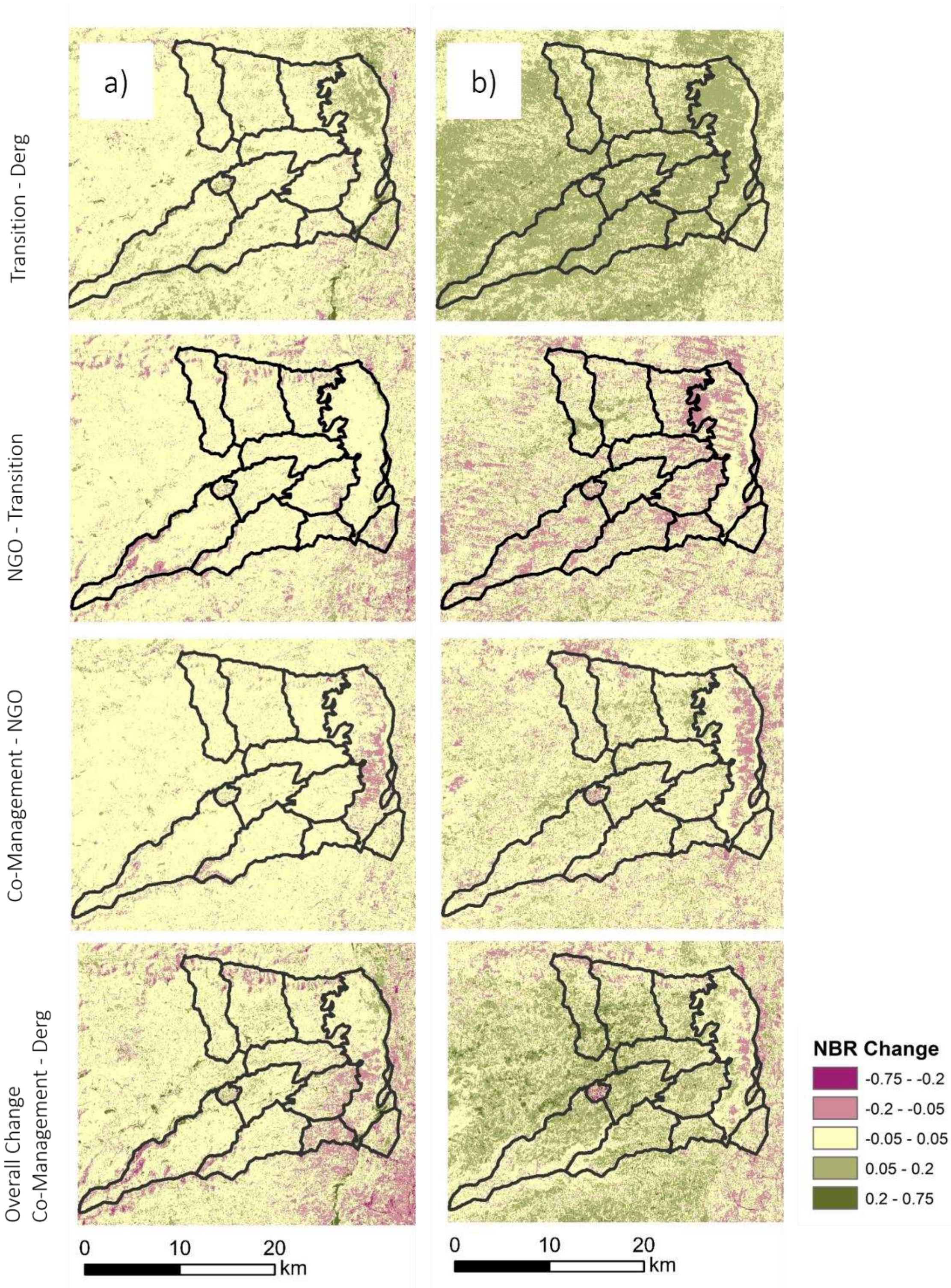

Figure 3.5. Normalized Burn Ratio change across four periods of political and management history. Column a) shows dry season change, while column b) shows wet season change. The first row shows change between the Transition period (1991 – 2003) and Derg period (1985 – 1991), the second row shows the NGO period (2003 – 2012) minus the Transition period, and the third row the Co-Management period (2012 – 2017) minus the NGO period. The fourth row shows the overall change across the entire Landsat record (Co-Management minus Derg). Note that wet season results in the first and second rows are being influenced by the scan-line corrector failure in Landsat 7, resulting in some striping patterns that are not a reflection of vegetation change on the landscape.

Vegetation change across the entire time period (i.e., between Co-management and Derg periods) revealed particularly severe dry season NBR declines in the northern and southern ravines and in the southeastern parts of Guassa, Ferkuta, and Yedi. Overall change in the wet season showed general NBR increase in the kebele lands and patches of NBR decrease inside the Guassa area. Of the land classes, only water and plantation forest showed a significant change (NBR change +/- 0.2) across the study area. The mean NBR change across all plantation forest pixels was 0.2 in the dry season, though the increase was lower in Tesfomentier and higher in Guassa (Table D6). Water NBR values increased in Chare and Gedenbo due to the creation of the reservoir. Bare land NBR values increased in Gragne (i.e., bare land became more vegetated), while grazing land NBR values increased in Gedenbo. Farmland NBR values increased in all but Dergagne and Yedi. Native forest showed overall decrease in Gragne, Kewula, and Tesfomentier, and an overall increase in Ferkuta and Gedenbo (Table D6). While Dergagne kebele reported native forest increase in the local narratives, we did not see this in the vegetation analysis.

See Appendix D for a detailed breakdown of percent land area and direction of NBR change for each kebele and each time period, separated by wet season (Table D3) and dry season (Table D4), and a summary of overall mean NBR change values by land class (Table D6).

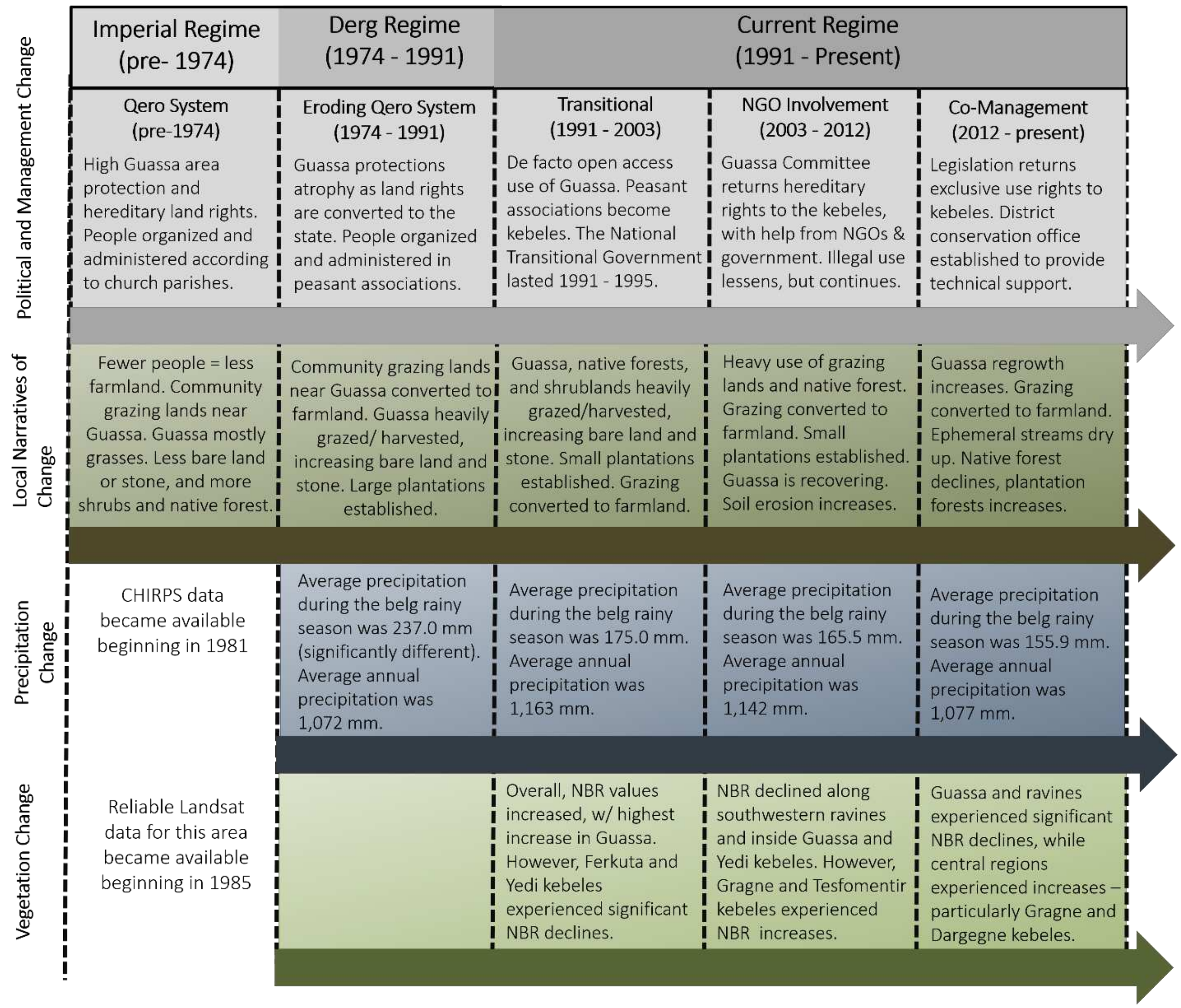

Figure 3. 6. Timeline of change across multiple data sources.

3.3.5 Precipitation Changes

The precipitation analysis supported local narratives of a delayed and disappearing belg rainy season (Figure 3.7). The Mann-Kendall tests revealed a significant decreasing trend in precipitation during the belg season ($\tau = -0.31$, $p = 0.01$). However, there was no significant trend in either the total annual precipitation ($\tau = 0.09$, $p = 0.46$) or the kiremt season precipitation ($\tau = 0.15$, $p = 0.20$). The Kruskall-Wallis tests indicate a significant difference in belg precipitation values across the four periods of political and management change ($\chi^2 = 8.13$, $p = 0.04$). The average belg precipitation during the Derg regime was 237mm, falling to 175mm (Transitional period), 165mm (NGO period), and finally 162mm (Co-management period). Again, no significant differences were detected across these political-management periods for the kiremt precipitation ($\chi^2 = 4.21$, $p = 0.24$) or total annual precipitation ($\chi^2 = 1.79$, $p = 0.61$).

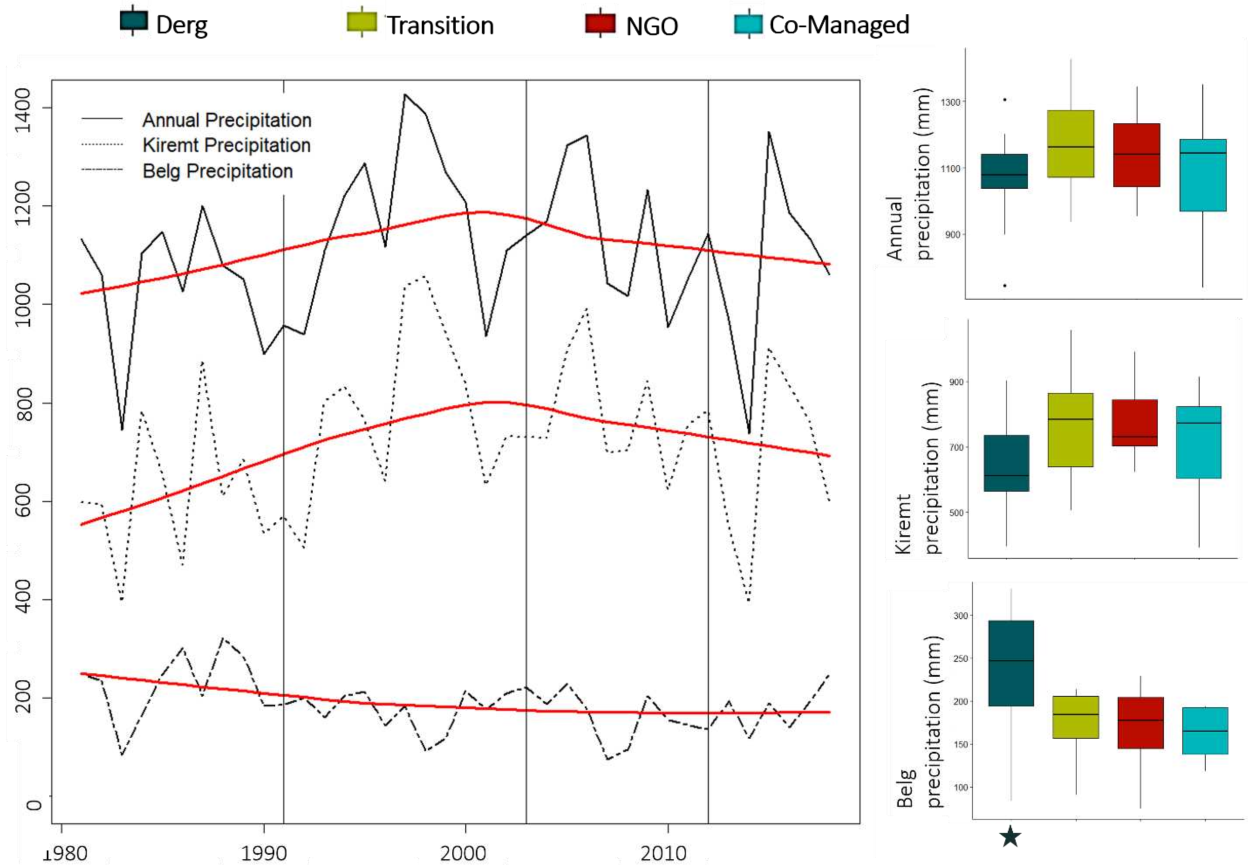

Figure 3.7. Trends in kiremt season (~July 1 – September 30), belg season (~Feb 1 – April 30), and total annual precipitation. Red lines indicate a lowess smoothing function applied across the entire time series. Vertical lines indicate the four periods of political and management change. Box plots illustrate differences in median and range of precipitation across those four periods. The star indicates a significantly higher belg season precipitation during the Derg period.

3.4 Discussion

The iterative MEB process improved our project in multiple ways. First, local participants had time to reflect and become more comfortable with interpreting scientific products, and were offered the chance to refute or add nuance to the interpretation of remote sensing results. This produced a more holistic understanding of environmental change. Second, feedback from local participants ensured final products were valid and relevant to their needs and objectives. While not every analysis was considered valid or relevant to every participant group, the process resulted in mutual benefits for both science and management. Third, the identification of uncertainties and contradictions across knowledge systems encouraged new learning. These differences point to productive areas of future research to enhance our understanding of the Guassa social-ecological system. Below, we elaborate on these three themes.

3.4.1 Knowledge Co-production Yields Holistic Understanding of Change

In our study, local knowledge provided a fine-grained perspective of place-based environmental change, offering the potential to extend interpretation of our remote sensing analysis back in time in the absence of other ground truth data (Herrmann et al. 2014; Eddy et al. 2017). Similarly, the broad spatial scale of the remote sensing analysis enabled us to extend the situated local knowledge of a limited number of participants across the entire study area. The temporal continuity of local knowledge is one of the reasons it is so valuable for interpreting remote sensing time series (Verburg et al. 2011; Smith et al. 2019), yet temporal biases have been observed in other studies that should be recognized. For example, people tend to view the past move positively than the present (Hermann et al. 2014); emotional experiences tend to influence the way people describe those years (Daw 2010); and general trends are sometimes less noticeable compared to extreme events due to a "shifting baseline" (Pauly 1995; Eddy et al. 2017). Remote sensing also experiences biases, notably from sensor, solar, atmospheric, and topographic effects that require extensive pre-processing (Young et al. 2017) and the disconnect sometimes observed between satellite-derived trends and the reality of ground conditions (Hermann et al. 2014; Eddy et al. 2017).

Our analysis demonstrates the complementarity of these approaches, illustrating some ways they worked to overcome each other's biases. For example, the remote sensing products were particularly effective for prompting participants to discuss what was happening around different dates of interest and how that might have impacted vegetation patterns on the landscape. This encouraged participants to move beyond their recollection of only high-profile, extreme events (Nazarea 2006; Daw 2010). For example, the rise and fall of the Derg regime were two extreme change points that were referred to repeatedly throughout the group interviews. By contrast, the vegetation change analysis instigated a new conversation about the ways in which NGO involvement unexpectedly triggered a brief episode of environmental degradation. It was during a local election in 2005, when one of the candidates ran on a platform telling everyone that "the white people stole your Guassa!" and that he would get it back for them if he was elected. Illegal grazing and harvesting increased during the months afterward because people believed the Guassa area had been sold to foreigners and this perceived land tenure insecurity led to unsustainable resource extraction. This recollection was prompted by the observed declines in NBR values during this period, which contradicted local narratives that said overall, Guassa was recovering (Figure 3.6). Stories like these, instigated by the remote sensing analysis, revealed the direct impact that Guassa's protected status has on peoples' behavior, reflecting the importance of secure land tenure throughout the highlands (Lanckriet et al. 2015).

The iterative MEB process allowed us to reflect on our learning over time and build more nuanced understanding of change across these multiple knowledge systems. In our first workshop, participants immediately attributed areas of vegetation decline to local behaviors related to changing land tenure and management (e.g., overgrazing or lack of soil conservation activities) rather than a result of biophysical differences across kebeles (e.g., precipitation or soil fertility). In the second workshop, we introduced the precipitation analysis and multiple vegetation change maps across different days of the year in response to participant uncertainties regarding the impact of seasonal activities on NBR. Participants in the second workshop, who were almost entirely the same individuals, then proposed more nuanced explanations for how regional to global drivers of change were interacting with local behaviors to produce the patterns observed in the maps. For example, we noticed the kebeles closest to Guassa, and particularly Yedi kebele, seem to be experiencing the greatest vegetation losses over time. Participants explained that the kebeles closest to Guassa experience different precipitation patterns, which is supported by scientific observations of the rain shadow produced by orographic rainfall in the Ethiopian highlands (Dinku et al. 2011). The rain is therefore less abundant and less consistent in areas close to Guassa, causing farmers to rely more heavily on two growing seasons to accumulate enough crops to meet subsistence needs. The loss of the belg rainy season is thus causing a shift in farmer behavior across the study area; farmers farther from Guassa are more likely to shift to a single growing season, while farmers closest to Guassa are not willing to risk this change. These differences in perceived risk and behavior change were thought to have impacted the spatial patterns of NBR change observed at the kebele level (Figures 3.5 and 3.6).

3.4.2 Mutual Benefits for Science and Management

Our findings support the idea that projects that draw on a diversity of knowledge systems can produce new knowledge with high validity and utility across diverse participants (Laidler 2006; Armitage et al. 2011; Berkes 1999). For example, our MEB approach resulted in maps that contributed to the ability of Guassa area managers to understand and react to environmental change. Local knowledge further enabled us to contextualize this environmental change in terms of ecosystem services affected (Naidoo & Hill 2006). Anderson's land cover classification is widely used by remote sensing analysts and considers stone and bare land to be part of the same land cover class (Anderson et al. 1976). However, local participants rejected merging these two classes in the supervised classification due to the extreme differences in ecosystem services provided by them. Participants explained it was important to distinguish these classes spatially because bare land has much higher potential for reclamation than does stone, so identifying specific locations helped administrators target their conservation and restoration activities. In the workshops, local participants listed several benefits and uses for the supervised classification maps, including: to help delineate and agree on boundaries, to advertise for tourism, to identify bare lands for restoration projects, and to facilitate long-term planning. These maps characterized the landscape using land classes that were meaningful to local residents in terms of the ecosystem services they provided, which increased their perceived value.

Tailoring the maps to local understandings of the landscape also produced unexpected and useful information for scientists. Grazing lands and protected grasslands were separated in the classification as a result of local knowledge about differences in species composition and land uses. An examination of the ecosystem services provided by these two types of grassland helped us identify potential differences in ecosystem function that may translate to broader implications for soil fertility and carbon storage. For example, the high value of guassa grass as a construction material indicates that it may be more recalcitrant, slower to decompose, and lead to more carbon accumulation in soil compared to grazing land grasses that are higher quality forage (DeDeyn et al. 2008). While the implications of these findings are beyond the scope of this paper, they were important results to discuss as a group because although the guassa grass is a cultural keystone species providing unique and valuable ecosystem services, very little is known about its ecological role in the conservation area.

Our findings emphasize the importance of achieving a balance between internally valid observations, and observations that carry weight and meaning across knowledge systems (Tengö et al. 2014). From a scientific perspective, the NBR and CHIRPS change results were rigorous and helpful for triangulating our spatial and temporal observations of change. However, these analyses were not considered particularly useful by local participants, who viewed them as providing different perspectives on the same problem. "We told you this the last time you came," they said to the researchers. "Your research keeps showing us the problem…we need research that shows us the solution." Local participants felt that their descriptions of precipitation and vegetation change did not need to be confirmed by these additional sources, even though contradictions arose between the different types of knowledge. These results point to the role of compromise in collaborative environmental research, indicating that all participants need not find the same value in all aspects of the project in order for successful knowledge co-production to occur.

3.4.3 Uncertainty and Contradiction Encourage New Learning

While the general results of our classification and vegetation change analysis reflect those of other studies in the Ethiopian highlands, for example the timing of vegetation declines and emergence of plantation forests (Jacob et al. 2016; de Mûelenaere et al. 2014), we also observe some differences with other studies conducted in the region. Our precipitation change results indicate that the vegetation changes observed are likely not due to differences in precipitation across time periods, though the significantly higher belg precipitation during the Derg period may have influenced the increasing NBR values from the Derg to Transition periods to some degree. These results differ from other studies that show a strong relationship between precipitation variation across time periods and particularly woody vegetation cover (Annys et al. 2017). One potential explanation for these differences is the relatively high mean annual precipitation of the Guassa area compared to other places in the highlands; vegetation in wetter areas does not always respond in direct and proportional ways to precipitation (Rishmawi et al. 2016) and woody vegetation in particular shows a saturating relationship with precipitation whereby maximum tree cover is observed at any level above 650 mm (Sankaran et al. 2005). To better quantify and explain these differences, future research should focus on a more nuanced analysis of antecedent rainfall and attempt to de-couple the impacts of climate from other impacts to vegetation (Eddy et al. 2017).

Our findings revealed a need for greater attention to the spatial and temporal variability of environmental change across this seemingly homogeneous cultural landscape. Farmland, stone, and shrublands occupy the largest land areas in the region, yet farmland and shrublands also have some of the greatest inconsistencies among local narratives of change, while stone and shrublands have some of the highest classification errors (though still within acceptable error ranges). These inconsistencies and errors indicate there is a need for improved understanding of variability within these dominant land classes, as kebeles may be experiencing different changes to those classes across the landscape. On the other side of the spectrum, careful attention is also required for the land classes with the smallest land areas. Native and plantation forest occupy the smallest areas across the kebeles, yet provide the highest number of ecosystem services. Many of the ecosystem services found in native forest, plantation forest, and shrublands are overlapping, and that redundancy may act as a buffer against future environmental change (Raudsepp-Hearne et al. 2010) for the most important ecosystem services. However, lesser valued services found exclusively in native forest are doubtlessly facing eradication given the high agreement across knowledge systems that this land class is rapidly declining in both area and quality (Figure 3.6). Our MEB approach thus enabled us to assist decision makers in understanding the need to assess how each kebele is differently impacted by on-going environmental, land use, and land tenure change.

While our MEB approach revealed multiple complementary findings across knowledge systems, we also identified compelling areas of disagreement that point to areas for future research. The most pronounced contradiction between local narratives of change and the vegetation change analysis regarded the health of vegetation within Guassa. Local narratives focused on local grazing and firewood harvesting practices, maintaining that Guassa was experiencing a re-greening period after decades of unsustainable use caused by insecure land tenure. However, the remote sensing analysis revealed large areas of vegetation decline in Guassa since 2003 using NBR as an indicator of vegetation productivity and structure (Figure 3.6). Iterative conversations at the co-production workshops revealed that nachillo, a native shrub considered by locals to be a pest, had been expanding within the grasslands since about 1995. Given the differences in vegetation structure between the shrubs and grasses, we determined it was likely that this change in species composition was responsible for the moderate declines observed in NBR values. Specifically, we posit that shifts from satellite detection of primarily photosynthetic vegetation to woody shrubs with low leaf area could depress near infrared reflectance and increase shortwave infrared reflectance. Thus, these differences in spectral signatures led scientists to initially interpret the remote sensing results as contradictory to the re-greening trends observed by locals. The invasion of this shrub is considered a threat to the future sustainability of Guassa as it appears to be competing with the guassa grasses for habitat. Due to the potential impacts on ecosystem function and ecosystem services, we collectively agreed shrub encroachment was the most valuable issue to address next using our co-production process. This process of discovering new insights and ideas for future study is an integral part of knowledge co-production, which emphasizes the importance of investigating contradictions rather than concealing or overlooking them (Huntington et al. 2004; Moller et al. 2004; Gagnon & Berteaux 2009; Gearheard et al. 2010; Etienne 2013, Klein et al. 2014; Tengö et al. 2014).

3.5 Conclusion

In this paper, we present the results from a multiple evidence based (MEB) approach (Tengö et al. 2014) to knowledge co-production, which brought together insights from local and scientific knowledge using ethnographic and remote sensing methods. We produced a holistic understanding of environmental change in a community-protected grassland in the Ethiopian highlands, informing potential impacts on locally-defined land classes and their associated ecosystem services. Our results highlight how integrating local and scientific knowledge can reveal gaps in system understanding, and how contradictory observations across knowledge systems can inspire new understanding and future research. Our project emphasizes the value of iterative approaches that allow local participants to more confidently inform remote sensing interpretations, and in turn allow scientists to clarify translations and interpretations so that local knowledge is accurately represented.

CHAPTER 4

MENTAL MODELS OF A SOCIAL-ECOLOGICAL SYSTEM ENCOURAGE LEARNING AMONG A DIVERSE MANAGEMENT TEAM[3]

4.1 Introduction

Social-ecological systems are complex, adaptive systems that often exhibit nonlinear dynamics, indirect effects and feedbacks, emergent properties, and heterogeneous links across space and time (Liu et al. 2007; Lambin & Meyfroidt 2010). These characteristics can cause unanticipated outcomes that make environmental management extremely difficult, especially considering the rapid rate of global environmental change occurring worldwide (Cleland et al. 2007; Pepin et al., 2015; Steffen et al., 2011). Many times, the challenges facing social-ecological systems are multidimensional "wicked problems" that lack clear definitions or solutions (Rittel and Webber 1973; Chapin et al. 2008). Managing these complex systems and challenges increasingly requires collaboration among diverse teams with a range of knowledge types and worldviews so that the boundaries of the problem can be understood from multiple perspectives, and the scope of potential solutions can be expanded (Polasky et al. 2011; Tengö et al. 2014; Bernstein 2015; Hoffman et al. 2017). Diverse teams with trusting relationships and open channels of communication have been shown to have high adaptive capacity, which is critical for decision-making under the high uncertainty facing social-ecological systems (Kates et al. 2001; Dietz et al. 2003; Fazey et al. 2014; Fujitani et al. 2017). In practice however, the benefits of collaborative environmental management have proven difficult to achieve, and recent syntheses have shown this

[3] This research will be submitted for publication consideration along with co-authors Julia Klein, Shambel Alemu, Jake Marinkovich, Kflay Gebrehiwot, Sisay Wubie, and Bikila Warkineh Dullo

failure is often due to insufficient attention to the social and cultural factors that shape environmental outcomes (McCusker & Carr 2006; Beratan 2014).

Social-ecological systems can be conceived as existing simultaneously as objects in the physical world (e.g., plants, rocks, people) and as cognitive constructs in the minds of the humans living there (Cronon 1996; Demeritt 2002). These cognitive constructs or "mental models" are internal representations of the external world that guide an individual's thinking and behavior (Gentner & Stevens, 1983; Jones et al. 2011; Gray et al. 2014). Because an individual is inseparable from their cultural and social environment (Roberts 1964; D'Andrade 1981), mental models are shared within a broader culture or social group (Holland & Quinn 1987) and influence the formation of norms and institutions in that group (Halbrendt et al. 2014). Group mental models are comprised of culturally-derived ideas and practices (Fryberg & Markus 2007), and are partly a reflection of individuals' lived experiences and partly the product of socially transmitted knowledge about how the world functions. Mental models are critical elements of collaborative environmental management because they shape our understanding of human-environment relationships, our perceptions of environmental problems, and our preferences for advocating certain decision options over others (Kempton et al. 1996; Jones et al. 2011; Moon et al. 2019). Differences in the mental models of people involved in managing social-ecological systems are neither good or bad, but may exacerbate barriers to effective communication and decision-making if they are not adequately understood and respected.

Mental models, as a reflection of knowledge and culture, evolve and change over time in response to new information and interactions among people in social networks (Chi 2008; Reed et al. 2010; Moon et al. 2019). Understanding this change, and how it impacts collaborative environmental management, requires better understanding of how people learn – both as individuals and in groups. Social learning, which derives largely from theories of organizational management (Argyris & Schon 1978), is often defined as an iterative group process where learning occurs at the level of the individual but is situated in a particular social and cultural context (Lave & Wenger 1991; Keen et al. 2005; Fernández-Giménez et al. 2019). This is the definition we use in this paper, which differs slightly from those who consider social learning to occur when change permeates throughout an entire society (Reed et al. 2010), or learning conducted by society at large (Friedman & Abonyi 1976; Woodhill 2002). Scholars largely agree that social learning is a normative and desirable outcome in environmental management (Armitage et al. 2008), though some have called for a more nuanced approach to particular types or elements of learning (Reed et al. 2010; Baird et al. 2014). Social learning has been shown to improve understanding of social-ecological systems (Walters & Holling 1990), to foster adaptation and collective action (Pahl-Wostl et al. 2007), and to build trust among diverse individuals (Reed et al. 2010), all of which contribute to improved collaborative environmental management (Lang et al. 2012; Jahn et al. 2012; Cundill et al. 2015).

Structured mental modeling exercises, where mental models are collectively described and discussed, can facilitate social learning (Özesmi & Özesmi, 2004; Gray et al. 2014). Sharing mental models can enhance communication among members of a social-ecological system management team by making visible (i.e., graphically representing or describing) the similarities and differences in system understanding, and thus enabling teams to overcome obstacles that can prevent the incorporation of diverse knowledge types (Reed et al. 2010; Biggs et al. 2011; Henly-Shepard et al. 2015). Individual mental modeling exercises can promote more equitable collaborative processes by allowing participants to construct and reflect on their own knowledge of the system without certain individuals dominating (Reed 2008; Gray et al. 2014). However, small group mental modeling exercises have been shown to increase the likelihood of social learning, largely due to the detailed discussions that emerge from the process (Gray et al. 2014).

In this paper, we describe an iterative process of constructing and revising mental models at both individual and small group levels over the course of a year. We present a case study of a community-based conservation area in the Ethiopian highlands, with participants from four social groups involved in the community conservation area management. We conceptualize these groups on a gradient from local to scientific knowledge (women farmers, men farmers, local government workers, and scientists), based primarily on their occupation, level of formal education, and social networks. The objectives of the research are to (1) understand how mental models of the social-ecological system differ among these groups involved in management, and (2) assess the level of social learning experienced by participants in the mental modeling process, with the aim of contributing to more empirically-informed theories and methods for facilitating collaborative environmental management. We anticipated that mental models would be more similar between groups with stronger local knowledge (women and men farmers) and between groups with more scientific or Western knowledge (government workers and scientists). Because our collaboration was relatively new, and the mental model exercises occurred over the course of only a single year, we expected only single- and double-loop (but not triple-loop) learning to occur. We describe these social learning loops below before presenting the detailed process and results of our study.

4.1.1 Multiple-loop Social Learning

Despite the integral role of learning in collaborative environmental management, confusion persists over how to conceptualize and measure social learning (Keen et al. 2005; Armitage et al. 2008, Muro & Jeffrey 2008; Pahl-Wostl 2009; Crona & Parker 2012; Baird et al. 2014; Fernández-Giménez et al. 2019). Social learning is often portrayed as a series of loops (single, double, and triple), but has alternatively been explained as different types of change (conceptual, relational, and normative) (Baird et al. 2014). Efforts to connect these social learning paradigms have linked single-loop learning to conceptual change and triple-loop learning to normative change (Fernández-Giménez et al. 2019), while relational change remains difficult to place within the loop paradigm. To better integrate these multiple conceptualizations of social learning, we propose that the three loops of social learning are enabled or constrained by time and the strength of the relationships among members of the social learning group (i.e., relational change) (Figure 4.1). We outline three possible trajectories of social learning to clarify the theoretical impact of relationship strength on the speed of a social learning process. When projects target relationship building among learners, social learning may occur at an accelerated pace due to shared problem identification, mutual understanding and respect for each other's worldviews, and the creation of both formal and informal relationships (Lang et al. 2012; Pohl et al. 2015; Hoffmann et al. 2017). However, when relationships suffer from mistrust or miscommunication, social learning may occur at a much slower pace as learners struggle to compromise or reach agreement (Tengö et al. 2014, Tengö et al. 2017).

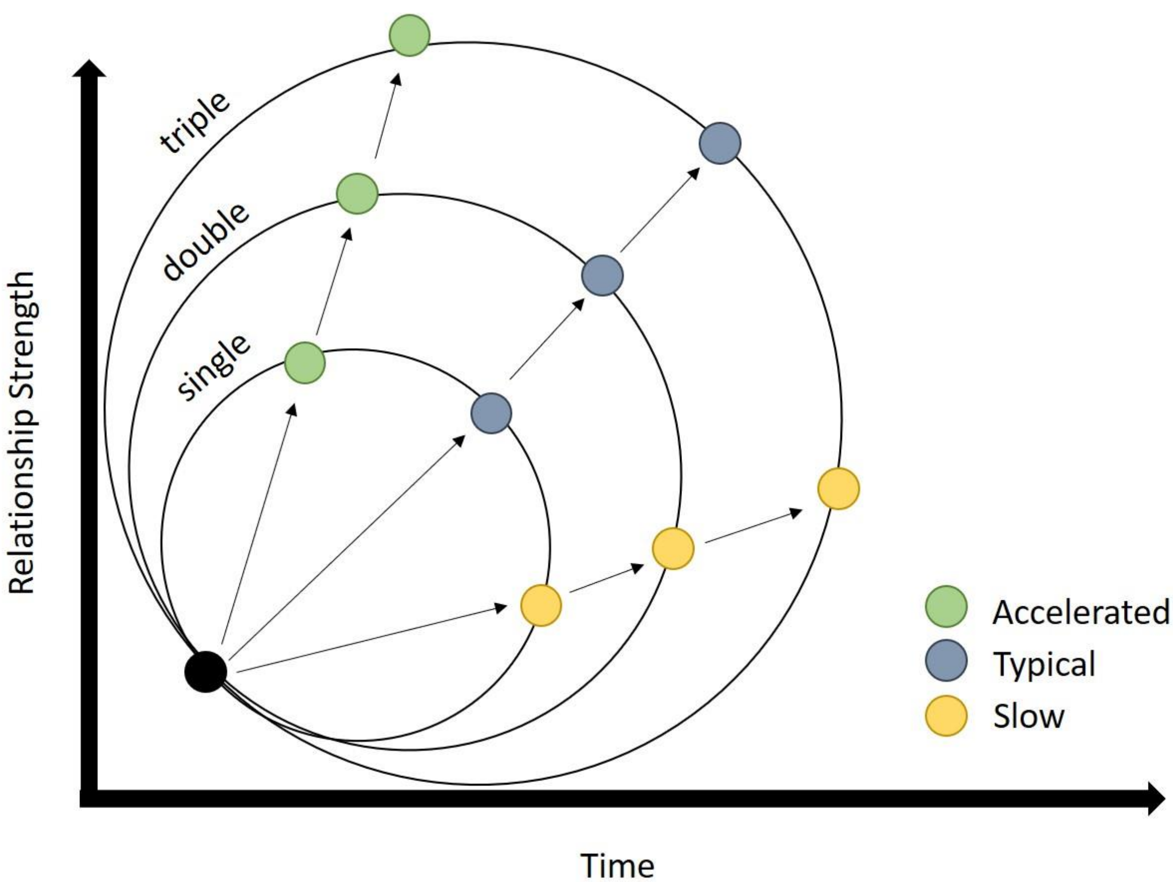

Figure 4.1. A conceptual model for understanding how the strength of relationships among learners can enable or constrain the speed of triple-loop social learning.

We suggest this integrated definition can bring about greater clarity regarding the conception and application of social learning for collaborative environmental management. In our definition, single loop learning refers to learning that seeks to refine or incrementally improve upon an existing goal or institution (Pahl-Wostl 2009). Single loop learning may involve changing one's ideas about the efficacy of particular actions (Armitage et al. 2008) or the direction and strength of cause-and-effect relationships (Fernández-Giménez et al. 2019), but it does not result in changes to the project goals or overall system organization. In Figure 4.1, single loop learning is portrayed as a relatively fast process, in part because it does not require as strong relationships among the social learning participants compared to double or triple loop learning. Double-loop learning occurs when learners call into question the assumptions that underlie their understanding of the system or problem (Keen & Mahanty 2006). Double loop learning may involve changing one's ideas about the boundaries of the problem (Pahl-Wostl 2009) or expanding the scope of the system and range of possible solutions. In this regard, double-loop learning is akin to "systems thinking" (Dyball et al. 2007). In Figure 4.1, we show that double-loop learning can take much longer to occur compared to single-loop learning because it requires mutual understanding and clear communication to be established among learners (Diduck et al. 2005). Finally, triple-loop learning occurs when changes are made to the norms and institutions governing the project or broader system (King & Jiggins 2002; Keen et al. 2005). Triple-loop learning may involve changing culturally-shared behaviors or socially-defined rules and structures. Some have likened triple-loop learning to a stage of "transformation" (Pahl-Wostl 2009), where power structures and regulatory frameworks are entirely replaced. Triple-loop learning is particularly desirable when seeking societal-scale transformations towards long-term adaptive strategies (Berkes & Jolly 2002). In Figure 4.1, we illustrate that triple-loop learning requires substantial time and trusting relationships with clear channels of communication (Dietz et al. 2003).

4.2 Methods

4.2.1 Study Area Description

The Guassa Community Conservation Area (Guassa) is located in the Menz Gera woreda (similar to a county) of the Amhara Region of Ethiopia. Ranging from 2,600 – 3,560 meters above sea level, this 78 km^2 area receives a mean annual precipitation of 1,650 mm. Guassa supports many endemic and threatened species, including the critically endangered Ethiopian wolf (*Canis simensis*) and the gelada monkey (*Theropithecus gelada*) (Ashenafi et al. 2005). Guassa is named after the guassa grasses (*Festuca macrophylla*) that are valuable to the local communities for their use as thatch, rope, construction material, and forage.

Guassa has undergone significant political and land management changes throughout its history (Steger et al. in review). The area was managed for hundreds of years (c. 1600 – 1974) according to the Qero system of communal management that restricted access to the grasses through two to three month open seasons every three to five years (Ashenafi & Leader-Williams 2005). The 1975 Agrarian Reform transferred land ownership to the state and community control over Guassa management declined over the following 17 years (Admassie 2000; Ashenafi & Leader-Williams 2005). Community efforts to re-establish exclusive rights to the area were supported by international conservation efforts in the late 1990s, leading to a new co-management regime between local farmers and government agencies (Fischer et al. 2014). In 2012, exclusive use rights to the area were formally restored to the communities with ancestral rights by Amhara Regional Regulation No. 97. Since about 2010, grazing and firewood collection have been banned inside Guassa due to perceived threats to sustainability and the endangered Ethiopian wolf.

Currently the management team is composed of five representatives from each of the nine kebeles (the "Guassa Committee"), of which ten form an executive committee (the "Tourism Board"), and about twenty other individuals spread across two government offices – one administrative office at the local county ('woreda') level, and the Guassa Conservation Office that is sponsored by the Amhara Regional State. They manage the area collaboratively, with final decision-making power in the hands of the Guassa Committee, which meets monthly on their own and quarterly with the government offices. This diverse and relatively new co-management team makes Guassa a compelling case study for investigating the role of social learning and mental models in collaborative environmental management.

4.2.2 An Iterative Process of Clarifying and Communicating Mental Models

We chose an iterative structure for our mental modeling process because we wanted to give participants adequate time to reflect on their responses, think critically about the system, and become comfortable sharing their perspectives (Figure 4.2). This iterative approach is rare in the literature, despite its theorized benefits for social learning (Henly-Shepard et al. 2015). In August 2018, we convened a workshop as part of an on-going effort to better align scientific research in Guassa with the needs of local communities and managers. Participants came from the Guassa Committee (n=27, three each from nine communities), the Guassa Conservation office (n=3), scientists (n= 6), and the local administration office (n=5). These 41 workshop participants (12 women and 29 men) included the first, third, fifth, sixth and seventh co-authors. Together, workshop participants collaboratively identified a series of variables thought to impact the sustainability of the Guassa area, which was defined as a desired future with abundant guassa grass harvests, continued co-management, increased wildlife populations, and increased tourism. Workshop participants then ranked the variables in small groups to identify which variables they thought were the most influential on Guassa sustainability. We used the software package ANTHROPAC (Borgatti 1996) to analyze the variable ranking data and calculate Smith's salience value (S) from zero to one for each variable, considering both the frequency of the variable across lists from each respondent and its position within each of those lists (Borgatti 1996; Levine et al. 2017). Salience values closer to one indicate good agreement across the respondents regarding the relative influence that variable is thought to have on the future sustainability of the Guassa area.

At a second workshop in February 2019, 38 participants were asked to help clarify the strength and direction of relationships between each variable. Of the original participants, one woman farmer and two government workers (one man and one woman) were unable to attend this second workshop. Participants were given a matrix with 25 variables listed across the first column and the first row, corresponding to the 19 variables identified in the first workshop plus six additional variables derived from their descriptions of valuable ecosystem services in the area (Steger et al. in press). We asked participants to fill in the relationship each variable has with the others. In each cell, participants described how the variable in that column header impacts the variable in each row (e.g., "If human population increases, what will happen to rainfall?"). There were six response options: "Strong Increase," "Weak Increase," "Strong Decrease," "Weak Decrease," "No Impact," and "I don't know". Participants were given as much time as necessary to complete the matrix (ranging from one to two hours), with translators present if questions arose. A total of 35 people completed their matrices.

After processing the responses, we included 30 responses in the development of aggregated, small group mental models. We excluded five responses because those participants did not appear to understand the exercise (e.g., they had the same answer for all relationships). We grouped respondents according to livelihood and gender, resulting in four primary groups: government workers (7 people), women farmers (7 people), men farmers (13 people), and scientists (3 people). One woman was present in the government worker group, and one in the scientist group. We transformed the categorical data into values on a scale of -1 to +1, where a strong relationship was +/-0.75, a weak relationship was +/-0.25, 'No impact' was 0, and 'I don't know' was NA. We then calculated the mean and standard error for each variable relationship to identify where respondent groups had the highest and the lowest agreement. We considered a relationship to have high agreement when the 95% confidence interval did not include zero.

At a third workshop in August 2019, we asked 37 participants to review and revise the mental models created for their small group. Of the original participants, one member of the conservation office, one scientist, and two government workers were unable to attend – resulting in a government worker group composed of all men. One woman farmer replaced another, and two Ethiopian scientists familiar with the area replaced their colleagues who could not attend. The aim was for small groups to discuss the uncertain relationships in the aggregated mental models, attempt to resolve their differences, and produce a single new matrix for the small group following their discussions. In addition to producing a group mental model with less uncertainty, these kinds of conversations have been shown to promote social learning (Gray et al. 2014; Henly-Shepard et al. 2015) and provided participants an opportunity to better understand the reasoning behind the relationships each group identified. We divided the men farmers into two smaller groups (those living in communities near to Guassa and those living far from Guassa) to facilitate conversations with more equal participation from everyone involved. On the second day of this workshop, we came together as a large group to discuss the most significant differences among groups. During this final discussion, several groups started changing their responses to better align with one another. We do not present these changes here as the purpose of this conversation was to understand the reasoning behind their small group decisions and not to produce a single unified mental model for the entire management team.

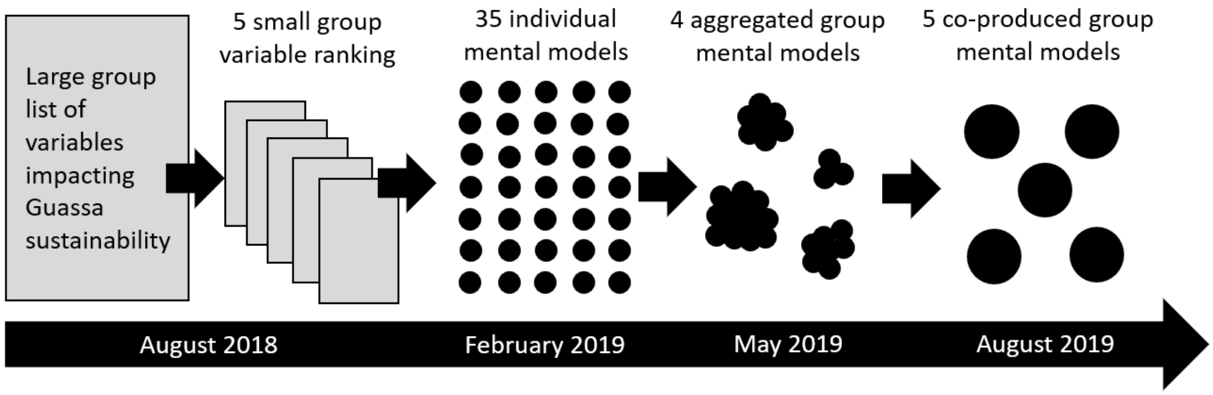

Figure 4.2. The iterative process of eliciting, refining, and communicating mental models about the Guassa Community Conservation area. Community workshops were held in August 2018, February 2019, and August 2019.

We digitized the five small group mental models in the online software Mental Modeler (mentalmodeler.org). Mental Modeler uses graph-theory based analysis (Gray et al. 2012) to quantify which variables have the most frequent influence on other variables in the system (outdegree centrality) and which variables are most frequently influenced by other variables (indegree centrality). We used these two metrics to compare across mental models, referring to variables with high outdegree centrality as "key drivers" in the system and variables with high indegree centrality as "key sensitivities" in the system. We ranked the variables in descending order of indegree and outdegree centrality to identify the key drivers and key sensitivities according to each group.

4.2.3 Assessing Learning through Mental Modeling

We assessed participants' learning using interviews. Each non-scientist participant was interviewed briefly (approximately 15-20 minutes per person) after each workshop about what they learned from the modeling exercise and discussion, how they anticipate using the model in their management decisions, and whether their understanding of other participants' perspectives changed throughout the workshop. Ethiopian scientists participating in the workshop (including the third, fifth, six, and seventh co-authors) conducted these interviews in Amharic. Interviews were translated to English and transcribed. The first author used in vivo coding (Corbin and Strauss 2015) and inductive thematic analysis to describe trends in the kinds of learning reported by participants (Boyatzis 1998). We compare how participants' learning changed across the three workshops and discuss this learning in relation to our conceptualization of the three loops of social learning (Figure 4.1). This research was reviewed and approved by Colorado State University's Institutional Review Board (361-18H), and was conducted with free, prior and informed consent of all participants. Participants were modestly compensated for their time.

4.3 Results

4.3.1 Mental Models of Guassa by Individuals and Small Groups

We present the variables that workshop participants collectively identified as influencing the sustainability of the Guassa area in Table 4.1. Results from the first workshop indicated that participants considered human population (S=0.92), rainfall (S=0.86), and community awareness (S=0.84) to be the most important variables (Table 4.1). However, results from the second workshop and subsequent aggregated small group models revealed a more nuanced interpretation of the system dynamics across participant groups. Of the 600 possible relationships between variables, female farmers agreed on only 120 of them (20%), male farmers agreed on 212 (35.3%), scientists agreed on 288 (48%), and government workers agreed on 332 (55.3%) – resulting in a more complicated mental model for government workers compared to the other groups. Male and female farmers also appeared more likely to agree on positive relationships (i.e., an increase of variable X causes an increase in variable Y) compared to negative ones (i.e., an increase of variable X causes a decrease in variable Y). Of the relationships with high agreement, 61.3% were positive for male farmers and 56.7% were positive for female farmers, whereas this bias was not observed in scientists and government workers as they had high agreement on an equal number of positive and negative relationships. Scientists were the only group to agree on a 'No impact' relationship (i.e., the absence of a relationship between variables), and they did this quite often (n=87, 14.5%).

Table 4.1. The 19 variables identified in workshop 1, representing variables with the highest perceived impact on the sustainability of Guassa. These variables were ranked to identify which are considered most influential. An additional six variables were added based on group interviews regarding the most important ecosystem services in the region (Steger et al. in review), but these were not included in the ranking and therefore do not have Salience values.

Variable	Description	Salience
Human population	The number of people living around Guassa	0.92
Rainfall	Amount of precipitation in and around Guassa	0.86
Community awareness	The level of awareness community members have about the importance of protecting Guassa	0.84
Unemployment	The number of people without land, livestock, or wage labor	0.79
Illegal users	The number of people who cut guassa grass and shrubs outside the agreed-upon time	0.67
Livestock population	The number of livestock belonging to the people living around Guassa	0.65
Political instability	The degree of uncertainty about future actions the government might take	0.57
Temperature	Temperature in and around Guassa	0.56
Firewood consumption	The amount of firewood used by households	0.55
Uncoordinated protection	The degree of independent actions taken by community members regarding Guassa	0.54
Agricultural expansion	The expansion of agricultural lands into previously uncultivated areas	0.49
Invasive plants	Plants (both native and exotic) that are rapidly expanding their range into previously unoccupied areas	0.42
Fire	Wildfire in and around Guassa	0.41
Deforestation	Harvesting trees from native and plantation forests	0.40
Leadership	The strength of local leadership	0.38
Animal diseases	The presence of animal diseases	0.36
Plant diseases	The presence of plant diseases	0.23
Regime change	A change in the ruling party or change in the structure of the national government	0.17
Research	Scientists (Ethiopian and foreigners) conducting research in and around Guassa	0.13
Freshwater	The amount of freshwater originating from Guassa	---
Guassa grass	The amount of guassa grass occurring in Guassa	---
Crops	The amount of crops produced by farmland	---
Income	Household income	---
Wildlife population	The number of wildlife living in and around Guassa	---
Tourism	The number of non-residents visiting the area	---

The aggregated small group models provided insights into how each group thinks about the impacts of particular variables on the rest of the Guassa system (Table 4.2). Male farmers had the highest internal agreement around the impact of illegal users, political instability, and unemployment on other variables in the system, and they had the least agreement around the impact of invasive plants and plant diseases. Women farmers had the highest internal agreement around the impact of political instability and uncoordinated protection, and they had no agreement regarding the impact of wildlife populations. Scientists had the highest internal agreement about the impact of leadership and political instability, and they had low agreement about impacts of invasive plants and firewood consumption. Finally, government workers had the highest internal agreement regarding the impacts of illegal users, regime changes, and human population, and they had low agreement about the impact of livestock populations. All four groups had relatively high internal agreement about the impacts of political instability on other variables in the system, though it is worth noting that women farmers only agreed on 46% of these impacts while government workers agreed on 71% of them. Overall, women had the lowest internal agreement of all the groups when evaluating the aggregated group models, as their highest level of agreement was still less than half the number of potential impacts.

Table 4.2. Aggregated small groups differed in their agreement surrounding the impacts of particular variables on the rest of the system. The percent internal agreement is given for each group and each variable in the columns; highlighted cells indicate highest (blue) and lowest (orange) internal agreement for each group.

Variable	Salience	Women Farmers (%)	Government (%)	Men Farmers (%)	Scientists (%)
human population	0.92	29	79	46	50
rainfall	0.86	38	38	42	58
community awareness	0.84	21	67	54	63
unemployment	0.79	21	46	58	58
illegal users	0.67	29	88	67	38
livestock population	0.65	8	25	13	50
political instability	0.57	46	71	58	67
temperature	0.56	21	46	21	46
firewood consumption	0.55	17	50	21	21
uncoordinated protection	0.54	46	71	46	63
agricultural expansion	0.49	13	38	21	42
invasive plants	0.42	4	50	8	21
fire	0.41	13	54	21	38
deforestation	0.4	38	42	50	33
leadership	0.38	8	38	38	88
animal diseases	0.36	21	38	33	38
plant diseases	0.23	25	46	8	33
regime change	0.17	8	79	42	58
research	0.13	4	71	33	58
crops	---	33	50	38	33
freshwater	---	4	75	38	38
guassa grass	---	4	54	38	58
income	---	25	50	29	54
tourism	---	21	67	46	50
wildlife population	---	0	54	17	46

During the third and final workshop, small groups were given the opportunity to discuss these areas of high and low agreement and prepare a single mental model for their group. After this small group discussion, scientists presented the least complicated mental model while government workers presented the most complicated model. Government workers and men farmers from both groups created models that showed relationships between almost every single variable in the system (91 – 93% of the possible 600 relationships), while scientists only identified 48.7% of the possible relationships and women farmers identified 54.5%, illustrating either differences in how these groups think about the complexity of the system, or differences in how these groups respond to requests for information. Specifically, scientists presented a model with 292 relationships (50% of them positive), women farmers presented a model with 327 relationships (62.1% positive), men farmers living far from Guassa presented a model with 547 relationships (49.0% positive), men farmers living near Guassa presented a model with 558 relationships (54.7% positive), and government workers presented a model with 560 relationships (49.5% positive). As with the aggregated group models, we observed a tendency for women farmers and some men farmers (near Guassa) to identify larger proportions of positive relationships, focusing on how variables caused increases rather than decreases in other system components.

Scientists also identified an additional 26 relationships that represented uncertainties in the system (i.e., by marking them "I don't know"); they were most uncertain about the potential impacts of invasive plants and regime change on social variables like community awareness and uncoordinated protection (see Appendix E for the full list). Men farmers living near Guassa identified four uncertain relationships, while men farmers living far from Guassa identified 11 uncertain relationships, all targeted at the potential impacts of temperature and firewood consumption on other variables. Women farmers identified only two uncertain relationships, while government workers produced a final mental model with no uncertainties marked.

When examining all the components and relationships, there appears to be an overall lack of agreement across groups regarding the key drivers and sensitivities in the Guassa system. Only 7.2% (n=9) of the shared driver rankings (Figure 4.3) and 12% (n=15) of the shared sensitivity rankings (Figure 4.4) showed overlap among small groups. Of these, government workers and men farmers near Guassa had the most frequent shared rankings (n=5), and women shared four rankings with each group of men farmers. There was greater variability across groups regarding the drivers of the system compared to the sensitivities, indicating higher disagreement across groups when it comes to identifying key drivers. Still, certain variables were ranked similarly enough across groups to indicate their general importance in the system; for example, most groups consistently ranked human population and unemployment as key drivers in the system, with relatively small standard deviations indicating high agreement as to the number of impacts they have on other system components. Groups universally ranked guassa grass as a mid-level driver, while all groups except men farmers living far from Guassa considered freshwater to be the weakest driver (Figure 4.3). Meanwhile, groups ranked income as one of the most sensitive components of the system, with a very small standard deviation indicating good agreement across groups. Groups considered illegal users a mid-level sensitivity, while they ranked invasive plants a consistently low-level sensitivity (Figure 4.4).

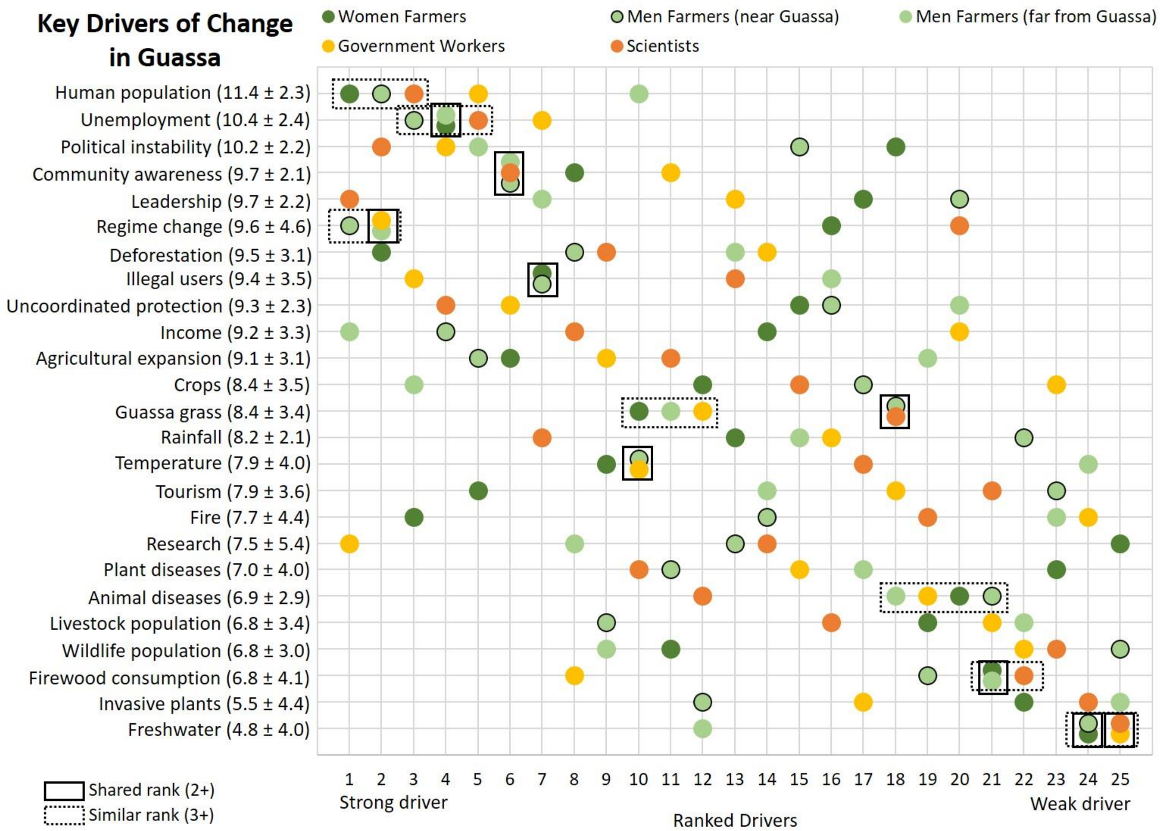

Figure 4.3. We define variables with the highest outdegree centrality as the strongest drivers of change in the Guassa system, as they most frequently impact other variables. Variables are presented in order of declining mean outdegree centrality, with the relative ranks of each small group given as colored circles. Mean and standard deviation outdegree centrality are given in parentheses next to the variable names. Solid black boxes indicate a variable that received the same rank across two or more small groups, while dashed black boxes indicate a variable that received similar ranks across three or more groups.

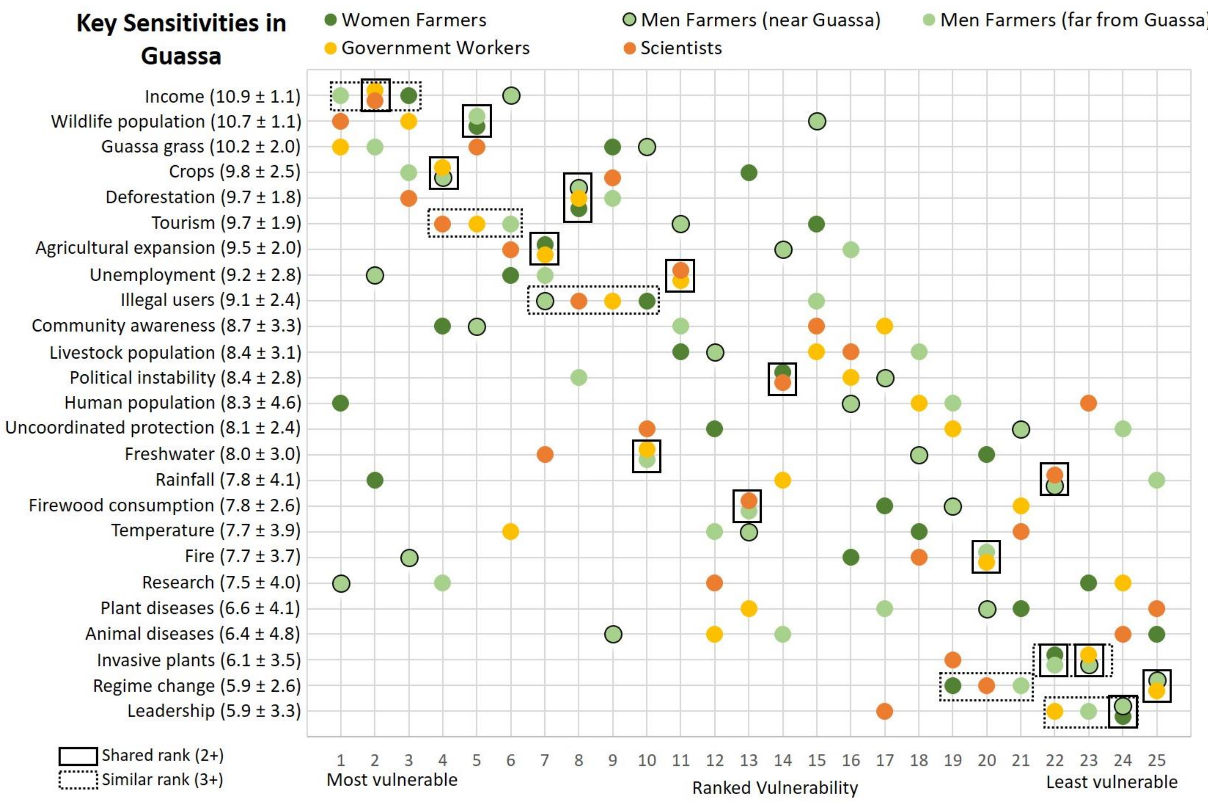

Figure 4.4. We define variables with the highest indegree centrality as the most sensitive components of the Guassa system, as they are most frequently impacted by other variables. Variables are presented in order of declining mean indegree centrality, with the relative ranks of each small group given as colored circles. Mean and standard deviation indegree centrality are given in parentheses next to the variable names. Solid black boxes indicate a variable that received the same rank across two or more small groups, while dashed black boxes indicate a variable that received similar ranks across three or more groups.

When focusing only on the four strongest drivers and four most sensitive components (Figure 4.5), more consistent patterns emerge within and across groups. Women farmers identified human population as both the strongest driver and the most sensitive component in the Guassa system, highlighting the central role of humans in their worldview. Men living far from Guassa identified income as both the strongest driver and the most sensitive aspect of the system, while men living near to Guassa considered unemployment, another economic component, both a strong driver and a strong sensitivity. Both groups of men farmers considered crops a highly sensitive system component, and men living far from Guassa also considered crops a strong driver of the system. Government workers identified research as the strongest driver of change in the Guassa system, while both groups of men farmers considered it a highly sensitive component of the system. Scientists and government workers identified wildlife populations as a highly sensitive component of the system.

Overall, government workers and men living far from Guassa agreed on five out of nine key system components (55.6%), men farmer groups agreed on five out of eight (62.5%), and women agreed with men living near Guassa on four out of ten components (40%). Scientists had low agreement with all other groups, as their highest agreement was with women (25%) and government workers (23%). Women and government workers had the least agreement across groups, with income as the only shared key component between them (7%). Women farmers, scientists, and government workers had final models with unique key components that were not found in other groups' mental models (Figure 4.5). Finally, women were the only group that retained all of the top four variables from the initial ranking exercise (Table 4.1) in their final mental model.

All groups except women considered some aspect of government (i.e., political instability or regime change) a key driver of the system, and government workers considered both of these to be critically important. All groups considered economics (i.e., income or unemployment) a key sensitivity. However, the relationships between these variables were not consistent across groups (Figure 4.5). Government workers and scientists viewed these as mutually negative relationships – they reported that an increase in income would cause a decrease in political instability or regime change, and an increase in political instability or regime change would likewise cause a decrease in income. Men farmers from both groups agreed with government workers and scientists that a regime change would cause a decrease in income. However, both groups of men farmers believed an increase in income would lead to higher likelihood of a regime change, which differs from how government workers and scientists thought about this relationship.

The large group discussion revealed some of the logic behind the decisions that small groups made and shed light on why relationships differed across groups. For example, women farmers and men farmers far from Guassa agreed that as human population increases, income also increases because there is more work available when there are more people around. The other groups felt that an increasing human population would decrease income because limited resources would have to be shared among more people, and the increased pressure on the Guassa area would result in lower income opportunities from it. Another key difference in understanding related to the influence of leadership on regime change. Scientists and government workers agreed that strong leadership would decrease the likelihood of regime change because people would be less likely to revolt when their needs are being met. Men and women farmers disagreed, saying that good leadership brings about increasingly democratic processes and equal power sharing so that regime change is more likely when there is good leadership. These descriptions reflect significantly different understandings of governance among participant groups and help clarify why conflicting relationships were reported between income/unemployment and political instability/regime change.

As the discussion continued, small groups became more likely to change their answers to reflect the opinions of the other groups. Women farmers often had the only dissenting opinion, and scientist facilitators halted the conversation when we realized the women were immediately changing their answers without offering a rationale for their original perspective. In our wrap-up session, we came together as a large group and collectively identified five variables that will require additional research: political instability, fire, plant disease, invasive plants, and temperature. Scientist facilitators asked whether other participants wanted to use the group mental models to evaluate potential scenarios of the future, but there was no interest.

Final Group Mental Models

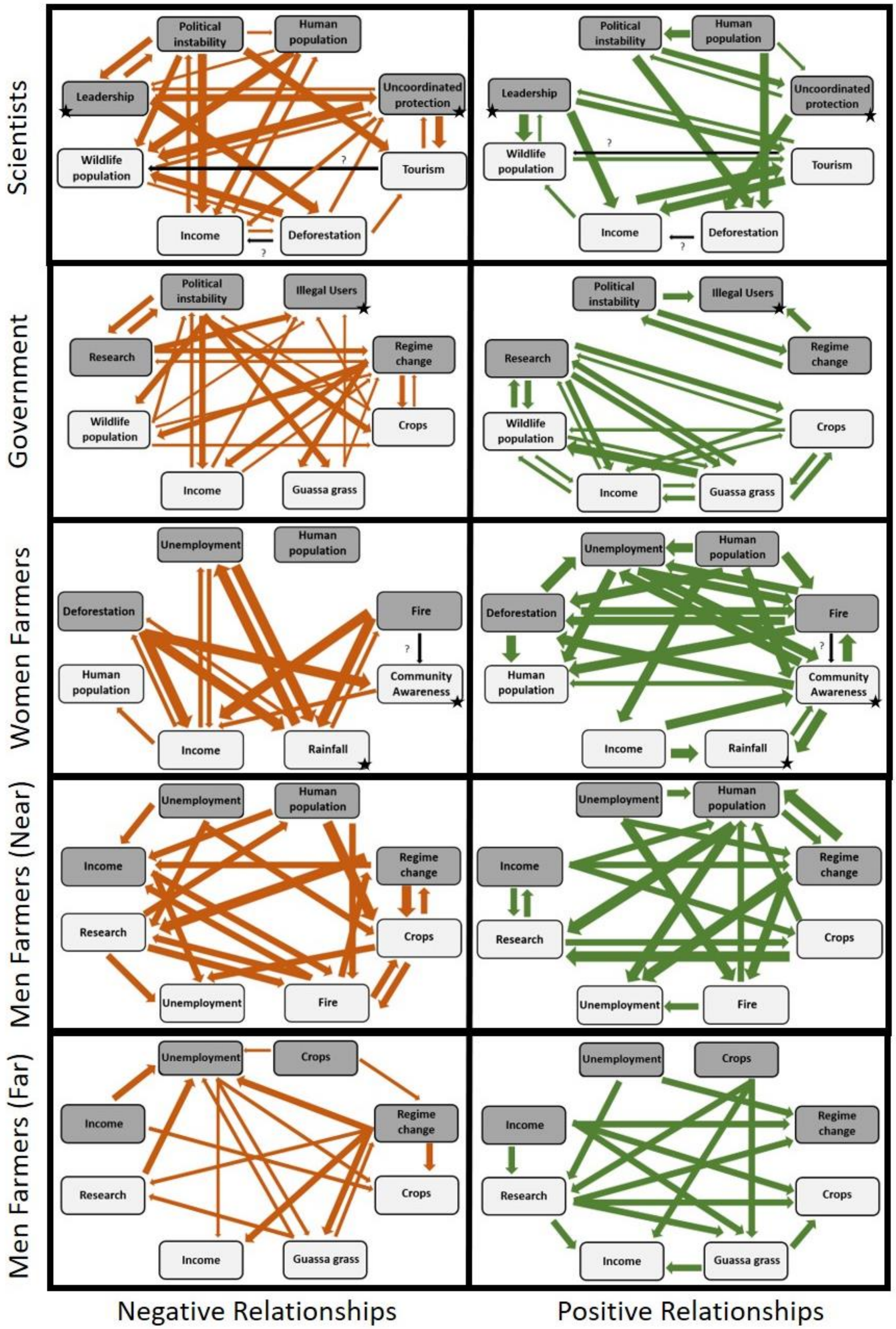

Figure 4.5. Final group mental models for the five small groups showing only the strongest drivers (in grey) and most sensitive components (in white). Positive relationships are shown with green arrows, while negative relationships are shown with orange arrows. Uncertain relationships are marked with black arrows and a question mark, while unique key components are marked with a black star to indicate that other groups did not include that variable.

4.3.2 Learning Experienced by Workshop Participants

Over the course of the three workshops, participant interview responses became increasingly more nuanced as the conceptual modeling exercises became more complex. There were 29 participants who completed all three post-workshop interviews, six participants with two interviews each, and two participants with only one interview each (total = 37 participants). In the first workshop, one of the common themes in participant responses was the importance of identifying threats to Guassa (n=20, 54.1%), often with additional insights into how this can assist in future planning. One farmer commented, "By ranking the variables, I learned that if we prioritize the problems early it can help our future preparedness." However, some respondents took a more extreme interpretation, focusing on the need to "control all the threats to Guassa" rather than reflecting on the overall importance of identifying threats. The novelty and importance of long-term planning was another common theme in the first workshop (n=22, 59.5%). "We are used to planning for five years but not twenty," remarked a conservation officer. By the third workshop, responses focused more on the complexity of the Guassa system (n=19, 51.4%). One farmer commented, "I learned that everything is connected, and that harming one aspect may cause unintended consequences." Another farmer similarly exclaimed, "the guassa grasses are dependent on so many things!" These kinds of observations were complemented by a less ubiquitous theme, the idea that computers could ease the burden of this complex thinking. "Computers can make complex information very simple and understandable," reported a farmer.

In the third workshop, the most common theme across responses was the importance of discussion as the source of learning (n=18, 48.6%). "Discussion is always better for our community," reported a priest. The value of discussion for most participants was the opportunity to understand other people's perspectives, without a need to find consensus. One woman reflected, "it is always better to see things and ideas in different ways." However, a subset of respondents valued discussion for the opportunity to reach a consensus (n=4). One man explained, "Before the discussion, there were different ideas. After the discussion, we came to one idea. Discussion makes us change our ideas." Participants frequently reported changing the way they thought about one another's ideas and perceptions of the Guassa system, though it was usually a general statement without concrete examples. One pre-conceived bias emerged from the responses of just a few government workers. At the first workshop, one conservation officer commented that he felt there were "gaps in understanding between government officials and the public." Then, at the second workshop, a government worker commented that another man had "surprised me a lot, because he put forward constructive ideas even though he is a farmer." These kinds of biases were not observed in interviews from the third workshop, which emphasized the differences in individual ideas and perspectives rather than group-level assumptions or stereotypes.

The value of the women's participation in the workshop was a common theme in the women's interviews, with nearly half the women (n=5, 45.5%) saying something about the importance of including women in these kinds of meetings. One woman in particular showed a clear escalation in this theme over time: at the first workshop, she remarked how happy she was that women had been included. In the second workshop, she stated there should be even more participation from women in Guassa research, and at the third meeting she confidently stated, "there must be women scouts." These responses demonstrate growing within-group support for stronger women voices in Guassa management. However, none of the men participants made any remarks in their interviews regarding the importance of including women.

4.4 Discussion

In this study, we iteratively constructed and revised mental models at both individual and small group levels over the course of a year. Participants were solicited from four social groups involved in managing a community conservation area in the north central Ethiopian highlands. We sought to understand how mental models of the Guassa social-ecological system differed among these management groups, and to assess what kinds of social learning occurred throughout the collaborative mental modeling process. We found some evidence that system understanding was more similar among groups with stronger local knowledge, though surprisingly we did not find many similarities between groups with more scientific or Western knowledge. As expected from the short length of our process and relatively new collaborative relationships, we found evidence of single- and double-loop (but not triple-loop) learning. We discuss these findings in greater detail below.

4.4.1 Comparing Mental Models

Enough similarities emerged across mental models to sketch a picture of the most important drivers and sensitivities in the Guassa system. For all groups except women, government featured prominently as a driver of change in the system, mainly through political instability or regime change. This is likely related in part to the on-going civil unrest throughout Ethiopia, which began with protests over the Addis Ababa Integrated Development Master Plan in the spring of 2014. Protests have continued to the present, escalating to include long-standing grievances over the marginalization of Oromo people within the current national government. Guassa has felt the impacts of this instability directly through the loss of tourism to the conservation area. However, previous research into the history of environmental change in this area revealed the importance of secure land tenure for influencing people's behavior towards the Guassa area (Steger et al. in press), indicating that governance has been a critical driver in this social-ecological system for decades before the current unrest.

Economic variables were the most common sensitivities in the system, reflecting a primarily subsistence economy that is only recently transitioning to market-based production. While more market-oriented variables like income and unemployment were widely important across groups, crops also featured prominently in the mental models of men farmers and government workers. The absence of livestock populations as a key component indicates that while most farms in this area operate as mixed crops-livestock systems (Tadesse 2009), the cultural tendency is to value crops as the primary subsistence product of the household. Sheep breeding operations have been implemented as development projects in this region for decades due to the highly desirable characteristics of local Menz sheep breeds (Tadesse 2009; Gizaw et al. 2010). This may explain why livestock were not considered key components in mental models, as they may be considered a part of income-generating activities rather than an independent subsistence product. While the Guassa area traditionally operated as a key resource area for grazing during drought (Ashenafi & Leader-Williams 2005), the current management team does not intend to allow this use in the future. Many households are now turning towards household cattle fattening in the face of decreasing communal grazing areas (Steger et al. in press).

Overall, these results provide some support for our expectation that groups with strong local knowledge will demonstrate similar system understanding, though it appears to be mediated by gender and occupation. Regarding the final group mental models, the strongest overlap occurred between the groups of men farmers, and among men farmers and government workers, who all considered political regime change a key driver and crops a key sensitivity in the system. Yet, occupation also seemed to influence their selection of key components in a way that reflects their dominant interests and role in society, as government workers identified two governmental variables as key drivers while men farmers identified two economic variables as both key drivers and key sensitivities. Similarly, women farmers identified human population as both a key driver and a key sensitivity, which may reflect the highly domestic role of women in Ethiopian culture

(Fenster 1998; Coppock et al. 2011). Insights from cognitive anthropology reveal that all the knowledge about a culture cannot be stored within a single brain, and in fact there is a division of labor in who knows what – certain social positions or experts will know more than others (D'Andrade 1981). Therefore, it stands to reason that mental models would vary even among groups that share a dominant culture depending on the everyday activities and values of the individual participants, as people will tend to focus on variables and processes that are of direct importance to them (Klein et al. 2014).

Differences in mental models also revealed how groups perceived and valued the Guassa system. Scientists, government workers, and men farmers far from Guassa identified a roughly even split of positive and negative relationships in their final group models. However, women farmers and men farmers living near Guassa identified larger proportions of positive relationships. A similar result was seen in the aggregated small group models, with farmers of both genders agreeing on positive relationships more than negative ones. These findings may help explain why so many participants considered the "identification of threats" to be a key learning outcome from the first workshop, as it seems they were not used to thinking about negative relationships in this system. In panarchy theory (Gunderson & Holling 2002), positive feedbacks ('amplifying' feedbacks) are destabilizing processes that can drive systems across a threshold and into an alternative state, while negative feedbacks ('dampening' feedbacks) are stabilizing forces that reduce fluctuations and reinforce existing states (Scheffer & Carpenter 200; Nyström et al. 2012). When considered in this light, the mental models of farmers in the Guassa system emphasize positive relationships that, if they are reciprocated in positive feedback loops, are more likely to move the system into a new state, while the mental models of scientists and government workers describe a more balanced, stable state. These results may indicate that farmers are more sensitive than other management groups to the conditions that drive change in the Guassa system, though further research with larger numbers of participants is needed to evaluate this finding.

Another key difference in group mental models revolved around the level of complexity and the identification of uncertainty. Government workers and both groups of men farmers presented highly complicated mental models with nearly every relationship marked, while scientists and women farmers presented models with roughly half the possible relationships marked. This could indicate a more nuanced understanding of the system among government workers and men farmers, as they identified relationships that women farmers and scientists did not think existed. However, scientists also expressed the highest number of uncertain relationships, more than twice as many as the next largest group (men living far from Guassa), while government workers identified no uncertain relationships. Together, these results suggest that men in the Guassa area are less likely than women or outsiders to admit to a lack of understanding, regardless of their occupation or level of education. Interpreted in this light, the highly complicated models presented by government workers and men farmers may instead be an attempt to reinforce their positions as leaders in the area who can be counted on to provide all the answers. In this cultural context, it may be seen as a weakness or shortcoming in their masculinity to admit to a lack of knowledge or understanding, which is supported by observations of hegemonic masculinity in Ethiopian culture (Hussein 2005; Mjaaland 2018). However, additional interviews and ethnographic research are needed to clarify the source of these differences in the Guassa context.

These findings emphasize the need for diverse perspectives in a collaborative process (Paulus & Nijstad 2003; Bernstein 2015; Hoffman et al. 2017), and together with the aggregated model results point to the complementarity of both individual and group-level mental modeling for nuanced system understanding. For example, the aggregated small group models illustrated wide disparities at the level of the individual. Even in the government group, which had the highest internal agreement, participants only agreed on the direction and intensity of roughly half the relationships in the system. Therefore, although the group-level modeling process is more likely to encourage social learning (Gray et al. 2014; Henly-Shepard et al. 2015), we believe individual-level modeling should be part of any mental modeling exercise as it can provide much-needed points of clarification when group models are hampered by socio-cultural barriers such as disagreement in a group discussion, or resistance in the identification of knowledge gaps or uncertainty.

4.4.2 Social Learning Process and Outcomes

Our study was strengthened by the iterative process that allowed individuals and small groups to reflect on their own understanding and share it with others. While this was an intensely time-consuming process, we find it has been quite valuable to explore and understand the diversity of knowledge and system understanding at the early stages of our collaborative research efforts. One advantage has been the increased communication among members of the management team. As a critical element of successful collaborative research (Dietz et al. 2003; Lang et al. 2012; Jahn et al. 2012), this communication and the increased mutual respect and understanding that emerged from it are promising indicators for future adaptive management of the Guassa area (Fazey et al. 2014; Popa et al. 2015; Fujitani et al. 2017; Cockburn & Cundill 2018). Our interview results, which describe how discussion enhances learning, underscore the "social" component of social learning, as participants valued the opportunity to compare and evaluate their individual and shared knowledge. Discussion also appears to facilitate the development of more trusting and open relationships, which is an under-appreciated enabling factor for social learning (Figure 4.1). In particular, the observed social divisions between men farmers and government workers stand out as an example of relationship building that occurred during this process. These groups had the most similar mental models, yet post-workshop interviews indicated that they did not recognize how much they had in common until discussions revealed their shared perspectives.

A second advantage has been the identification of baseline mental models, which will enable us to monitor changes to mental models over time. Because mental models are a reflection of the particular culture in which they are created, and culture is dynamic, we expect mental models to change over time in reaction to both the collaborative research process and external events in the socio-political and biophysical context (Chi 2008). This study lays the foundation for semi-quantitative evaluation and monitoring of changing mental models, which can contribute to theories of learning and best practices in collaborative environmental management (Armitage et al. 2008; Lang et al. 2012; Steger et al., in prep).

Our interview results suggest a few types of social learning were on-going throughout the workshops. Most participants reported some change to the way they were thinking about the Guassa system, which is an indication of single-loop or conceptual learning (Pahl-Wostl et al. 2009; Baird et al. 2014). For example, the large group discussion about how human population impacts household income caused some individuals to change their thinking about that cause and effect relationship. Women farmers and men farmers far from Guassa had considered this a positive relationship, but then wanted to change their answers to match scientists and government workers after the discussion. We did not make these changes to the final models because we wanted to acknowledge the validity of diverse perspectives rather than seeking out consensus at this early stage of our collaboration, especially given the more powerful positions of scientists and government workers in this context.

The theme of “identifying threats”, which was reported by over half of the first workshop’s participants, is another example of single-loop learning. In the space of a two-day workshop, participants were able to identify gaps in the way they were thinking about the Guassa system (i.e., not recognizing threats) and use other people’s ideas and perspectives to fill those gaps. The focus on “threats” may have arisen through issues with translation, as words like “variables” or “system components” did not retain their meaning when translated into Amharic and we used words like “threats” and “benefits” to help generate the list of important variables (Table 4.1). However, there was a clear tendency for participants to focus on threats rather than benefits, as evidenced by the kinds of variables included in the initial list and the interview results. When considered along with the bias towards positive relationships in farmers’ mental models, we conclude that farmers experienced increase learning about potential threats to the Guassa area that they had not considered before this workshop.

We also found evidence of double-loop learning, as participants reported increasing the time-frame they use to think about Guassa planning and expanding their understanding of the complexity of the system – both aspects of improved "systems thinking" (Dyball et al. 2007). Men farmers and government workers reported expanding their planning time frame more than women farmers, probably because women are not as integral to Guassa planning processes, as evidenced by the lack of women on the executive committee. Participants from all groups reported expanding the way they thought about the complexity of the system. While we did not see clear evidence of triple-loop learning, the need for increasing women's perspectives in management was vocalized by a subset of women participants. If women's roles in Guassa management continue to grow, this may be an indication of a normative change just beginning to shift.

4.5 Conclusion

There is a need for greater understanding of the social and cultural factors that influence outcomes in collaborative environmental management. Mental modeling is an under-utilized approach for understanding how different people perceive social-ecological systems, which can improve system understanding as well as clarify the assumptions and values held by diverse groups of people involved in management. Sharing mental models can also inspire social learning among diverse participants, though the people facilitating these processes need to be highly aware of power asymmetries among the people involved to prevent certain groups capturing the process for their own benefit. Iterative sharing of mental models can allow people to become more comfortable with the modeling process as well as the other participants, which can improve the quality of the models produced.

CHAPTER 5

CO-DESIGNING AN AGENT-BASED MODEL OF SHRUB ENCROACHMENT IN AN AFROALPINE GRASSLAND [4]

5.1 Introduction

Environmental managers today are challenged by anticipating future change and making decisions in the context of limited data and high uncertainty (Polasky et al. 2011). As social-ecological systems continue to change rapidly, the future becomes increasingly uncertain due to the lack of a historical analog and the complex dynamics and feedbacks that cause unexpected outcomes in these systems (Ostrom 2007; Liu et al. 2007). In this context, attempts to analyze trade-offs in alternative management practices and decisions require tools that can interweave social and ecological components across diverse spatial and temporal scales (Zimmerer & Basset 2003; Cumming et al. 2006; Rammer & Seidl 2015). Spatially-explicit, grid-based simulation models (e.g., some agent-based models, or ABMs) can integrate interactions among agents (e.g., people or animals) with landscape-scale processes (e.g., water cycling or vegetation growth) so that emergent phenomena can be observed arising from their dynamics over time. This makes ABM effective at representing complex, social-ecological systems in intuitive ways (Janssen 2005; Barnaud et al. 2008). ABMs are also able to mix qualitative, threshold-based rules with quantitative data and mathematical equations (Li et al. 2018), making them particularly useful tools for exploring social-ecological problems when data are limited.

An emerging generation of modelers seeks to co-design ABM with non-academic stakeholders so that the model has direct relevance for decision-making and management (Verburg et al. 2016; Voinov et al. 2018; Schluter et al. 2019). This collaborative approach combines

[4] This research will be submitted for publication consideration along with co-authors Randall B. Boone, Julia A Klein, Paul Evangelista, Bikila Warkineh Dullo, and Shambel Alemu.

scientific and societal objectives to advance system understanding as well as collective learning among the diverse people involved in managing a system (Bousquet & LePage 2004; Barnaud et al. 2008). Collaborative ABM is an effective tool for exploring systems in a prospective rather than a purely predictive way (Anselme et al. 2010), which can aid environmental managers in formulating new ideas about how to anticipate and manage systems under future uncertainty. By shifting adaptation planning from reactionary to forward-looking strategies, these collaborative modeling processes can foster complex and long-term thinking, social learning, and collective action (van Notten et al. 2003; Kok et al. 2006), thus improving the adaptive capacity of managers.

Current debates in collaborative ABM revolve around the level of detail needed for a model to promote this kind of learning among participants. Some scholars insist that highly detailed models are required for decision support, as this allows realistic individual processes to be represented (Barthel et al. 2012) and enables stakeholders to understand how they reflect their everyday, lived experiences (Lange 2001). However, other scholars have demonstrated that highly realistic models can impede system exploration, leading participants to think in terms of barriers and preventing them from finding innovative solutions (Barnaud et al. 2013). Multiple modeling paradigms have highlighted the existence of what we are calling an "intermediate learning hypothesis," whereby models are most useful for learning and decision-making when they are constructed to reflect intermediate levels of system complexity. Grimm et al. (2005) present this as the "Medawar zone", while members of the Companion Modeling network have articulated it as a "KILT: Keep It a Learning Tool" approach (Le Page & Perrotton 2018). Yet few recommendations exist to guide the construction of models at this level of complexity, potentially leading to inconsistent use of this design concept.

In this paper, we describe the process of co-designing an agent-based model of shrub encroachment in a community-managed Afroalpine grassland (known as Guassa) in the highlands of Ethiopia. The purpose of this model is to enable people involved in managing Guassa to explore the individual and combined effects, as well as tradeoffs, of social and ecological factors controlling the spread of these native shrubs, and to evaluate the efficiency of different strategies to control their expansion. Due to the scarcity of data from this site, parameter values are derived largely from the literature, remote sensing, and expert opinion from scientists and local managers. Therefore, while there is some level of realism in the landscape and parameterization, we do not intend to produce highly accurate predictions of the future of this area. Rather, we seek to explore potential futures and use these to facilitate discussion and planning among the diverse co-management team. We assess the learning experienced by participants in the co-design process to contribute to empirical measurements of learning in relation to model complexity.

5.1.1 The Problem of Shrub Encroachment

Shrub encroachment into grasslands has been observed over the last 100 years across the globe, resulting in increased density, cover, or biomass of woody plants and the displacement of grasses (Archer et al. 1995; Van Auken 2009; Eldridge et al. 2011; Sala & Maestre 2014; Myers-Smith et al. 2015). Changes to ecosystem structure, function, and subsequent goods and services makes shrub encroachment an issue of critical concern, particularly for systems that are dependent on livestock production (Archer et al. 2017). Shrub encroachment arises from complex, interacting factors such as changing resource availability (e.g., precipitation, soil nutrients, atmospheric CO_2), growing conditions (e.g., microclimate changes, irradiation, topography), and disturbance (e.g., herbivory or the lack thereof, fire, and soil erosion), with the relative influence of these factors differing according to the particular location (Bestelmeyer et al. 2003, Sankaran et al. 2005, Fuhlendorf et al. 2008, Sankaran et al. 2008, D'odorico et al. 2012, Lehmann et al. 2014, Midgley & Bond 2015, Schweiger et al. 2015).

While the causes and consequences of shrub encroachment have been examined thoroughly in the context of arid and semi-arid grasslands (Archer 1994, Knapp et al. 2008) and temperate mountain ecosystems like the European Alps (Anthelme et al. 2007, Anselme et al. 2010, Komac et al. 2013) and the Tibetan Plateau (Klein et al. 2007; Hopping et al. 2018), little research has been done to understand how these factors play out in wet, tropical mountain systems like Afroalpine grasslands (Buytaert et al. 2011). In areas of high mean annual precipitation, shrub encroachment generally leads to increased primary production (Eldridge et al. 2011) and a competitive advantage for woody species in the absence of disturbance mechanisms through herbivory, fire, and soil characteristics (Sankaran et al. 2005). This is the opposite of drylands, which tend towards decreased productivity and diversity, and increased desertification (Lett & Knapp 2003, Reynolds et al. 2007). However, shrubs and grasses also tend to have similar rooting depths in wet systems due to their shallow water tables, which can mitigate competitive effects from shrub taproot development (Molinar et al. 2002; Rossatto et al. 2014). Therefore, the continued existence of Afroalpine grasslands indicates some type of disturbance mechanism or below-ground control operates to prevent woody plant encroachment under these high precipitation conditions.

Another potential difference for shrub encroachment in wet versus dry grasslands is the impact of increased atmospheric carbon dioxide (CO_2). In drylands, grasses tend to use C4 photosynthetic pathways, which are not directly affected by increased atmospheric CO_2. This enables shrubs and trees with C3 photosynthetic pathways to outcompete them (Ehleringer et al. 1997; Archer et al. 2017). Some scholars have theorized that increased atmospheric CO_2 is not as significant a driver of shrub encroachment when grasses and shrubs both use C3 pathways (Buytaert et al. 2011; Archer et al. 2017) – which is the case in tropical mountain systems like the Afroalpine. Other scholars maintain that woody species like shrubs and trees require larger amounts of carbon to build their woody structure, and that demand can be met much more efficiently in conditions of elevated atmospheric CO_2 (Drake et al. 1997; Ceulemans et al. 1995; Bond et al. 2003). Therefore, they propose that woody shrubs will have a competitive advantage under these conditions regardless of the presence of C3 or C4 grasses. Because elevated atmospheric CO_2 has elicited a wide range of growth responses in the presence of other co-limitations (e.g., light, nutrients, temperature, reproductive strategies), other scholars urge a context-specific approach to understanding local impacts of elevated atmospheric CO_2 (Körner 2006).

5.2 Methods

5.2.1 Study Area Description

The Guassa Community Conservation Area (Guassa) is 78 km^2 and located within the Menz Gera woreda of the Amhara Region of Ethiopia. Ranging from 2,600 – 3,560 m.a.s.l., this area was historically characterized by two rainy seasons known as the 'belg' (~March 1 – May 30) and 'kiremt' (~July 1 – September 30), though that has been shifting to a largely unimodal pattern in recent years (Fashing et al. 2014). Guassa supports many endemic and threatened species, including the critically endangered Ethiopian wolf (*Canis simensis*) and the gelada monkey (*Theropithecus gelada*) (Ashenafi et al. 2005). Guassa is named after the guassa grasses (*Festuca macrophylla*) that are valuable to the local communities for their use as thatch, rope, construction material, and forage. In the last 20 years or so, local managers have observed the expansion of three shrub species: a cushion shrub (*Helichrysum splendidum*) and two evergreen shrubs (*Erica arborea* and *Euryops pinifolius*). The Helichrysum shrubs are of greatest concern, as they have no perceived value for humans or wildlife, and are thought to compete directly with the guassa grasses as they are often found growing together.

Similar to the European Alps (Anthelme et al. 2007; Anselme et al. 2010; Komac et al. 2013), grass-shrub interactions in the Ethiopian highlands have been regulated by a long history of human activities. Guassa has undergone significant political and land management changes throughout its history (Ashenafi & Leader-Williams 2005; Steger et al. in press). The area was managed for hundreds of years (c. 1600 – 1974) according to the Qero system of communal management that restricted access to the grasses through short (two to three month) open seasons every three to seven years (Ashenafi & Leader-Williams 2005). The 1975 Agrarian Reform transferred land ownership to the state and community efficacy over Guassa management declined over the following 17 years (Admassie 2000; Ashenafi & Leader-Williams 2005). Community efforts to re-establish exclusive rights to the area were supported by international conservation efforts in the late 1990s, leading to a new co-management regime between local farmers and government agencies (Fischer et al. 2014). In 2012, exclusive use rights to the area were formally restored to the communities with ancestral rights by Amhara Regional Regulation No. 97.

Since about 2010, grazing and firewood collection have been banned inside the Guassa area due to perceived threats to sustainability and the endangered Ethiopian wolf. While illegal grazing and harvesting continues to a degree, public opinion is largely against grazing livestock in the conservation area due to the degradation seen from 1975 – 2000. Fire has never been used as a management tool in the Guassa area, and in fact it is considered a major threat to the sustainability of the area (Steger et al. in prep), which differs from other regions of Ethiopia (Jacobs & Schloeder 2002). Therefore, we do not include grazing or fire in our model as potential management options, though we suspect that shrub encroachment has been influenced by the combined effects of decreased grazing by large animals (cattle, sheep), increased grazing by small animals (rodents), and potentially other yet-unknown dynamics of resource competition. Impacts from changes to the microclimate (amelioration effects) may also exist, as studies of *Helichrysum* spp. and *Festuca* spp. in South Africa showed that Helichrysum positively impacts the growth of other species without benefiting Festuca as well, an indication of strong below-ground competition between the shrubs and grasses (Schweiger et al. 2015). We remain uncertain as to the potential impacts of increasing atmospheric CO_2, and encourage future research into this important issue as it could be having synergistic effects on shrub growth along with observed changes in disturbance regimes.

5.2.2 Co-design Workshops and Proposed Management Strategies

Local members of the Guassa management team identified shrub encroachment as a critical sustainability concern in the conservation area, following several years of collaborative learning and problem identification. In August 2019, we convened a workshop as part of this on-going effort to better align scientific research in Guassa with the needs of conservation area managers. Participants were invited from the Guassa Committee and the Tourism Board (n=28), the Guassa Conservation office (n=2), Ethiopian and American scientists (n= 4), and the local woreda administration office (n=3). There were more men (n=26) than women (n=11) present, and the average age of participants was 40 years. During the workshop, we presented an initial version of the model with the aim of refining it based on the needs of participants, and generating discussion and learning over its purpose and future application in Guassa. As the model was co-designed to support management action, we assessed the kinds of learning experienced by participants at the workshop. Each non-scientist participant was interviewed briefly (approximately 15-20 minutes per person) after each workshop about what they learned from the modeling exercise and discussion, how they anticipate using the model in their management decisions, and whether their understanding of other participants' perspectives changed throughout the workshop. Ethiopian scientists participating in the workshop conducted these interviews in Amharic. Interviews were translated to English and transcribed. The first author used in vivo coding (Corbin & Strauss 2008) and inductive thematic analysis to describe the kinds of learning reported by participants (Boyatzis 1998).

We discussed several potential management options to test with the model with the goal of reducing Helichrysum shrubs and increasing guassa grass provisioning. Recent management has allowed harvesting guassa grasses in May every three years, though in the past they have waited as long as five to seven years between harvests. In recent years, local people have pushed for more frequent harvesting. Therefore, we decided to test the impacts of harvesting every two, three, or four years. Scientists originally estimated that approximately 200 people would harvest guassa in this area of the conservation area, but we increased that number to 500 after conferring with workshop participants. Scientists also originally estimated that each person would not harvest more than 360 kg of guassa grass each harvest (approximately 11 shekams in local measurement units). However, workshop participants described seeing people cut anywhere from 4-20 shekams in a single day, over multiple if not all the days in the 10-day harvest window. Workshop participants were unable to estimate the average total amount of guassa grass harvested per person, as there has never been a record kept. Therefore, we used the model to determine a sustainable per person harvest limit for each climate regime in our scenarios to help inform management.

We also discussed the need for mechanical removal of the Helichrysum shrubs, though removal of Erica and Euryops shrubs was not considered an urgent need by managers – the difference being that Helichrysum shrubs are considered a nuisance with no ecological or human value. Therefore, we aimed to use the model to estimate the intensity and frequency of shrub harvest that would produce the desired reduction (but not elimination) of Helichrysum shrubs. Local community members identified September as a good time of year to remove the shrubs, as the long rainy season will have loosened the soil by that time and seeds already dropped. Workshop participants suggested that people would be less motivated to participate in Helichrysum removal compared to guassa grass harvests, and would thus cut fewer shekams per person. We tested the impact of each person's effort in the shrub removal to find what level of removal per person is sufficient to produce the desired outcome, and examined the impacts to vegetation dynamics under different climate regimes. Though workshop participants did not feel it necessary to use the model to test Erica and Euryops removal, they did insist that these species be modeled separately rather than grouped into a "non-Helichrysum shrubs" category as they were in the original model.

5.2.3 Model Description

The virtual world of the model consists of 95 x 95 cells, each 30m x 30m, which together represent an 812ha landscape (Figure 5.1). We use the agent-based modeling software Netlogo to produce this model (Wilensky 1999). One time step represented one week in the virtual world. The landscape was modeled after the area surrounding the Guassa lodge. We used a supervised random forest classifier of a February 2019 Landsat image to produce a baseline distribution of the dominant vegetation types in this area, with an overall accuracy of 77.6% (see Appendix F for more information). The eight dominant vegetation types are: Erica shrubs (*Erica arborea*), Euryops shrubs (*Euryops pinifolius*), grassland/shrub mix (not including our target species), guassa grasses (*Festuca macrophylla*), Helichrysum shrubs (*Helichrysum splendidum*), forest (mainly *Eucalyptus globulus* and *Cupressus lusitanica*), stone, and wetlands (mainly *Carex* and *Cyperus* species). Forests, stone, and wetlands do not change in the virtual world; they do not spread and they are unable to be invaded. The grassland/shrub mix also does not spread, but it is able to be invaded by the four vegetation types that do: guassa grasses, Helichrysum shrubs, Erica shrubs, and Euryops shrubs. We initialize patches containing these four vegetation types so that each cell contains some biomass (kg/m^2) of each type, following a random normal distribution. For example, cells dominated by Erica shrubs contain a mean of 0.5 kg Erica shrubs with a standard deviation of 0.2kg, with a mean and SD of 0.1kg for the three other species.

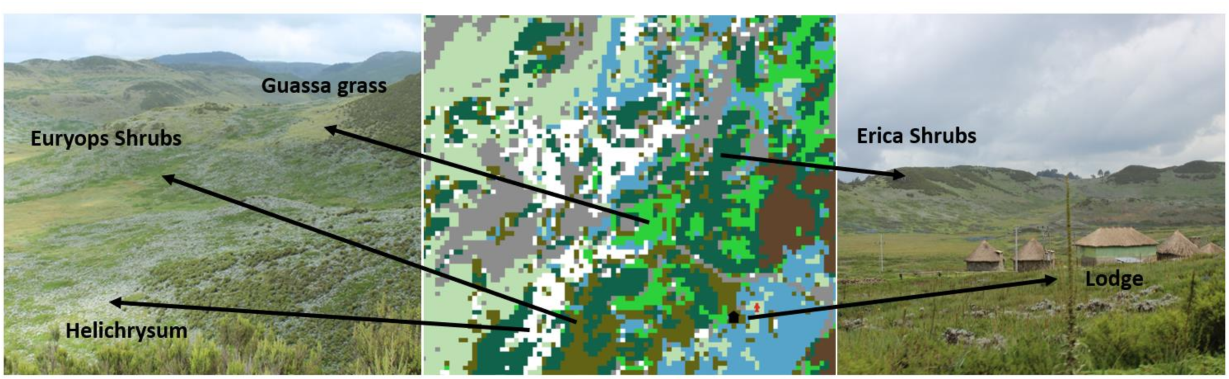

Figure 5.1. Guassa grasses (bright green), Helichrysum shrubs (white), Erica shrubs (dark green), and Euryops shrubs (olive green) are the only dynamic plant communities in this model. Forest

(brown), stone (grey), and wetlands (blue) do not change. Other grasslands (sage green) do not grow or expand but are able to be invaded by the four dynamic communities.

5.2.3.1 Precipitation Patterns

We used the Climate Hazards group Infrared Precipitation with Stations data (CHIRPS; Funk et al., 2015), processed through the Climate Engine Application (climateengine.org), to understand past precipitation patterns over Guassa, stretching from 1981 – 2018 (Figure 5.2). CHIRPS data integrates 0.05° resolution satellite imagery with available in-situ station data to produce a gridded time series product that estimates precipitation every day. In conjunction with these historical patterns, we use a published measurement of average annual precipitation from a private climate station in the Guassa area (Fashing et al. 2014). We drew on these data to identify realistic and stochastic patterns of precipitation for our future trends. We estimate average annual precipitation for normal (1,600 mm ± SD 200 mm), wet (1,900 mm ± SD 200 mm) and dry (1,300 mm ± SD 200 mm) climate regimes. Annual precipitation in a year where the early season rains do not arrive (i.e., a “No Belg” climate regime) is about 24% lower than a normal year and changes are concentrated in the Belg rainy season of March - May. The dry, average, and wet trends follow the bi-modal seasonal distribution that is historically common throughout the Ethiopian highlands (Figure 5.2).

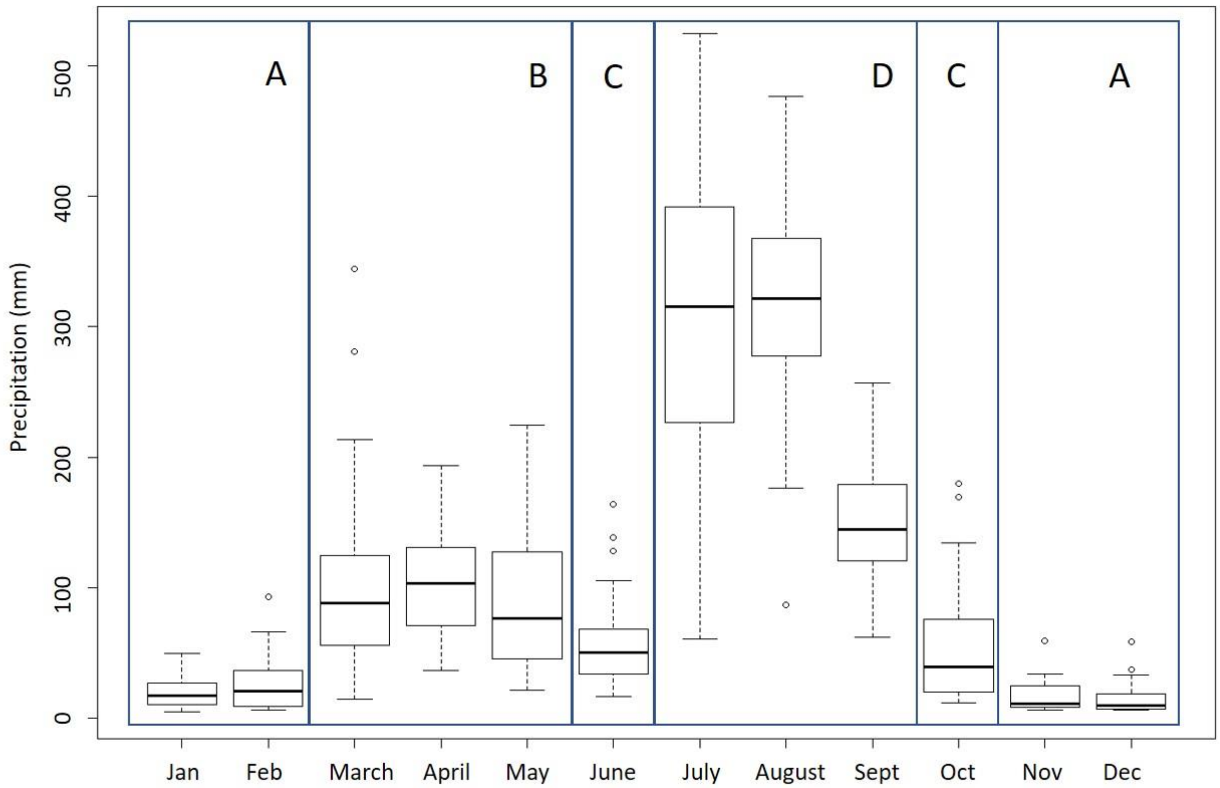

Figure 5.2. Box plot showing CHIRPS estimates of monthly precipitation for the Guassa area ranging from 1981 – 2018. A) Nov – Feb receives 0.5% of the annual precipitation per week, B) March – May (Belg rains) receives 3% per week, C) June and October receive 1% per week, and D) July – September (Kiremt rains) receives 3.7% per week. In the No Belg scenario, B) March – May receives 1% of the annual precipitation instead of 3%.

5.2.3.2 Vegetation Growth

We estimated carrying capacity for each of the four spreading vegetation types in our model. Data from 2008 provides an above ground biomass estimate for the Guassa area of 480.38 g/m^2 (no variance reported), with most plots dominated by herbaceous ground covers and guassa grass (Wodaj et al 2016). On Mount Kilimanjaro, 95% of Afroalpine biomass estimates for *Helichrysum*-tussock grass vegetation range between 220 – 1,040 g/m^2, with a mean around 630g/m^2 (Ensslin et al. 2015). Subalpine *Erica* shrubland has biomass estimates around 880g/m^2 from Mount Kilimanjaro, ranging from about 470 – 1290g/m^2 (Ensslin et al. 2015). In South Africa, communal lands with mountain shrubland vegetation dominated by *Euryops* spp. and other woody shrubs had biomass ranging from 199g/m2 to 2,244 g/m^2, but was typically around 600 g/m^2 (Anderson et al. 2010). Therefore, we use the maximum biomass estimates to define the carrying capacity for guassa grasses at 0.8 kg/m^2, for Euryops shrubs and Helichrysum shrubs at 1 kg/m^2, and for Erica shrubs at 1.2 kg/m^2. Following Fryxell et al. (2005), we linked the carrying capacity of these vegetation types to precipitation using a coefficient (ψ). We divided each carrying capacity by the average weekly precipitation in the Guassa area (24.5 mm), yielding estimates of $\psi_{\text{guassa grass}}$ = 0.0327, $\psi_{\text{Helichrysum shrubs}}$ = 0.0408, $\psi_{\text{Euryops shrubs}}$ = 0.0408, and $\psi_{\text{Erica shrubs}}$ = 0.0490. In the stochastic simulations, ψ is multiplied by the weekly precipitation.

We represent the growth of these four vegetation types through individual modified logistic growth equations. We assume weekly growth rates are at a maximum when vegetation biomass is low, as at the beginning of the rainy season or after a disturbance event (Parsons et al. 2001, Fryxell et al. 2005). Therefore, we include a factor that relates the growth rate to standing biomass and precipitation. We further assume that competition for resources influences both grass and shrub dynamics, and we modify the logistic growth equation to reflect that total biomass from all species restricts growth dynamics in each species equation (D'Odorico et al. 2012). For example, the growth of guassa grass can be represented:

$$\frac{dB_{guassa}}{dt} = r_{max} \times \left[B_{guassa} + \psi(R)\right] \times \left[1 - \frac{B_{guassa} + B_{Helichrysum} + B_{Euryops} + B_{Erica} + \psi(R)}{2 \times \psi(R)}\right]$$

Where B = dry weight biomass (per species), r_{max} = weekly growth rate (per species), and ψ (R) = carrying capacity multiplied by weekly rainfall. This allows both the maximum rate of grass growth and the carrying capacity to rise and fall with rainfall patterns. Senescence occurs during the 10 weeks following the end of the kiremt season rains. Each week, guassa grass biomass declines by 8%, resulting in 20% biomass remaining in each cell at the start of the next belg rains. Following expert opinion and observation, we programmed Helichrysum shrubs to senesce at a rate of 4% per week so that 60% of their biomass remains the following year, Euryops shrubs retain 80% of their biomass, and Erica shrubs retain 90% of their biomass in the following year.

Growth rate estimates were derived from MODIS Net Annual Primary Production (NAPP) product (MOD17A3H; Running & Zhao 2015, ORNL DAAC 2018). First, NAPP was converted from kg carbon (kgC) to biomass by dividing by 0.5 (0.67 kgC/m2 / 0.5 = 1.34 kg/m^2). Based on gross primary productivity curves, maximum growth occurs during the kiremt rainy season, which contains 44.4% of the annual precipitation over a twelve week period. Given that precipitation is a well-established driver of plant growth in most biomes (O'Connor et al. 2001, Knapp et al. 2002), we assumed that the percent of NAPP during this period was roughly the same as the percent of annual precipitation, yielding a maximum per week growth rate of 0.444*1.34 kg/m^2/12 weeks = 0.0496 kg/m^2/week. We then divided this maximum growth rate into sections for each vegetation type, assuming that guassa grasses and Helichrysum shrubs are able to grow faster than Euryops shrubs (Everson et al. 2009), which can grow faster than Erica shrubs (Wubie 2018). Due to the highly derivative nature of this parameterization, we tested a range of maximum growth rate estimates in a sensitivity analysis before conducting the management scenarios, and selected growth rates that produce biomass and distribution patterns that match local perspectives.

5.2.3.3 Seed Production and Dispersal

In the model, seeds from the three shrub species are produced and stored in the seed bank of each cell, and germinate in the coming spring when the belg rains arrive. Seeds of guassa grasses germinate shortly after being shed in July-August, following evidence from observations of *Festuca arundinacea* and *Festuca bromoides* (Bartolome 1979; Grime et al. 1988; Thompson et al. 1997) and preliminary findings that guassa grass seeds are largely absent from the Guassa seed bank (Wubie 2018). Seed production for each vegetation type occurs as a proportion of the aboveground biomass present in each cell, following studies of reproductive allocation and effort (Reekie & Bazzaz 1987). We took the average reproductive allocation (shoots, flowers, and seeds) of three

Festuca species in the literature: *F. arundinacea* (7.6%), *F. gigantea* (18.9%), and *F. ovina* (6.9%) (Wilson & Thompson 1989), to estimate that roughly 11% of standing guassa grass biomass is converted to seeds each year. Because reproductive allocation is generally lower in species with low relative growth rates (Bazzaz et al. 1987), we estimate shrub reproductive allocation will be closer to 8% for Euryops shrubs and 7% for Erica shrubs (Vosse et al. 2008). We selected 9% for Helichrysum because our sensitivity analysis revealed larger proportions caused guassa grasses to outcompete Helichrysum, which did not match local perceptions.

Each seed that germinates contributes a small amount towards the total biomass (0.5 g). Maximum germination rates of Erica shrubs are 62% under ideal conditions in the laboratory (Mesléard & Lepart 1991), therefore, we assume an average 40% germination rate under field conditions. Published data on germination rates for Helichrysum shrubs, Euryops shrubs, and guassa grasses do not exist; therefore, we used estimates from other species in the same genera. Germination rates for the Mediterranean species *H. stoechas* range between 30-50% (Doussi & Thanos 1997) while South Africa *H. foetidum* (12%) and *H. patulum* (24%) have much lower rates (Brown et al. 2003). We thus assume an average 25% germination rate for *Helichrysum* shrubs. Germination rates for seeds from U.S. *F. arundinacea* were between 97-98% (Rampton & Ching 1966); however, seeds from Canadian *F. hallii* had germination rates between 67 – 85% (Qiu et al. 2010). We assume a conservative average of 80% germination rate for guassa grasses. Finally, we take the average of three species of Euryops from South Africa - *E. linearis* (31%), *E. speciosissimus* (24%), *E. virgineus* (13%) (Brown et al. 2003), and assume a 23 % germination rate for Euryops shrubs in Guassa.

Due to the absence of aerial dispersal structures (Molinier & Muller 1938), Erica seeds do not typically spread more than 14m from their source plant (Mesléard & Lepart 1991). Therefore, we assume 80% of the seeds produced will stay in the same 30m x 30m cell of the model, while 20% will spread to neighboring cells equally. We assume the same distribution for guassa grass seeds, some species of which have been shown to have highly restricted dispersal distances (Rabinowitz & Rapp 1981). Helichrysum shrubs observed in South Africa have parachute-type seeds that are adapted for long distance dispersal by wind (Shiponeni 2003; Shiponeni & Milton 2006). Helichrysum shrubs have been observed to dominate South African seed banks and become the first shrubs to colonize eroded or overgrazed land, largely due to the papery texture of the seeds and their relative unpalatability (Everson et al. 2009). Therefore, we assume 30% of the seeds produced will stay in the same cell of the model, while 70% will spread to neighboring cells equally. While we were unable to find Euryops seed dispersal observations, research from South Africa (Vosse et al. 2008) shows similar Euryops and Helichrysum seed densities in the soil seedbank. Based on this limited information, we assume 50% of the Euryops seeds produced will stay in the same cell of the model, while 50% will spread to neighboring cells.

5.2.3.4 Dominant Vegetation Cover and Transitions

In week 39 of a simulation (late September), we calculate the biomass dominance in each cell with over 0.1 kg/m2 total biomass across the four spreading vegetation types. We selected this week because it falls after the majority of ecological functions are simulated in the model (seed production and spreading), yet biomass is still high at the end of the main rainy season. We selected the 0.1 kg/m2 threshold to ensure we did not evaluate cells with only very small concentrations of the species of interest. We assume guassa grasses and Helichrysum shrubs need to occupy 40% of the total cell biomass to be considered dominant, while Erica and Euryops shrubs need to occupy 30% of the total cell biomass to be considered dominant. Because Erica and Euryops shrubs are larger, they can produce higher biomass values than guassa grass or Helichrysum shrubs in the same amount of space. Therefore, we consider a lower percent cover to be equivalent to the same amount of biomass.

Table 5.1. Parameter estimates with supporting literature.

Parameter	Description	Estimate	Citations
precipitation	annual precipitation	average (1,600 mm ± SD 200 mm), wet (1,900 mm ± SD 200 mm) and dry (1,300 mm ± SD 200 mm)	Fashing et al. 2014, Funk et al., 2015
Carrying capacity	Maximum carrying capacity	0.8 kg/m^2 (guassa grass); 1 kg/m^2 (Helichrysum and Euryops shrubs); 1.2 kg/m^2 (Erica shrubs)	Wodaj et al 2016; Ensslin et al. 2015; Anderson et al. 2010
growth rate	Maximum weekly growth rate	0.017 kg/m^2/week (guassa grass and Helichrysum shrubs); 0.01 kg/m^2/week (Euryops shrubs); 0.007 kg/m^2/week (Erica shrubs)	Running & Zhao 2015; ORNL DAAC 2018
seed production	Percent biomass allocation into seed production	11% (guassa grass); 9% (Helichrysum shrubs); 8 % (Euryops shrubs); 7% (Erica shrubs)	Wilson & Thompson 1989; Bazzaz et al. 1987; Vosse et al. 2008
seed bank	Percent seed biomass that stays in current cell	80% (guassa grass and Erica shrubs); 30% (Helichrysum shrubs); 50% (Euryops shrubs)	Rabinowitz &Rapp 1981; Shiponeni 2003; Shiponeni & Milton 2006; Everson et al. 2009; Molinier & Muller 1938; Mesléard & Lepart 1991; Vosse et al. 2008
germination rate	Percent of seeds that germinate from the soil seedbank	80% (guassa grass); 40% (Erica shrubs); 25% (Helichrysum shrubs); 23% (Euryops shrubs)	Rampton & Ching 1966; Qiu et al. 2010; Doussi & Thanos 1997; Brown et al. 2003; Molinier & Muller 1938; Mesléard & Lepart 1991; Olano et al. 2002
senescence	Percent biomass that dies back each year by species	80% (guassa grass); 40% (Helichrysum shrubs); 20% (Euryops shrubs); 10% (Erica shrubs)	Expert elicitation

5.3 Results

We used a sensitivity analysis to refine our parameterization (Appendix F), and designed a set of scenarios based on our conversations with workshop participants. Results from these scenarios are presented below in order of increasing complexity.

5.3.1 Guassa Harvest Limits and Baseline Scenario

We simulated 30 iterations of each scenario out to 30 years. We combined insights from the co-design process with a sensitivity analysis to determine that the maximum sustainable harvest limit per person was ~270 kg each harvest for no belg climate, ~700 kg each harvest for dry climate, ~900 kg each harvest for average climate, and ~1100 kg each harvest for wet climate (Appendix F). Increasing these limits by even 100-200 kg caused drastic declines in guassa grass biomass and distribution over just five to 15 years when harvesting every three years. These declines were more precipitous when harvests were more frequent (every two years), and less severe when harvests were less frequent (every four years).

We constructed a baseline scenario where people continue to harvest guassa grasses every three years under an average climate regime, which reflects a common desired future for the Guassa area. Under this baseline scenario, average total biomass for guassa grasses was 442 kg/year (Table 5.2), and the grasses occupied about 7% of the total landscape. Each of the 500 agents in our model ended up with an average of 7,024 kg of harvested guassa grass at the end of the 30 years, which equates to about 21,000 birr ($712 USD). Helichrysum shrubs had an average total biomass of 890 kg/year, and occupied 7% of the landscape at the end of the 30 year baseline scenario. Erica shrubs had an average total biomass of 1147 kg/year and occupied 21% of the landscape, while Euryops shrubs had an average total biomass of 1000 kg/year and occupied 9% of the landscape.

5.3.2 Scenario 1: No Human Intervention

In the first scenario, we explored what would happen under different climate regimes if the guassa grass harvest was stopped for the next 30 years. Compared to the baseline scenario, all species had higher biomass in the wet climate and lower biomass in the no belg climate (Table 5.2). Shrubs only performed better than the baseline under the wet climate. Under the dry climate, guassa grasses appeared to be the most resilient, as guassa biomass was about the same as the baseline while all shrub species had 20-22% lower biomass. In the average climate, guassa grasses had an average total biomass of 567 kg/year, an increase of 28% from the baseline scenario. Meanwhile, all shrub species declined slightly (2.3-2.8%) from the baseline scenario under average climate. When comparing across climates within scenario 1, we found that Erica and Euryops shrubs did not differ notably across the dry and no belg climate scenarios, but guassa grasses and Helichrysum shrubs had lower biomass in the no belg climate compared to the dry climate (Figure 5.3). The lack of harvest did not impact the landscape distribution of any species under any climate (Table F3, Appendix F).

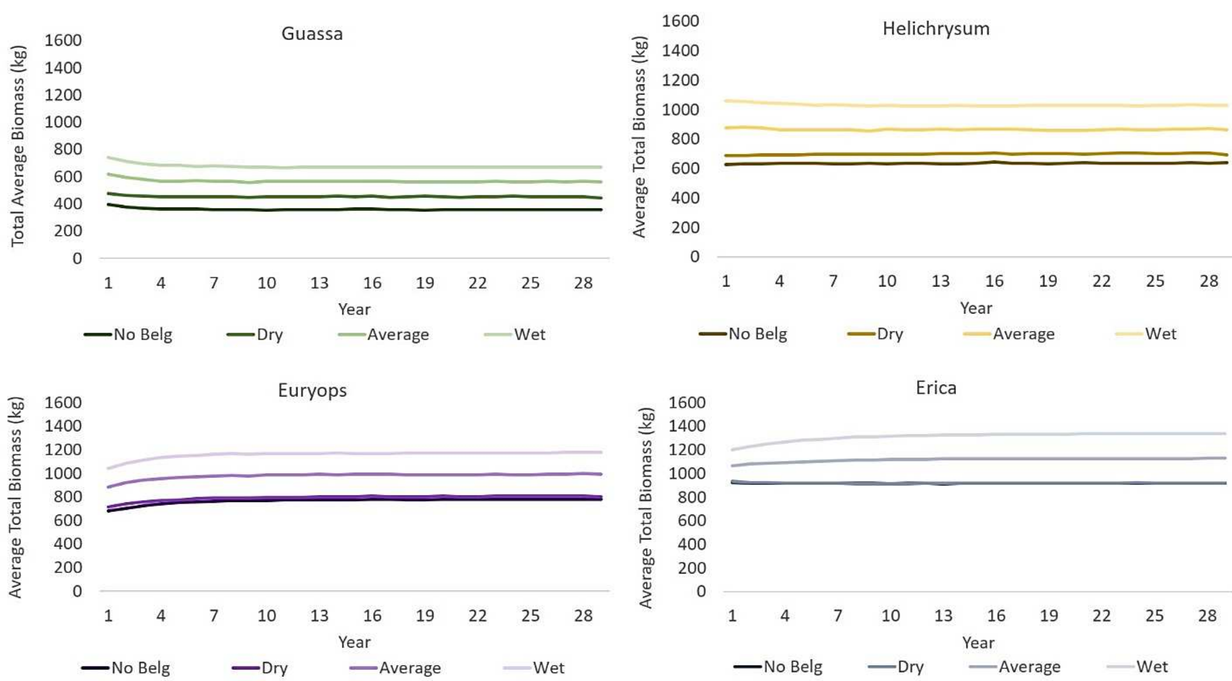

Figure 5.3. For scenario 1 (no guassa harvest), we summed the biomass across all cells in the landscape and calculated the average total biomass across the 30 iterations. While Erica and Euryops shrubs do not appear impacted by the lack of belg rains, both Helichrysum shrubs and guassa grasses declined in the no belg climate.

Table 5.2. Percent change in average total biomass compared to the baseline scenario.

	Average Total Biomass Per Species			
	Guassa	Helichrysum	Erica	Euryops
Baseline Scenario	442 kg/year	890 kg/year	1147 kg/year	1000 kg/year
Scenario 1: No belg climate	-19%	-29%	-20%	-24%
Scenario 1: Dry climate	2%	-22%	-20%	-21%
Scenario 1: Average climate	28%	-3%	-3%	-2%
Scenario 1: Wet climate	53%	16%	14%	16%
Scenario 2: No belg climate, 2 year harvest cycle	-31%	-28%	-19%	-22%
Scenario 2: Dry climate, 2 year harvest cycle	-24%	-18%	-17%	-17%
Scenario 2: Average climate, 2 year harvest cycle	-7%	2%	1%	2%
Scenario 2: Wet climate, 2 year harvest cycle	9%	21%	20%	22%
Scenario 2: No belg climate, 3 year harvest cycle	-27%	-28%	-19%	-23%
Scenario 2: Dry climate, 3 year harvest cycle	-18%	-19%	-18%	-19%
Scenario 2: Average climate, 3 year harvest cycle	0%	0%	0%	0%
Scenario 2: Wet climate, 3 year harvest cycle	18%	19%	18%	20%
Scenario 2: No belg climate, 4 year harvest cycle	-26%	-28%	-19%	-23%
Scenario 2: Dry climate, 4 year harvest cycle	-14%	-20%	-19%	-19%
Scenario 2: Average climate, 4 year harvest cycle	6%	0%	0%	2%
Scenario 2: Wet climate, 4 year harvest cycle	25%	19%	17%	19%

5.3.3 Scenario 2: Changing Guassa Harvest Frequency

In the second scenario, we explored how guassa grass harvests would impact vegetation dynamics if they were conducted more (every two years) or less (every four years) frequently than the baseline, and how this harvest frequency interacts with climate. Compared to the baseline, all species' biomass increased under a wet climate, though guassa performed better than the shrubs when harvesting occurred every four years, and worse than the shrubs when harvesting occurred every two years (Table 5.2). Under an average climate, harvesting more frequently reduced guassa biomass by 7% and harvesting less frequently increased guassa biomass by 6%, while changes to the shrub species were minimal (Figure 5.4). We observed the same pattern under the dry climate, though all species had a 18-19% decrease in biomass overall in this climate. The no belg scenario disproportionally impacted guassa grasses and Helichrysum shrubs, causing a 26-31% decrease in biomass for guassa and a 28% decrease for Helichrysum across all harvest frequencies, while Erica only decreased 19% and Euryops 22-23%. Under the no belg climate, harvesting more or less frequently did not significantly impact guassa biomass. Harvesting every three years resulted in roughly equal performance across species for both the dry and wet climates.

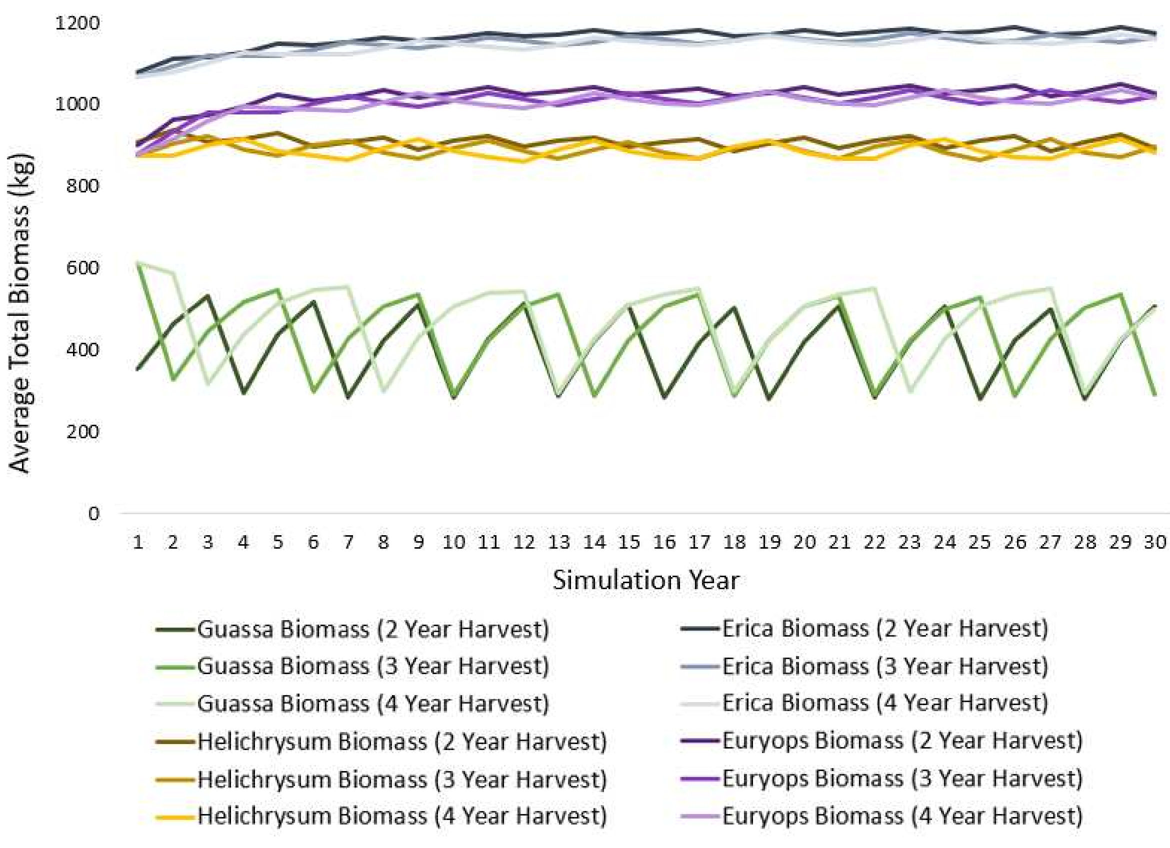

Figure 5.4. Under an average climate regime, harvesting more frequently reduced average total guassa biomass by 7% and harvesting less frequently increased guassa biomass by 6%, while changes to the shrub species were minimaL (0-2%).

Harvesting more frequently resulted in higher per person economic benefits, while harvesting less frequently did not result in proportional declines in economic benefits (Figure 5.5). For example, harvesting every two years in a wet climate increased per person benefits by $271, while harvesting every four years decreased them by only $192 (i.e., a buffer of $79 dollars). Harvesting guassa every two years under a dry climate produced the same per person benefit as harvesting every three years in an average climate. However, there were ecological consequences for guassa grass distribution across the landscape when harvesting every two years, as guassa distribution decreased to 5% of the landscape and Helichrysum shrubs expanded to 9% of the landscape under dry, average, and wet climates (Figure 5.6, Table F3). Meanwhile, harvesting less frequently did not increase guassa distributions across the landscape, indicating that the ecological benefits of harvesting less frequently may not outweigh the economic costs of a less frequent harvest.

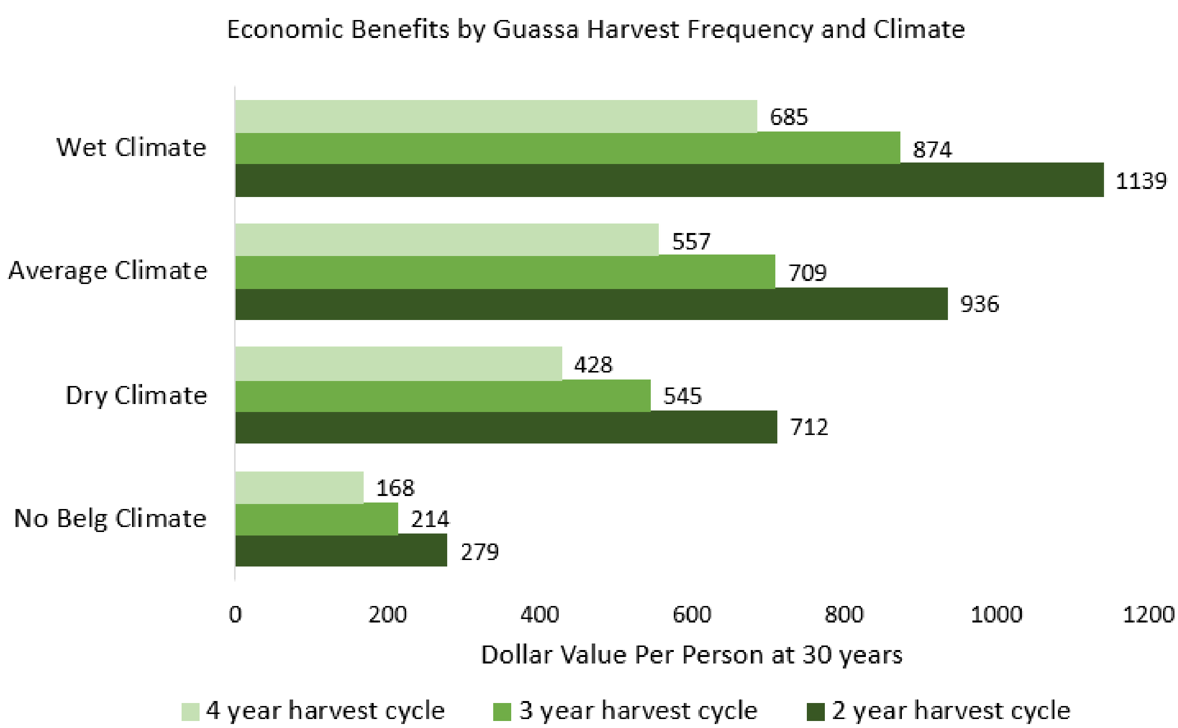

Figure 5.5. Per person economic benefits from guassa grass harvest, compared across climate and harvest frequency.

5.3.4 Scenario 3: Helichrysum Shrub Removal

In the third scenario, we explored how the addition of Helichrysum shrub removal impacted vegetation dynamics. We found that Helichrysum shrubs are much more sensitive to removal compared to the guassa grasses; each person only needs to cut an average of 7-11 shekams (250-350 kg) in any climate to observe drastic changes across the landscape. We maintained the baseline guassa harvest frequency of three years across all climates, using the maximum sustainable harvest we determined for each climate. According to workshop participants, the ideal timing for cutting Helichrysum would be the same year that guassa grasses are harvested, because people would be less likely to illegally harvest guassa during Helichrysum cutting in this situation. We therefore tested a three-year Helichrysum removal cycle and found it caused an 8% increase in guassa grass biomass under an average climate compared to the baseline, but did not change average Helichrysum biomass. This three-year removal cycle reduced guassa biomass losses in the dry and no belg climates without also benefitting Helichrysum, and increased guassa biomass in the wet climate by an additional 10% compared to Scenario 2 (with no Helichrysum removal). However, the Helichrysum cutting appeared to release competitive control on Erica shrubs, which expanded to occupy 34-35% of the landscape – causing range contraction in the three other species of interest (Figure 5.6, Table F3). Lengthening the removal cycle to four years mitigated the range contraction slightly, but many of the benefits to guassa biomass were lost. Increasing the removal cycle to two years had a similar impact on guassa biomass, but resulted in guassa occupying only 2% of the landscape at the end of the 30 year simulations (Figure 5.6).

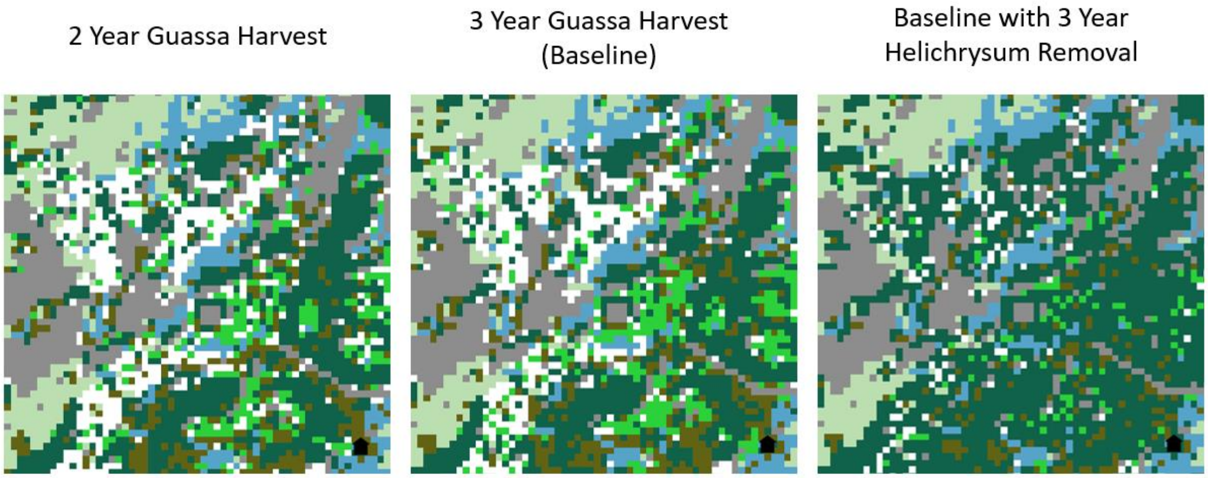

Figure 5.6. Guassa grasses (bright green), Helichrysum shrubs (white), Erica shrubs (dark green), and Euryops shrubs (olive green) forest (brown), stone (grey), and wetlands (blue) are shown across the modeled landscape. The baseline scenario had guassa grasses and Helichrysum shrubs each occupying 7% of the landscape. When harvesting increased to every two years, guassa grass distribution decreased to 5% of the landscape and Helichrysum shrubs expanded to 9% of the landscape under dry, average, and wet climate regimes. The addition of Helichrysum removal appeared to release competitive control on Erica shrubs, which expanded to occupy 34-35% of the landscape, causing range contraction in the three other species of interest.

5.3.5 Learning from ABM Co-design

The ABM itself was made more realistic as a result of the co-design workshops (see Section 2.2), indicating there was some level of mutual learning occurring among workshop participants, including the scientist facilitators. The post-workshop interviews (n=33) encouraged participants to reflect on their learning and describe it. The most common theme we found related to the way people saw the model helping them with planning and management of the Guassa area (n=23, 70%), particularly how it could help control the spread of Helichrysum shrubs, known locally as 'nachillo' (n=10, 30%). Only three people (9%) indicated that the model taught them something specific about the system, such as how harvesting impacts guassa grass growth, or how much each individual should be able to harvest at a time. Four others (12%) explained that the model helped them expand the way they were thinking about options for Guassa management. For example, one man said, "I learned it is possible to plan on the computer about the future of Guassa." Other people attributed learning to the model when it actually came from conversation around the model. For example, one woman "learned from the model that nachillo has to be removed" while another woman reported that she "learned it is possible to control and manage nachillo" – even though the initial model did not show any Helichrysum cutting, it merely inspired conversation about the need for cutting. Still others seemed to use the model to reinforce their existing understanding of system management. For example, one man said, "if we protect our guassa, we will always have green guassa."

Another common theme was how the model helped people see and understand the future (n=17, 51%). This theme occasionally overlapped with the planning and management theme, with one priest explaining "It is important to forecast into the future in order to control the Guassa area." Others emphasized that they would share with people who could not attend the workshop how "it is possible to predict the future of Guassa," even though the scientist facilitators repeatedly explained that the model was not a true prediction of the future. Four people (12%) seemed to understand this caveat well, as they described the need to put only very high quality information into the model to produce good results and see "different possibilities."

A large subset of people emphasized the ecological insights they gained from the model (n=15, 45%), such as the interactions between Helichrysum shrubs and guassa grass. Though only a few people mentioned it in their interviews, there was much excitement in our group discussion when the scientists discussed guassa seed production. Most people had never seen guassa seeds before and did not know they existed, probably because the conservation area is always closed during the main rainy season. Another subset of people valued the model for the way it displayed the different vegetation types in the conservation area (n=13, 39%), both their distribution and amount across the landscape. This level of realism seemed important for making the model accessible to them; one man explained, "the model matches our understanding."

5.4 Discussion

We developed a spatially-explicit model of shrub-grassland dynamics in a community conservation area in the Ethiopian highlands, with parameters derived from remote sensing, literature review, and expert opinion. The purpose of this model was to enable people involved in managing Guassa to explore the individual and combined effects of social and ecological factors controlling the spread of these native shrubs, and to evaluate different strategies to control their expansion while maximizing the amount of guassa grass available for harvest.

Our model results supported continuing current management of harvesting guassa grasses every three years, as this frequency appears to mitigate negative ecological impacts across climate types while retaining economic benefits for local communities. However, we stress the need for managers to be sensitive to climatic conditions, as our model identified significantly lower maximum harvest limits during the no belg climate in particular. Our model admittedly treated climate in a simplified way, where each year followed the same seasonal pattern and general precipitation amount. This discrete treatment of climatic conditions was helpful during this initial exploration as it allowed us to isolate the impacts of precipitation patterns in relation to harvest frequency and intensity. A second version of the model that integrates periodic no belg, dry, and wet years into the average climate would create a more realistic model that could help managers identify consistent harvest amounts and frequencies.

The removal of only Helichrysum shrubs in our model caused an unexpectedly rapid increase of Erica shrubs across the conservation area, and a decrease in the distribution of guassa grasses. However, guassa grass biomass increased despite this range constriction. These results indicate that managers should be cautious of even low-level Helichrysum removal, and should weigh the benefits and drawbacks of increasing guassa biomass while losing overall landscape cover as a possible unexpected outcome. Unlike guassa grasses, we did not find that altering the amount of Helichrysum removed was needed to preserve desirable outcomes across climate types.

However, our current model has each person removing 90% of biomass in each cell they visit, which we would consider decreasing in further iterations of the model.

Another possible management option to test with the model would be to allow harvesting of Erica shrubs, which are considered a highly desirable firewood species. Firewood harvest was banned due to possible negative impacts to rodent populations, which account for more than 80% of the diet of the endangered Ethiopian wolf (Ashenafi et al. 2005). Research in the Guassa area showed that while total rodent populations were unaffected by firewood harvest, the proportion of wolves' preferred prey species, the Abyssinian grass rat (*Arvicanthis abyssinicus*), was lower where firewood harvesting occurred (Ashenafi et al. 2012). However, the method of removal and shrub species are important to consider, as Euryops shrubs are often uprooted completely, leaving open areas that may be less desirable habitat for rodents (Ashenafi et al. 2012). We propose that selective cutting of Erica shrubs in addition to Helichrysum shrubs may present a viable management option for controlling shrub expansion, which would likely not have such negative consequences for rodent populations and which would have additional economic benefits for local people.

Because the model was designed as a decision support and learning tool, we selected to represent the vegetation dynamics at a landscape scale using a modified logistic growth curve rather than a highly detailed process-based model. We feel this simplification is justified given that our focus has been to use the model as an exploratory rather than a predictive tool to shed light on how multiple interacting factors impact vegetation dynamics. However, the co-design process resulted in a more realistic model than scientists originally intended, and workshop participants continuously sought quantifiable outcomes rather than qualitative or exploratory learning through the model. Our inclusion of multiple shrub species is a novel aspect of the model that is not seen in most spatial shrub encroachment models (Komac et al. 2013; Cao et al. 2018), and which was due in large part to the co-design process, as workshop participants insisted on a certain level of realism in the vegetation patterns seen in the model. In fact, one of the most common types of learning experienced by workshop participants was an improved understanding of how these vegetation types are distributed across the landscape. Yet, workshop participants were more interested in the model for its ability to provide quantitative answers such as the ideal amount of Helichrysum to cut, how much guassa grass could be harvested at what frequency, and what that meant for the amount of income generated for the community. One local leader ended the co-design process with a very clear statement, "if you tell us how much Helichrysum to cut, we will cut it." This statement reflected a high level of trust in the model and scientific process, despite the caveats and cautions presented by scientists throughout the co-design process. Therefore, while this exploratory model has been helpful for scientists thinking about the system, we believe the next iteration of this model needs to be calibrated to locally-collected data to provide more accurate estimations and better meet the needs of local management.

5.5 Conclusion

Our results support the idea that collaboratively designed agent-based models can inspire learning among the people involved in managing a social-ecological system. We intentionally attempted to design our model at an intermediate level of complexity, as this has been suggested as a way to maximize learning (Grimm et al. 2005; Le Page & Perrotton 2018). However, participants in our co-design process urged increasingly realistic representations in the model, and did not find a qualitative, exploratory use of the model particularly helpful for achieving their management objectives. Yet, the co-design process did encourage learning, particularly about the ecology and biogeography of the area, and illuminated the ability of people with local knowledge to improve scientific tools and outputs. Additionally, this process garnered support among the local management team for increased ecological data collection in the Guassa area, so that future iterations of this model can better meet management needs.

CHAPTER 6

CONCLUSION

This dissertation advances our understanding of how social-ecological models can support knowledge co-production and learning in collaborative environmental management. Key insights from a global survey emphasize the importance of mutual respect and power sharing among participants in a collaborative process, and evidence from an Ethiopian case study demonstrates the impact of different kinds of social-ecological models on knowledge co-production and learning in a particular socio-cultural context.

In Chapter 2, I presented a conceptual model to guide the implementation of environmental transdisciplinary work (TDW), which is gaining momentum as a research approach that brings together diverse teams to produce solutions to social-ecological problems. Survey results provided support for 24 activities that can be considered TDW best practices for a wide range of social-ecological contexts, including things like identifying activities to build credibility across participants and fostering capacity to conduct the proposed methods. I demonstrated how these activities can help overcome the key barriers in environmental TDW, such as insufficient time and power dynamics, with additional lessons from the broader literature. Our results suggest that flexibility, mutual respect, and collaborative spirit are the most important skills and characteristics for successful TDW. I hope these best practices will help people organizing future TDW projects to focus limited time and resources on activities with demonstrated effectiveness, though a grain of salt is needed as the survey respondents were largely academics from Western countries. I also hope that the conceptual model will impress upon TDW participants the value of deep, place-based understanding through an exploratory phase at the beginning of a project.

In Chapter 3, I presented findings from my own implementation of an exploratory phase at the beginning of a TDW process in a community conservation area in the Ethiopian highlands

(Guassa). I used a multiple evidence based (MEB) approach (Tengö et al. 2014) to knowledge co-production, which brought together insights from local and scientific knowledge using ethnographic and remote sensing methods to produce a holistic understanding of environmental change and its impacts on ecosystem services. Results with high agreement across knowledge systems clarified and reinforced understanding of certain threats and changes to Guassa, such as the rapidly declining native forests, the disappearing belg rainy season, and the impact of insecure land tenure on natural resource extraction. Compelling areas of disagreement highlighted topics in need of further investigation, including increased attention to the spatial and temporal variability of change across a seemingly homogeneous cultural landscape, and the process of shrub encroachment into the protected grassland. These results highlight how integrating local and scientific knowledge can reveal gaps in system understanding, and how contradictory observations across knowledge systems can inspire new understanding and future research. Findings from this exploratory phase emphasize the value of an iterative approach that allows local participants to more confidently inform remote sensing interpretations, and in turn allow scientists to clarify translations and interpretations so that local knowledge is accurately represented.

In Chapter 4, I presented an analysis of mental models held by four social groups involved in managing Guassa, which we iteratively constructed and revised over the course of a year. These mental models emphasized the primacy of governance (e.g., political instability, regime change) and economics (e.g., income, unemployment, crops) in peoples' conception of the social-ecological system. I also assessed the learning experienced by participants in this collaborative modeling process, revealing that participants experienced both single- and double-loop social learning. For example, some people changed the timeline they used to think about the Guassa area (from 5 years to more like 20-30 years), and others formed a newfound appreciation for the number of factors influencing each other in the system. The collaborative modeling process also encouraged learning among the different social groups, which contributed to stronger and more trusting relationships.

This kind of iterative exploration of individual and group mental models is quite rare in the literature, and holds promise as a tool for promoting mutual respect and understanding in collaborative environmental management.

In Chapter 5, I presented the process of co-designing a spatially-explicit agent-based model of shrub encroachment into the Guassa area, which we identified in Chapter 3 as a critical sustainability concern. The model enabled people involved in managing Guassa to explore the individual and combined effects of social and ecological factors controlling the spread of these native shrubs, and to evaluate different strategies to control their expansion while maximizing the amount of guassa grass available for harvest. The model results suggested that cutting Helichrysum shrubs might have the unexpected and unintended consequence of removing competitive controls on other shrub species in the conservation area, thus reducing rather than improving the growth and distribution of the desirable guassa grasses. Though the model was intended as a prospective rather than predictive model, participants in the co-design process desired increasingly realistic representations of the system so that it could be used to answer specific management questions like how many kilos of Helichrysum shrubs to cut each year. I assessed the learning experienced by participants in this collaborative modeling process, revealing that the process enhanced learning about the ecology and biogeography of the area, and encouraged people to plan for and consider the future of the Guassa area. This process allowed Guassa managers to become more familiar with scientific tools like simulation models, and empowered them to suggest improvements to the model so that it would fit their needs.

Chapters 3-5 of this dissertation describe several years of collaborative research, which corresponds roughly to Steps 1-6 of the conceptual model in Chapter 2. This process has been incredibly important for building strong, trusting relationships among the local farmers, government workers, conservation officers, and scientists (including myself) involved in management. As the issue of shrub encroachment rose to the foreground through this collaborative process, we started writing grants to support another collaborative project that would investigate the ecological shrub-grass interactions in Guassa. We secured funding to support another PhD student from Addis Ababa University, Shambel Alemu, to continue this important work and begin another TDW cycle. In the co-design workshop from Chapter 5, we used half a day to discuss Shambel's proposed research and what kinds of community support he needed, corresponding with Step 7 of the conceptual model. The core team for this next project will likely be much smaller in scope, more like 9-15 people instead of the 40+ involved in my dissertation fieldwork. However, we plan to continue large-group meetings at least once a year to discuss initial findings from Shambel's work, and to refine the agent-based model based on the data he collects.

Moving forward, I urge future research on the social and cultural aspects of collaborative environmental management in different contexts around the world, and the way that different modeling paradigms enable or constrain these processes. Common pool resource theory tells us that the ecological characteristics of the system matter for how people use and make decisions about resources (Epstein et al. 2013), thus the way we choose to model ecological systems may also impact the socio-cultural processes involved in collaborative environmental management. However, the relationship between model design and management concepts like social learning, adaptive capacity, and collective action has not been well studied (Radinsky et al. 2017). Because long-term adaptive strategies are only thought to be sustainable when they move beyond the individual and permeate a broader culture or society (Berkes & Jolly 2002), it is critical to understand how modeling can facilitate or constrain social learning and the subsequent impacts on adaptive capacity and collective action.

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APPENDICES

APPENDIX A

Survey: Collaborative Research for Environmental Sustainability

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Q1 This study aims to provide a global assessment of collaborative research practices related to environmental sustainability. Results will be used to better understand the activities and outcomes associated with successful collaborative environmental research worldwide.

Thank you for taking the time to contribute to our survey. Please remember that your responses are voluntary, and will remain confidential. We estimate the survey will take 20 - 25 minutes to complete.

If you have any questions about the research, please contact Cara Steger at Cara.Steger@Colostate.edu. If you have any questions about your rights as a volunteer in this research, please contact the CSU Institutional Review Board at: RICRO_IRB@mail.colostate.edu; (970) 491 - 1553.

Q2: Screening Question

In this study, we define collaborative research as sustained engagement between researchers (professional scientists or scholars) and practitioners (e.g., resource users, natural resource managers, policy makers). Do you have previous experience with collaborative research?

○ Yes (1)

○ No (2)

Q9 The Mountain Sentinels Collaborative Network identified seven broad phases of collaborative research and practice, with specific activities within each phase. We ask that you draw on your overall experience with collaborative research to rank the activities within each section in order of importance for project success, even if you have not used them yourself.

Q10 1. Activities Involved in **Exploration**

Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.
______ Identify activities to build credibility across participants (researchers and practitioners)
______ Identify concerns of the different groups involved
______ Learn a locally-spoken language
______ Connect with individuals who are well-informed, helpful, or who have extensive networks
______ Connect with stakeholders who are often marginalized in this area (e.g., women, youth)
______ Attend meetings of the different groups involved
______ Assess the context, history, or on-going initiatives surrounding this place or problem
______ Other
______ Other

Q11 2. Activities Involved in **Partnership Formation and Design**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.
______ Identify shared interests among participant groups
______ Identify a core leadership team composed of individuals from each participant group
______ Identify mutually appropriate spaces for interactions (e.g., village center, classrooms)
______ Include researchers who are interdisciplinary (i.e., work across disciplines)
______ Include individuals with experience working with these participant groups or in this location
______ Conduct a smaller, preliminary project
______ Engage face-to-face outside of project-related meetings (e.g., social events, ice breakers)
______ Define the roles and duties of individuals and participant groups
______ Hold regular meetings with diverse participant groups
______ Check the credentials or history of key participants, formally or informally
______ Other
______ Other

Q12 3. Activities Involved in **Co-Designing Research and Practice**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.
______ Collaboratively define the specific issue(s) being addressed
______ Collaboratively develop project goals for both research and practice
______ Collaboratively develop data collection methods
______ Collaboratively develop research questions or hypotheses
______ Other
______ Other

Q13 4. Activities Involved in **Co-Producing Research and Practice**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.
______ Foster capacity to conduct agreed upon methods (i.e., hold training sessions)
______ Collaboratively analyze data collected (e.g., can be qualitative, assess trends)
______ Collaboratively develop outputs or outcomes (e.g., maps, capacity building)
______ Distribute responsibilities among participants
______ Collaboratively interpret results (e.g., mutual review of data and analyses)
______ Other
______ Other

Q14 5. Activities Involved in **Learning From Each Other**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.
______ Attend each other's meetings and events
______ Express mutual respect for one another's knowledge, experiences, or worldviews
______ Share experiences with each other (e.g., participate in household tasks, go on field trips)
______ Try to accommodate different processes for learning, understanding, or decision-making
______ Explore how you will use different types of knowledge in the research and practice
______ Other
______ Other

Q15 6. Activities Involved in **Communicating and Acting on Relevant Learning**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.

______ Hold workshops or meetings to exchange feedback with decision makers
______ Discuss how to expand upon the learning from this research
______ Create a group of high profile individuals with power to impact the issue of interest
______ Communicate results to practitioners beyond the immediate project partners
______ Communicate results to the broader public
______ Communicate results to the academic community
______ Other
______ Other

Q16 7. Activities Involved in **Developing Future Collaborative Opportunities**
Please rank the top **three** activities in order of importance for successful collaborative research, where 1 =most important.

______ Reflect on the strengths and weaknesses of the collaborative research process
______ Discuss opportunities for the next collaborative experience
______ Assess participants' learning
______ Reflect on the quality of outcomes and outputs from the collaborative process
______ Reflect on the usefulness of outcomes and outputs for practitioner groups
______ Other
______ Other

Q17 In your opinion, what is the most difficult phase of collaborative research?

○ Exploration

○ Partnership Formation and Design

○ Co-Designing Research and Practice

○ Co-Producing Research with Practice

○ Learning From Each Other (on-going throughout project)

○ Communicating and Acting on Relevant Learning

○ Developing Future Collaborative Opportunities

Q18 Is there a phase missing from the process we propose? If so, what kinds of activities might be involved in that phase?

____

____

____

____

____

Q41 Below are some of the most common barriers encountered in collaborative research. Please rank the **three** most significant barriers to project success, where 1 = most important.

______ Participants were not very interested in collaborative research
______ Participants did not have enough time to contribute to collaborative research and practice
______ Participants unable to agree on actions to take
______ Participants were unable or unwilling to take action
______ Language barriers led to miscommunication
______ Lack of effective communication between participants (e.g., trouble with honesty or clarity)
______ Power inequalities were present among participants
______ Certain participants' goals, plans, outputs, or methods dominated over other groups
______ Difficulty identifying shared interests among participants early on
______ Difficulty building consensus on specific methods and protocols
______ Difficulty finding practitioners willing to teach other partners about their culture
______ Difficulty finding researchers willing to train less-experienced partners in scientific analysis
______ The methods carried out did not address the original questions
______ The project lacked financial support to carry out the full collaborative process.
______ Certain participants were not willing to explore other ways of knowing (e.g., natural scientist rejects validity of qualitative approach, or policy maker refuses to acknowledge importance of cultural perspective)
______ Other
______ Other

Q42 Do you have any recommendations for how to overcome the three most significant barriers you identified?

____

____

____

____

____

Q19
Collaborative research requires skills that are not historically emphasized in academic training, and which may not be culturally shared by practitioners. Please select (by clicking) the **three** most important skills and characteristics for successful collaborative research.

- ☐ Generosity
- ☐ Flexibility
- ☐ Humility
- ☐ Patience
- ☐ Collaborative spirit
- ☐ Interdisciplinary training
- ☐ Mutual respect
- ☐ Persistence
- ☐ Trust
- ☐ Other ____

Q20 Please think of your most successful collaborative research project. Describe briefly what it was about and why you consider it successful.

____

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Q21 On a scale from 1 - 10, how successful was this project?

(1 = "not at all successful" and 10 = "perfect, just as planned or better")

	0	1	2	3	4	5	6	7	8	9	10
Your Most Successful Collaborative Research Project ()											

Q22 In what country or countries did your most successful collaborative research occur?

____

Q23
Who initiated your most successful collaborative research project? (select all that apply)

- ☐ Researchers (professional scientists/scholars/academics)
- ☐ Practitioners (e.g., environmental managers, policy makers, NGO workers, etc.)
- ☐ Other Stakeholders (e.g., resource users, concerned citizens, etc.)

Q24 How long did you work in this area before beginning your most successful collaborative research project?

____

Q61 How long did your most successful collaborative research project last?

____

Q25 In what system(s) did your most successful collaborative research project occur? (select all that apply)

- ☐ Arctic or Antarctic zones
- ☐ Coastal Areas
- ☐ Deserts
- ☐ Forests
- ☐ Grasslands
- ☐ Mountains
- ☐ Oceans
- ☐ Protected Areas
- ☐ Urban or peri-urban Areas
- ☐ Other (please describe): ____

Q26 What kinds of people did you collaborate with on your most successful collaborative research project? (select all that apply)

- ☐ Farmers
- ☐ Fishers
- ☐ Government
- ☐ Non-profit or NGO
- ☐ Pastoralists or Ranchers
- ☐ Private Industry (e.g., mining, timber, manufacturing)
- ☐ Service Sector (e.g., trade, tourism)
- ☐ Other ____

Q27 What kinds of learning, if any, did participants experience throughout your most successful collaborative research project? Learning can be assessed formally or informally. (select all that apply)

- ☐ We did not assess participant learning in any way.
- ☐ Participants changed their ideas about which actions to take regarding the problem.
- ☐ Participants realized the problem was more complicated, or expanded how they thought about the problem.
- ☐ Participants changed their understanding of how things are related to each other within the system of interest.
- ☐ Participants reported different values motivated them over the course of the project.
- ☐ Participants changed formal or informal norms, rules, or institutions for addressing the problem of interest.
- ☐ Participants changed their religious or moral beliefs about the problem of interest.

Q28 We are interested in understanding how models are used in collaborative research. Did you use qualitative and/or quantitative modeling in your most successful collaborative research project? (select all that apply)

- ☐ Qualitative modeling
- ☐ Quantitative modeling
- ☐ We did not use any modeling
- ☐ I do not know what kinds of modeling approaches were used in the project

---

Display This Question:

If We are interested in understanding how models are used in collaborative research. Did you use qua... = Quantitative modeling

Or We are interested in understanding how models are used in collaborative research. Did you use qua... = Qualitative modeling

Q29 Please describe the modeling approach briefly.

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____

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____

____

Q30 Please refer to your most successful collaborative research problem when answering the questions below.

Q31 1. Activities Involved in **Exploration**

Please **select (by clicking) all the activities** you conducted in your most successful collaborative research project.

- ☐ Assess the context, history, and on-going initiatives surrounding this place or problem (e.g., through situation analysis, participatory mapping, etc.)
- ☐ Identify activities to build credibility across participant groups (i.e. researchers and practitioners)
- ☐ Identify concerns of the different participant groups involved
- ☐ Learn a locally-spoken language
- ☐ Connect with individuals who are well-informed, helpful, or who have extensive networks
- ☐ Connect with stakeholders who are often marginalized in this area (e.g. women, youth)
- ☐ Attend meetings of the different participant groups involved
- ☐ Other ____
- ☐ Other ____

Q32 2. Activities Involved in **Partnership Formation and Design**
Please **select all the activities** you conducted in your most successful collaborative research project.

- ☐ Identify shared interests between participant groups
- ☐ Identify a core leadership team composed of individuals from each participant group
- ☐ Identify mutually appropriate spaces for interactions (e.g., village center, classrooms)
- ☐ Include researchers who are interdisciplinary (i.e., work across disciplines)
- ☐ Include individuals who have experience working with these participant groups or in this location
- ☐ Conduct a smaller, preliminary project
- ☐ Engage face-to-face outside of project-related meetings (e.g., social events, ice breakers)
- ☐ Define the roles and duties of individuals and participant groups
- ☐ Hold regular meetings with diverse participant groups
- ☐ Check the credentials or history of all participants, formally or informally
- ☐ Other ____
- ☐ Other ____

Q33 3. Activities Involved in **Co-Designing Research and Practice**
Please **select all the activities** you conducted in your most successful collaborative research project.

- ☐ Collaboratively define the specific issue(s) being addressed
- ☐ Collaboratively develop project goals for both research and practice
- ☐ Collaboratively develop data collection methods
- ☐ Collaboratively develop research questions or hypotheses
- ☐ Other ____
- ☐ Other ____

Q34 4. Activities Involved in **Co-Producing Research and Practice**
Please **select all the activities** you conducted in your most successful collaborative research project.

- ☐ Foster capacity to conduct agreed upon methods (i.e., hold training sesions)
- ☐ Collaboratively analyze data collected (e.g., can be qualitative, assess trends)
- ☐ Collaboratively develop outputs or outcomes (e.g., maps, manuscripts, capacity building)
- ☐ Distribute responsibilities among participants
- ☐ Collaboratively interpret results (e.g., mutual review of data and analyses)
- ☐ Other ____
- ☐ Other ____

Q35 5. Activities Involved in **Learning From Each Other**
Please **select all the activities** you conducted in your most successful collaborative research project.

- ☐ Attend each other's meetings and events
- ☐ Express mutual respect for one another's knowledge, experiences, or worldviews
- ☐ Share experiences with each other (e.g., participate in household tasks, go on field trips)
- ☐ Try to accommodate different processes for learning, understanding, or decision-making
- ☐ Explore how you will use different types of knowledge in the research process
- ☐ Other ____
- ☐ Other ____

Q36 6. Activities Involved in **Communicating and Acting on Relevant Learning**
Please **select all the activities** you conducted in your most successful collaborative research project.

☐ Hold workshops or meetings to exchange feedback with decision makers

☐ Discuss how to expand upon the learning from this research

☐ Create a group of high profile individuals with power to impact the issue of interest

☐ Communicate results to practitioners beyond the immediate project partners

☐ Communicate results to the broader public

☐ Communicate results to the academic community

☐ Other ____

☐ Other ____

Q37 7. Activities Involved in **Developing Future Collaborative Opportunities**
Please **select all the activities** you conducted in your most successful collaborative research project.

- ☐ Reflect on the strengths and weaknesses of the collaborative research process
- ☐ Discuss opportunities for the next collaborative experience
- ☐ Assess participants' learning
- ☐ Reflect on the quality of outcomes and outputs from the collaborative process
- ☐ Reflect on the usefulness of outcomes and outputs for practitioners and stakeholders
- ☐ Other ____
- ☐ Other ____

Q38
Please continue to refer to your most successful collaborative project when responding.

This is the second to last page of questions - you're almost finished!

Q39 How many of these outputs did you produce during the course of your most successful collaborative research project?
_______ Curriculum materials
_______ Feedback workshops
_______ Maps
_______ News media
_______ Peer-reviewed publications
_______ Policy briefs
_______ Radio programs
_______ Videos or films
_______ Other:
_______ Other:

Q40 To what extent did your most successful collaborative research project impact decision-making and/or policy?

- ○ Not at all
- ○ Low Impact
- ○ Medium Impact
- ○ High Impact

Q62
Congratulations, you made it! This is the last page of the survey.

Q3 Approximately how many collaborative research projects have you been involved in throughout your career? Please include attempted collaborative research projects that may not have been successful.

- ○ 1 - 3 projects
- ○ 4 - 6 projects
- ○ 7 - 9 projects
- ○ 10 + projects

Q4 For how many years have you been conducting collaborative research?

- ○ <1 – 5 years
- ○ 6 - 10 years
- ○ 11 - 15 years
- ○ 16 - 20 years
- ○ 21 + years

Q5 Where has most of your collaborative research occurred? (select all that apply)

- ☐ North America
- ☐ South America
- ☐ Central America
- ☐ Europe
- ☐ Africa
- ☐ Asia
- ☐ Oceania

Q6 How do you self-identify? (select all that apply)

- ☐ Researcher (professional scientist/scholar)
- ☐ Practitioner (e.g., environmental manager, policy maker, NGO worker, etc.)
- ☐ Other Stakeholder (e.g., resource user, concerned citizen, etc.)

Q7 With which gender do you most identify? (Select all that apply)

- ☐ Male
- ☐ Female
- ☐ Non-binary
- ☐ Transgender
- ☐ Other (please define or prefer not to respond) ________________

Q8 Where are you primarily based geographically?

- ☐ North America
- ☐ South America
- ☐ Central America
- ☐ Europe
- ☐ Africa
- ☐ Asia
- ☐ Oceania

Q43 Is there anything else you would like to share about your collaborative research experiences?

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Q44 Would you allow us to follow up with you regarding your responses to this survey? If so, please include your name and email address here. (Please note that your name and contact information will be kept confidential within the research team.)

____

APPENDIX B

Table B.1. All chi-squared and Fisher's exact tests of association conducted in Chapter 2.

Pearson's Chi-squared test with Yates' continuity correction OR Fisher's Exact Test						
Test	**Predictor**	**Response**	**X-squared**	**df**	**p-value**	**Adjusted significance level**
Chi-squared	Gender	Geography	0.611	1	0.434	**0.017**
Chi-squared	Gender	Positionality	0.094	1	0.759	
Chi-squared	Geography	Positionality	1.864	1	0.172	
Chi-squared	Geography	Learning Outcomes	0.344	3	0.952	**0.017**
Chi-squared	Gender	Learning Outcomes	0.183	3	0.980	
Fisher's	Positionality	Learning Outcomes	---		0.604	
Fisher's	Geography	Policy Outcomes	---		0.542	**0.017**
Fisher's	Gender	Policy Outcomes	---		0.054	
Fisher's	Positionality	Policy Outcomes	---		0.439	
Fisher's	ProjectInitiated	Learning Outcomes	---		0.148	**0.01**
Fisher's	LengthPreProject	Learning Outcomes	---		0.520	
Fisher's	LengthProject	Learning Outcomes	---		0.520	
Fisher's	ModelingType	Learning Outcomes	---		0.118	
Chi-squared	Modeling	Learning Outcomes	7.193	3	0.066	
Fisher's	ProjectInitiated	Policy Outcomes	---		0.008	**0.01**
Fisher's	LengthPreProject	Policy Outcomes	---		0.642	
Fisher's	LengthProject	Policy Outcomes	---		0.024	
Fisher's	Modeling	Policy Outcomes	---		0.042	
Fisher's	ModelingType	Policy Outcomes	---		0.398	
Chi-squared	Curriculum/NoCurriculum	Learning Outcomes	5.271	3	0.153	**0.006**
Chi-squared	Maps/NoMaps	Learning Outcomes	0.064	3	0.996	
Chi-squared	NewsBrief/NoNewsBrief	Learning Outcomes	8.215	3	0.042	
Chi-squared	PolicyBrief/NoPolicyBrief	Learning Outcomes	0.964	3	0.810	
Fisher's	Workshop/NoWorkshop	Learning Outcomes	---		0.036	

Fisher's	Peer-ReviewedPubs/NoPeer-ReviewedPubs	Learning Outcomes	---		0.466	
Fisher's	Radio/NoRadio	Learning Outcomes	---		0.061	
Fisher's	Video/NoVideo	Learning Outcomes	---		0.077	
Fisher's	OtherPubs/NoOtherPubs	Learning Outcomes	---		0.479	
Fisher's	Curriculum/NoCurriculum	Policy Outcomes	---		0.128	**0.006**
Fisher's	Workshop/NoWorkshop	Policy Outcomes	---		0.909	
Fisher's	Maps/NoMaps	Policy Outcomes	---		0.523	
Fisher's	NewsBrief/NoNewsBrief	Policy Outcomes	---		0.420	
Fisher's	Peer-ReviewedPubs/NoPeer-ReviewedPubs	Policy Outcomes	---		0.018	
Fisher's	PolicyBrief/NoPolicyBrief	Policy Outcomes	---		0.593	
Fisher's	Radio/NoRadio	Policy Outcomes	---		0.036	
Fisher's	Video/NoVideo	Policy Outcomes	---		0.861	
Fisher's	OtherPubs/NoOtherPubs	Policy Outcomes	---		0.878	
Chi-squared	Farmer/NonFarmer	Learning Outcomes	6.181	3	0.103	**0.007**
Chi-squared	NGO/NonNGO	Learning Outcomes	3.473	3	0.324	
Fisher's	Fisher/NonFisher	Learning Outcomes	---		0.326	
Fisher's	Government/NonGovernment	Learning Outcomes	---		0.165	
Fisher's	Ranchers/NonRanchers	Learning Outcomes	---		0.396	
Fisher's	PrivateSector/NonPrivateSector	Learning Outcomes	---		0.752	
Fisher's	ServiceIndustry/NonServiceIndustry	Learning Outcomes	---		0.640	
Fisher's	Farmer/NonFarmer	Policy Outcomes	---		0.707	**0.007**
Fisher's	Fisher/NonFisher	Policy Outcomes	---		0.079	

Fisher's	Government/NonGovernment	Policy Outcomes	---		0.038	
Fisher's	NGO/NonNGO	Policy Outcomes	---		0.157	
Fisher's	Ranchers/NonRanchers	Policy Outcomes	---		0.077	
Fisher's	PrivateSector/NonPrivateSector	Policy Outcomes	---		0.598	
Fisher's	ServiceIndustry/NonServiceIndustry	Policy Outcomes	---		0.378	
Fisher's	Arctic/NonArctic	Learning Outcomes	---		0.260	**0.004**
Fisher's	Coasts/NonCoasts	Learning Outcomes	---		0.375	
Fisher's	Deserts/NonDeserts	Learning Outcomes	---		0.575	
Fisher's	Forests/NonForests	Learning Outcomes	---		0.799	
Fisher's	Grasslands/NonGrasslands	Learning Outcomes	---		0.560	
Fisher's	Mountains/NonMountains	Learning Outcomes	---		0.322	
Fisher's	Oceans/NonOceans	Learning Outcomes	---		0.852	
Fisher's	ProtectedAreas/NonProtectedAreas	Learning Outcomes	---		0.306	
Fisher's	Urban/NonUrban	Learning Outcomes	---		0.649	
Fisher's	Agriculture/NonAgriculture	Learning Outcomes	---		1.000	
Fisher's	Savanna/NonSavanna	Learning Outcomes	---		0.440	
Fisher's	Aquatic/NonAquatic	Learning Outcomes	---		0.028	
Fisher's	Arctic/NonArctic	Policy Outcomes	---		0.407	**0.004**
Fisher's	Coasts/NonCoasts	Policy Outcomes	---		1.000	
Fisher's	Deserts/NonDeserts	Policy Outcomes	---		0.245	
Fisher's	Forests/NonForests	Policy Outcomes	---		0.396	
Fisher's	Grasslands/NonGrasslands	Policy Outcomes	---		0.753	

Fisher's	Mountains/Non Mountains	Policy Outcomes	---		0.987	
Fisher's	Oceans/NonOceans	Policy Outcomes	---		0.328	
Fisher's	ProtectedAreas/NonProtectedAreas	Policy Outcomes	---		0.515	
Fisher's	Urban/NonUrban	Policy Outcomes	---		0.165	
Fisher's	Agriculture/Non Agriculture	Policy Outcomes	---		0.169	
Fisher's	Savanna/NonSavanna	Policy Outcomes	---		0.385	
Fisher's	Aquatic/NonAquatic	Policy Outcomes	---		0.391	
Chi-squared	Positionality	Flexibility/NoFlexibility	6.943	1	0.008	**0.017**
Chi-squared	Geography	Flexibility/NoFlexibility	1.543	1	0.214	
Chi-squared	Gender	Flexibility/NoFlexibility	0.000	1	1.000	
Chi-squared	Positionality	Humility/NoHumility	1.312	1	0.252	**0.017**
Chi-squared	Geography	Humility/NoHumility	0.134	1	0.714	
Chi-squared	Gender	Humility/NoHumility	0.470	1	0.493	
Chi-squared	Positionality	Patience/NoPatience	0.617	1	0.432	**0.017**
Chi-squared	Geography	Patience/NoPatience	0.013	1	0.909	
Chi-squared	Gender	Patience/NoPatience	0.959	1	0.328	
Chi-squared	Positionality	CollaborativeSpirit/NoCollaborativeSpirit	3.830	1	0.050	**0.017**
Chi-squared	Geography	CollaborativeSpirit/NoCollaborativeSpirit	0.148	1	0.700	
Chi-squared	Gender	CollaborativeSpirit/NoCollaborativeSpirit	0.000	1	1.000	
Chi-squared	Geography	Interdisciplinary/NoInterdisciplinary	0.031	1	0.861	**0.017**
Chi-squared	Gender	Interdisciplinary/NoInterdisciplinary	0.074	1	0.786	
Fisher's	Positionality	Interdisciplinary/NoInterdisciplinary	---		0.590	

Chi-squared	Positionality	MutualRespect/NoMutualRespect	0.123	1	0.725	**0.017**
Chi-squared	Geography	MutualRespect/NoMutualRespect	0.184	1	0.668	
Chi-squared	Gender	MutualRespect/NoMutualRespect	0.000	1	1.000	
Chi-squared	Positionality	Persistence/NoPersistence	0.330	1	0.566	**0.017**
Chi-squared	Geography	Persistence/NoPersistence	0.010	1	0.919	
Chi-squared	Gender	Persistence/NoPersistence	0.622	1	0.430	
Chi-squared	Positionality	Trust/NoTrust	0.175	1	0.676	**0.017**
Chi-squared	Geography	Trust/NoTrust	2.290	1	0.130	
Chi-squared	Gender	Trust/NoTrust	0.789	1	0.374	
Fisher's	Gender	Generosity/NoGenerosity	---		0.348	**0.017**
Fisher's	Geography	Generosity/NoGenerosity	---		1.000	
Fisher's	Positionality	Generosity/NoGenerosity	---		0.730	
Fisher's	A.1.1: Assess context	Learning Outcomes	---		0.771	**0.007**
Chi-squared	A.1.2: Attend meetings	Learning Outcomes	1.412	3	0.703	
Fisher's	A.1.3: Connect with individuals	Learning Outcomes	---		0.899	
Chi-squared	A.1.4: Connect with marginalized stakeholders	Learning Outcomes	7.311	3	0.063	
Chi-squared	A.1.5: Identify activities	Learning Outcomes	11.857	3	0.008	
Fisher's	A.1.6: Identify concerns	Learning Outcomes	---		0.031	
	A.1.7: Learn a language	Learning Outcomes	---		0.749	
Fisher's	A.1.1: Assess context	Policy Outcomes	---		0.423	**0.007**
Fisher's	A.1.2: Attend meetings	Policy Outcomes	---		0.448	

Fisher's	A.1.3: Connect with individuals	Policy Outcomes	---		0.314	
Fisher's	A.1.4: Connect with marginalized stakeholders	Policy Outcomes	---		0.713	
Fisher's	A.1.5: Identify activities	Policy Outcomes	---		0.024	
Fisher's	A.1.6: Identify concerns	Policy Outcomes	---		0.575	
Fisher's	A.1.7: Learn a language	Policy Outcomes	---		0.278	
Fisher's	A.2.1: Check credentials	Learning Outcomes	---		0.224	**0.005**
Fisher's	A.2.2: Conduct smaller project	Learning Outcomes	---		0.009	
Chi-squared	A.2.3: Define roles	Learning Outcomes	3.633	3	0.304	
Chi-squared	A.2.4: Engage face-to-face	Learning Outcomes	4.800	3	0.187	
Fisher's	A.2.5: Hold meetings	Learning Outcomes	---		0.013	
Chi-squared	A.2.6: Identify core leadership team	Learning Outcomes	5.926	3	0.115	
Chi-squared	A.2.7: Identify spaces	Learning Outcomes	4.374	3	0.224	
Fisher's	A.2.8: Identify shared interests	Learning Outcomes	---		0.654	
Chi-squared	A.2.9: Include experienced individuals	Learning Outcomes	2.944	3	0.400	
Fisher's	A.2.10: Include interdisciplinary researchers	Learning Outcomes			0.509	
Fisher's	A.2.1: Check credentials	Policy Outcomes	---		0.953	**0.005**
Fisher's	A.2.2: Conduct smaller project	Policy Outcomes	---		0.702	
Fisher's	A.2.3: Define roles	Policy Outcomes	---		0.544	
Fisher's	A.2.4: Engage face-to-face	Policy Outcomes	---		0.181	
Fisher's	A.2.5: Hold meetings	Policy Outcomes	---		0.646	

Fisher's	A.2.6: Identify core leadership team	Policy Outcomes	---		0.305	
Fisher's	A.2.7: Identify spaces	Policy Outcomes	---		1.000	
Fisher's	A.2.8: Identify shared interests	Policy Outcomes	---		0.060	
Fisher's	A.2.9: Include experienced individuals	Policy Outcomes	---		0.032	
Fisher's	A.2.10: Include interdisciplinary researchers	Policy Outcomes	---		0.850	
Chi-squared	A.3.1: Attend each other's meetings	Learning Outcomes	6.925	3	0.074	**0.01**
Chi-squared	A.3.2: Explore different knowledge	Learning Outcomes	10.787	3	0.013	
Fisher's	A.3.3: Express mutual respect	Learning Outcomes	---		0.233	
Fisher's	A.3.4: Share experiences	Learning Outcomes	---		0.076	
Fisher's	A.3.5: Accommodate learning processes	Learning Outcomes	---		0.064	
Fisher's	A.3.1: Attend each other's meetings	Policy Outcomes	---		0.839	**0.01**
Fisher's	A.3.2: Explore different knowledge	Policy Outcomes	---		0.886	
Fisher's	A.3.3: Express mutual respect	Policy Outcomes	---		0.166	
Fisher's	A.3.4: Share experiences	Policy Outcomes	---		0.079	
Fisher's	A.3.5: Accommodate learning processes	Policy Outcomes	---		0.255	
Fisher's	A.4.1: Define issue	Learning Outcomes	---		0.074	**0.013**

Chi-squared	A.4.2: Develop data collection protocols	Learning Outcomes	4.613	3	0.202	
Fisher's	A.4.3: Develop project goals	Learning Outcomes	---		0.009	
Chi-squared	A.4.4: Develop research questions	Learning Outcomes	3.175	3	0.366	
Fisher's	A.4.1: Define issue	Policy Outcomes	---		0.465	**0.013**
Fisher's	A.4.2: Develop data collection protocols	Policy Outcomes	---		0.281	
Fisher's	A.4.3: Develop project goals	Policy Outcomes	---		0.156	
Fisher's	A.4.4: Develop research questions	Policy Outcomes	---		0.038	
Chi-squared	A.5.1: Analyze data	Learning Outcomes	1.253	3	0.740	**0.01**
Fisher's	A.5.2: Develop outputs/outcom es	Learning Outcomes	---		0.174	
Fisher's	A.5.3: Interpret results	Learning Outcomes	---		0.091	
Chi-squared	A.5.4: Distribute responsibilities	Learning Outcomes	0.720	3	0.869	
Chi-squared	A.5.5: Foster capacity	Learning Outcomes	11.198	3	0.011	
Fisher's	A.5.1: Analyze data	Policy Outcomes	---		0.068	**0.01**
Fisher's	A.5.2: Develop outputs/outcom es	Policy Outcomes	---		0.718	
Fisher's	A.5.3: Interpret results	Policy Outcomes	---		0.916	
Fisher's	A.5.4: Distribute responsibilities	Policy Outcomes	---		0.253	
Fisher's	A.5.5: Foster capacity	Policy Outcomes	---		0.939	
Chi-squared	A.6.1: Communicate results to practitioners	Learning Outcomes	2.837	3	0.418	**0.008**

Fisher's	A.6.2: Communicate results to academics	Learning Outcomes	---		0.925	
Chi-squared	A.6.3: Communicate results to public	Learning Outcomes	2.377	3	0.498	
Fisher's	A.6.4: High profile group	Learning Outcomes	---		0.009	
Chi-squared	A.6.5: Discuss expanding learning	Learning Outcomes	0.985	3	0.805	
Fisher's	A.6.6: Hold workshops	Learning Outcomes	---		0.140	
Fisher's	A.6.1: Communicate results to practitioners	Policy Outcomes	---		0.152	**0.008**
Fisher's	A.6.2: Communicate results to academics	Policy Outcomes	---		0.813	
Fisher's	A.6.3: Communicate results to public	Policy Outcomes	---		0.626	
Fisher's	A.6.4: High profile group	Policy Outcomes	---		0.217	
Fisher's	A.6.5: Discuss expanding learning	Policy Outcomes	---		0.649	
Fisher's	A.6.6: Hold workshops	Policy Outcomes	---		0.573	
Fisher's	A.7.1: Assess learning	Learning Outcomes	---		0.000	**0.01**
Chi-squared	A.7.2: Discuss opportunities	Learning Outcomes	2.486	3	0.478	
Chi-squared	A.7.3: Reflect on quality	Learning Outcomes	19.819	3	0.000	
Chi-squared	A.7.4: Reflect on strengths/weaknesses	Learning Outcomes	7.254	3	0.064	
Fisher's	A.7.5: Reflect on usefulness	Learning Outcomes	---		0.187	
Fisher's	A.7.1: Assess learning	Policy Outcomes	---		0.538	**0.01**

Fisher's	A.7.2: Discuss opportunities	Policy Outcomes	---		0.102	
Fisher's	A.7.3: Reflect on quality	Policy Outcomes	---		0.301	
Fisher's	A.7.4: Reflect on strengths/weak nesses	Policy Outcomes	---		0.430	
Fisher's	A.7.5: Reflect on usefulness	Policy Outcomes	---		0.771	
Fisher's	Positionality	A.1.1: Assess context	---		0.309	**0.017**
Chi-squared	Gender	A.1.1: Assess context	0.000	1	1.000	
Chi-squared	Geography	A.1.1: Assess context	0.031	1	0.860	
Chi-squared	Positionality	A.1.2: Attend meetings	0.197	1	0.657	**0.017**
Chi-squared	Gender	A.1.2: Attend meetings	3.413	1	0.065	
Chi-squared	Geography	A.1.2: Attend meetings	2.549	1	0.110	
Chi-squared	Positionality	A.1.3: Connect with individuals	0.000	1	0.998	**0.017**
Chi-squared	Gender	A.1.3: Connect with individuals	4.802	1	0.028	
Chi-squared	Geography	A.1.3: Connect with individuals	0.068	1	0.794	
Chi-squared	Positionality	A.1.4: Connect with marginalized stakeholders	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.1.4: Connect with marginalized stakeholders	0.107	1	0.743	
Chi-squared	Geography	A.1.4: Connect with marginalized stakeholders	0.985	1	0.321	
Chi-squared	Positionality	A.1.5: Identify activities	1.943	1	0.163	**0.017**
Chi-squared	Gender	A.1.5: Identify activities	0.306	1	0.580	
Chi-squared	Geography	A.1.5: Identify activities	0.013	1	0.909	

Chi-squared	Positionality	A.1.6: Identify concerns	0.273	1	0.601	**0.017**
Chi-squared	Gender	A.1.6: Identify concerns	0.212	1	0.645	
Chi-squared	Geography	A.1.6: Identify concerns	0.386	1	0.535	
Fisher's	Positionality	A.1.7: Learn a language	---		1.000	**0.017**
Fisher's	Gender	A.1.7: Learn a language	---		0.039	
Chi-squared	Geography	A.1.7: Learn a language	3.853	1	0.050	
Chi-squared	Positionality	A.2.1: Check credentials	4.832	1	0.028	**0.017**
Chi-squared	Gender	A.2.1: Check credentials	0.095	1	0.758	
Fisher's	Geography	A.2.1: Check credentials	---		0.283	
Fisher's	Positionality	A.2.2: Conduct smaller project	---		0.145	**0.017**
Chi-squared	Gender	A.2.2: Conduct smaller project	0.125	1	0.724	
Chi-squared	Geography	A.2.2: Conduct smaller project	0.000	1	1.000	
Chi-squared	Positionality	A.2.3: Define roles	0.100	1	0.752	**0.017**
Chi-squared	Gender	A.2.3: Define roles	2.714	1	0.099	
Chi-squared	Geography	A.2.3: Define roles	0.000	1	1.000	
Chi-squared	Positionality	A.2.4: Engage face-to-face	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.2.4: Engage face-to-face	5.506	1	0.019	
Chi-squared	Geography	A.2.4: Engage face-to-face	1.294	1	0.255	
Chi-squared	Positionality	A.2.5: Hold meetings	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.2.5: Hold meetings	0.018	1	0.894	
Chi-squared	Geography	A.2.5: Hold meetings	0.247	1	0.619	
Chi-squared	Positionality	A.2.6: Identify core leadership team	0.140	1	0.708	**0.017**

Chi-squared	Gender	A.2.6: Identify core leadership team	2.423	1	0.120	
Chi-squared	Geography	A.2.6: Identify core leadership team	0.000	1	1.000	
Chi-squared	Positionality	A.2.7: Identify spaces	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.2.7: Identify spaces	1.107	1	0.293	
Chi-squared	Geography	A.2.7: Identify spaces	0.000	1	1.000	
Fisher's	Positionality	A.2.8: Identify shared interests	---		0.215	**0.017**
Chi-squared	Gender	A.2.8: Identify shared interests	0.043	1	0.836	
Chi-squared	Geography	A.2.8: Identify shared interests	3.095	1	0.079	
Chi-squared	Positionality	A.2.9: Include experienced individuals	1.268	1	0.260	**0.017**
Chi-squared	Gender	A.2.9: Include experienced individuals	0.000	1	1.000	
Chi-squared	Geography	A.2.9: Include experienced individuals	0.625	1	0.429	
Chi-squared	Positionality	A.2.10: Include interdisciplinary researchers	1.323	1	0.250	**0.017**
Chi-squared	Gender	A.2.10: Include interdisciplinary researchers	6.045	1	0.014	
Chi-squared	Geography	A.2.10: Include interdisciplinary researchers	1.011	1	0.315	
Chi-squared	Positionality	A.3.1: Attend each other's meetings	2.104	1	0.147	**0.017**
Chi-squared	Gender	A.3.1: Attend each other's meetings	4.613	1	0.032	
Chi-squared	Geography	A.3.1: Attend each other's meetings	1.279	1	0.258	
Chi-squared	Positionality	A.3.2: Explore different knowledge	0.095	1	0.758	**0.017**

Chi-squared	Gender	A.3.2: Explore different knowledge	0.143	1	0.705	
Chi-squared	Geography	A.3.2: Explore different knowledge	1.294	1	0.255	
Chi-squared	Positionality	A.3.3: Express mutual respect	0.127	1	0.722	**0.017**
Chi-squared	Gender	A.3.3: Express mutual respect	0.000	1	1.000	
Chi-squared	Geography	A.3.3: Express mutual respect	1.400	1	0.237	
Chi-squared	Positionality	A.3.4: Share experiences	1.268	1	0.260	**0.017**
Chi-squared	Gender	A.3.4: Share experiences	0.624	1	0.430	
Chi-squared	Geography	A.3.4: Share experiences	0.000	1	1.000	
Chi-squared	Positionality	A.3.5: Accommodate learning processes	0.000	1	0.985	**0.017**
Chi-squared	Gender	A.3.5: Accommodate learning processes	0.147	1	0.702	
Chi-squared	Geography	A.3.5: Accommodate learning processes	0.119	1	0.730	
Chi-squared	Positionality	A.4.1: Define issue	0.015	1	0.903	**0.017**
Chi-squared	Gender	A.4.1: Define issue	0.000	1	1.000	
Chi-squared	Geography	A.4.1: Define issue	0.258	1	0.612	
Chi-squared	Positionality	A.4.2: Develop data collection protocols	0.006	1	0.936	**0.017**
Chi-squared	Gender	A.4.2: Develop data collection protocols	0.023	1	0.879	
Chi-squared	Geography	A.4.2: Develop data collection protocols	0.235	1	0.628	
Chi-squared	Positionality	A.4.3: Develop project goals	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.4.3: Develop project goals	0.593	1	0.441	
Chi-squared	Geography	A.4.3: Develop project goals	0.001	1	0.974	

Chi-squared	Positionality	A.4.4: Develop research questions	0.047	1	0.829	**0.017**
Chi-squared	Gender	A.4.4: Develop research questions	0.122	1	0.727	
Chi-squared	Geography	A.4.4: Develop research questions	0.027	1	0.869	
Chi-squared	Positionality	A.5.1: Analyze data	2.397	1	0.122	**0.017**
Chi-squared	Gender	A.5.1: Analyze data	0.005	1	0.944	
Chi-squared	Geography	A.5.1: Analyze data	0.580	1	0.446	
Chi-squared	Positionality	A.5.2: Develop outputs/outcomes	0.017	1	0.897	**0.017**
Chi-squared	Gender	A.5.2: Develop outputs/outcomes	0.000	1	1.000	
Chi-squared	Geography	A.5.2: Develop outputs/outcomes	0.000	1	0.986	
Chi-squared	Positionality	A.5.3: Interpret results	0.827	1	0.363	**0.017**
Chi-squared	Gender	A.5.3: Interpret results	3.108	1	0.078	
Chi-squared	Geography	A.5.3: Interpret results	0.137	1	0.712	
Chi-squared	Positionality	A.5.4: Distribute responsibilities	3.160	1	0.075	**0.017**
Chi-squared	Gender	A.5.4: Distribute responsibilities	0.892	1	0.345	
Chi-squared	Geography	A.5.4: Distribute responsibilities	0.014	1	0.907	
Chi-squared	Positionality	A.5.5: Foster capacity	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.5.5: Foster capacity	0.002	1	0.965	
Chi-squared	Geography	A.5.5: Foster capacity	1.869	1	0.172	
Chi-squared	Positionality	A.6.1: Communicate results to practitioners	1.017	1	0.313	**0.017**
Chi-squared	Gender	A.6.1: Communicate results to practitioners	0.320	1	0.572	

Chi-squared	Geography	A.6.1: Communicate results to practitioners	0.000	1	1.000	
Chi-squared	Positionality	A.6.2: Communicate results to academics	7.892	1	0.005	**0.017**
Chi-squared	Gender	A.6.2: Communicate results to academics	1.746	1	0.186	
Chi-squared	Geography	A.6.2: Communicate results to academics	0.001	1	0.969	
Chi-squared	Positionality	A.6.3: Communicate results to public	1.616	1	0.204	**0.017**
Chi-squared	Gender	A.6.3: Communicate results to public	0.026	1	0.873	
Chi-squared	Geography	A.6.3: Communicate results to public	0.452	1	0.501	
Chi-squared	Positionality	A.6.4: High profile group	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.6.4: High profile group	0.193	1	0.660	
Chi-squared	Geography	A.6.4: High profile group	0.000	1	1.000	
Chi-squared	Positionality	A.6.5: Discuss expanding learning	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.6.5: Discuss expanding learning	2.551	1	0.110	
Chi-squared	Geography	A.6.5: Discuss expanding learning	0.065	1	0.800	
Chi-squared	Positionality	A.6.6: Hold workshops	0.584	1	0.445	**0.017**
Chi-squared	Gender	A.6.6: Hold workshops	0.212	1	0.645	
Chi-squared	Geography	A.6.6: Hold workshops	0.009	1	0.924	
Chi-squared	Positionality	A.7.1: Assess learning	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.7.1: Assess learning	0.909	1	0.340	
Chi-squared	Geography	A.7.1: Assess learning	0.446	1	0.504	
Chi-squared	Positionality	A.7.2: Discuss opportunities	0.856	1	0.355	**0.017**

Chi-squared	Gender	A.7.2: Discuss opportunities	0.004	1	0.947	
Chi-squared	Geography	A.7.2: Discuss opportunities	0.000	1	1.000	
Chi-squared	Positionality	A.7.3: Reflect on quality	0.621	1	0.431	**0.017**
Chi-squared	Gender	A.7.3: Reflect on quality	0.000	1	0.996	
Chi-squared	Geography	A.7.3: Reflect on quality	0.568	1	0.451	
Chi-squared	Positionality	A.7.4: Reflect on strengths/weaknesses	0.000	1	0.990	**0.017**
Chi-squared	Gender	A.7.4: Reflect on strengths/weaknesses	0.127	1	0.721	
Chi-squared	Geography	A.7.4: Reflect on strengths/weaknesses	0.090	1	0.764	
Chi-squared	Positionality	A.7.5: Reflect on usefulness	0.000	1	1.000	**0.017**
Chi-squared	Gender	A.7.5: Reflect on usefulness	1.257	1	0.262	
Chi-squared	Geography	A.7.5: Reflect on usefulness	0.000	1	1.000	

Table B.2. All Welch two sample t-tests and ANOVA tests conducted in Chapter 2.

Test	**Predictor**	**Response**	**t**	**df**	**p-value**	**Adjusted significance level**
T-test	Gender	Project Success	1.52	110.25	0.131	**0.017**
T-test	Geography	Project Success	-0.67	111.12	0.501	
T-test	Positionality	Project Success	-0.21	43.77	0.838	
			df	F value	Pr(>F)	
ANOVA	LengthProject	Project Success	4.00	0.28	0.890	**0.013**
ANOVA	LengthPreProject	Project Success	4.00	0.24	0.917	
ANOVA	ProjectInitiated	Project Success	2.00	0.52	0.595	
			t	df	p-value	
T-test	Modeling	Project Success	-2.31	85.53	0.023	
T-test	Farmer/NonFarmer	Project Success	0.96	110.91	0.341	**0.007**
T-test	Fisher/NonFisher	Project Success	1.22	18.12	0.239	
T-test	Government/NonGovernment	Project Success	-0.31	87.81	0.754	
T-test	NGO/NonNGO	Project Success	-0.38	112.81	0.707	
T-test	Ranchers/NonRanchers	Project Success	-0.98	36.08	0.335	
T-test	PrivateSector/NonPrivateSector	Project Success	0.07	41.38	0.941	
T-test	ServiceIndustry/NonServiceIndustry	Project Success	-1.64	24.86	0.113	
T-test	Arctic/NonArctic	Project Success	-0.47	7.60	0.649	**0.004**
T-test	Coasts/NonCoasts	Project Success	0.09	14.63	0.933	
T-test	Deserts/NonDeserts	Project Success	-1.51	9.02	0.164	
T-test	Forests/NonForests	Project Success	-0.63	78.33	0.533	
T-test	Grasslands/NonGrasslands	Project Success	-1.39	34.75	0.172	
T-test	Mountains/NonMountains	Project Success	0.02	54.27	0.984	
T-test	Oceans/NonOceans	Project Success	-1.77	9.48	0.109	
T-test	ProtectedAreas/NonProtectedAreas	Project Success	-0.14	24.23	0.889	

T-test	Urban/NonUrban	Project Success	-0.57	45.46	0.572	
T-test	Agriculture/NonAgriculture	Project Success	0.63	11.20	0.544	
T-test	Savanna/NonSavanna	Project Success	-2.30	1.15	0.235	
T-test	Aquatic/NonAquatic	Project Success	-0.40	6.06	0.702	
T-test	Video/NoVideo	Project Success	-1.83	65.91	0.072	**0.006**
T-test	Workshops/NoWorkshops	Project Success	-1.05	67.34	0.295	
T-test	CurriculumMaterials/NoCurriculum Materials	Project Success	0.40	91.31	0.691	
T-test	Maps/NoMaps	Project Success	-0.02	106.56	0.981	
T-test	NewsBriefs/NoNewsBriefs	Project Success	-0.91	118.66	0.367	
T-test	Peer-ReviewedPubs/NoPeer-ReviewedPubs	Project Success	-0.20	38.18	0.844	
T-test	PolicyBriefs/NoPolicyBriefs	Project Success	0.88	115.89	0.378	
T-test	Radio/NoRadio	Project Success	-0.57	48.84	0.569	
T-test	A.1.1: Assess context	Project Success	-0.61	46.27	0.546	**0.007**
T-test	A.1.2: Attend meetings	Project Success	0.73	119.32	0.470	
T-test	A.1.3: Connect with individuals	Project Success	-1.68	44.04	0.101	
T-test	A.1.4: Connect with marginalized stakeholders	Project Success	-0.75	109.26	0.453	
T-test	A.1.5: Identify activities	Project Success	-2.47	119.89	0.015	
T-test	A.1.6: Identify concerns	Project Success	-1.46	40.17	0.152	
T-test	A.1.7: Learn a language	Project Success	0.05	30.35	0.963	
T-test	A.2.1: Check credentials	Project Success	-1.62	18.42	0.122	**0.005**

T-test	A.2.2: Conduct smaller project	Project Success	-0.73	64.50	0.469	
T-test	A.2.3: Define roles	Project Success	-2.36	121.94	0.020	
T-test	A.2.4: Engage face-to-face	Project Success	0.04	121.56	0.969	
T-test	A.2.5: Hold meetings	Project Success	0.32	102.99	0.753	
T-test	A.2.6: Identify core leadership team	Project Success	-1.34	121.68	0.184	
T-test	A.2.7: Identify spaces	Project Success	-0.66	117.24	0.512	
T-test	A.2.8: Identify shared interests	Project Success	-0.49	38.43	0.627	
T-test	A.2.9: Include experienced individuals	Project Success	-0.71	77.87	0.483	
T-test	A.2.10: Include interdisciplinary researchers	Project Success	-0.93	102.45	0.356	
T-test	A.3.1: Attend each other's meetings	Project Success	-0.36	120.90	0.719	**0.01**
T-test	A.3.2: Explore different knowledge	Project Success	-2.14	120.52	0.035	
T-test	A.3.3: Express mutual respect	Project Success	-0.79	21.66	0.440	
T-test	A.3.4: Share experiences	Project Success	-1.70	72.73	0.094	
T-test	A.3.5: Accommodate learning processes	Project Success	-1.79	107.46	0.076	
T-test	A.4.1: Define issue	Project Success	-0.31	36.31	0.759	**0.013**
T-test	A.4.2: Develop data collection protocols	Project Success	-1.05	114.81	0.298	
T-test	A.4.3: Develop project goals	Project Success	-3.62	75.92	0.001	
T-test	A.4.4: Develop research questions	Project Success	-3.54	108.68	0.001	
T-test	A.5.1: Analyze data	Project Success	-1.01	118.41	0.316	**0.01**

T-test	A.5.2: Develop outputs/outcomes	Project Success	-1.93	68.99	0.057	
T-test	A.5.3: Interpret results	Project Success	-0.57	68.59	0.567	
T-test	A.5.4: Distribute responsibilities	Project Success	-0.77	116.33	0.443	
T-test	A.5.5: Foster capacity	Project Success	-1.00	120.13	0.320	
T-test	A.6.1: Communicate results to practitioners	Project Success	-0.78	70.94	0.437	**0.008**
T-test	A.6.2: Communicate results to academics	Project Success	-0.47	49.18	0.640	
T-test	A.6.3: Communicate results to public	Project Success	-1.17	115.56	0.244	
T-test	A.6.4: High profile group	Project Success	-0.78	45.87	0.440	
T-test	A.6.5: Discuss expanding learning	Project Success	-1.26	92.84	0.212	
T-test	A.6.6: Hold workshops	Project Success	0.97	57.86	0.339	
T-test	A.7.1: Assess learning	Project Success	-0.29	91.92	0.775	**0.01**
T-test	A.7.2: Discuss opportunities	Project Success	-1.50	93.27	0.137	
T-test	A.7.3: Reflect on quality	Project Success	-1.15	63.86	0.254	
T-test	A.7.4: Reflect on strengths/weaknesses	Project Success	-1.34	88.09	0.182	
T-test	A.7.5: Reflect on usefulness	Project Success	-1.07	50.72	0.290	

Table B.3. All Wilcoxon rank sum tests conducted in Chapter 2.

Wilcoxon Rank Sum Test w/ continuity correction				
Predictor	**Response**	**W**	**p-value**	**Adjusted significance level**
Positionality	Barrier_Time	1419	0.120	**0.017**
Gender	Barrier_Time	2209	0.495	
Geography	Barrier_Time	2153	0.601	
Positionality	Barrier_Money	1650.5	1.000	**0.017**
Gender	Barrier_Money	1944.5	0.593	
Geography	Barrier_Money	1888	0.446	
Positionality	Barrier_Power	1650	0.787	**0.017**
Gender	Barrier_Power	2209	0.501	
Geography	Barrier_Power	2210.5	0.422	
Positionality	Barrier_Communication	1804	0.519	**0.017**
Gender	Barrier_Communication	1828.5	0.164	
Geography	Barrier_Communication	1972.5	0.659	
Positionality	Barrier_Conflict	1863.5	0.253	**0.017**
Gender	Barrier_Conflict	1990.5	0.581	
Geography	Barrier_Conflict	1871	0.253	
Positionality	Barrier_SharedInterests	1609	0.595	**0.017**
Gender	Barrier_SharedInterests	2209	0.465	
Geography	Barrier_SharedInterests	2206	0.401	
Positionality	Barrier_NoAction	1624.5	0.536	**0.017**
Gender	Barrier_NoAction	1784.5	0.030	
Geography	Barrier_NoAction	1920	0.340	
Positionality	Barrier_WrongMethods	1686.5	0.897	**0.017**
Gender	Barrier_WrongMethods	2252	0.109	
Geography	Barrier_WrongMethods	2108	0.602	
Positionality	Barrier_Knowledge	1707	0.965	**0.017**
Gender	Barrier_Knowledge	2041.5	0.836	
Geography	Barrier_Knowledge	1916	0.404	

Positionality	A.1.1: Assess context	2078	0.044	**0.017**
Gender	A.1.1: Assess context	1683.5	0.055	
Geography	A.1.1: Assess context	2024	0.900	
Positionality	A.1.2: Attend meetings	1577	0.363	**0.017**
Gender	A.1.2: Attend meetings	1911	0.273	
Geography	A.1.2: Attend meetings	1903.5	0.316	
Positionality	A.1.3: Connect with individuals	1328	0.047	**0.017**
Gender	A.1.3: Connect with individuals	2329	0.210	
Geography	A.1.3: Connect with individuals	1894.5	0.448	
Positionality	A.1.4: Connect with marginalized stakeholders	1780.5	0.588	**0.017**
Gender	A.1.4: Connect with marginalized stakeholders	2005	0.665	
Geography	A.1.4: Connect with marginalized stakeholders	2292.5	0.134	
Positionality	A.1.5: Identify activities	1691	0.962	**0.017**
Gender	A.1.5: Identify activities	2331.5	0.180	
Geography	A.1.5: Identify activities	2101.5	0.793	
Positionality	A.1.6: Identify concerns	1972	0.151	**0.017**
Gender	A.1.6: Identify concerns	1982.5	0.657	
Geography	A.1.6: Identify concerns	2225.5	0.395	
Positionality	A.1.7: Learn a language	1659	0.649	**0.017**
Gender	A.1.7: Learn a language	2187	0.229	
Geography	A.1.7: Learn a language	1928	0.214	
Positionality	A.2.1: Check credentials	1733	0.429	**0.017**
Gender	A.2.1: Check credentials	2043.5	0.352	
Geography	A.2.1: Check credentials	2132	0.071	

Positionality	A.2.2: Conduct smaller project	1744.5	0.740	**0.017**
Gender	A.2.2: Conduct smaller project	2431	0.009	
Geography	A.2.2: Conduct smaller project	2077.5	0.848	
Positionality	A.2.3: Define roles	1948	0.138	**0.017**
Gender	A.2.3: Define roles	1868.5	0.256	
Geography	A.2.3: Define roles	2160	0.544	
Positionality	A.2.4: Engage face-to-face	1637	0.626	**0.017**
Gender	A.2.4: Engage face-to-face	1912	0.261	
Geography	A.2.4: Engage face-to-face	2204	0.275	
Positionality	A.2.5: Hold meetings	1502	0.202	**0.017**
Gender	A.2.5: Hold meetings	2193	0.485	
Geography	A.2.5: Hold meetings	1906	0.394	
Positionality	A.2.6: Identify core leadership team	1771	0.698	**0.017**
Gender	A.2.6: Identify core leadership team	1795.5	0.158	
Geography	A.2.6: Identify core leadership team	2027	0.910	
Positionality	A.2.7: Identify spaces	1673.5	0.818	**0.017**
Gender	A.2.7: Identify spaces	2272	0.113	
Geography	A.2.7: Identify spaces	2059	0.947	
Positionality	A.2.8: Identify shared interests	2024.5	0.077	**0.017**
Gender	A.2.8: Identify shared interests	2176	0.609	
Geography	A.2.8: Identify shared interests	2152.5	0.611	
Positionality	A.2.9: Include experienced individuals	1396	0.074	**0.017**
Gender	A.2.9: Include experienced individuals	1792.5	0.129	
Geography	A.2.9: Include experienced individuals	1981	0.713	

Positionality	A.2.10: Include interdisciplinary researchers	1653.5	0.760	**0.017**
Gender	A.2.10: Include interdisciplinary researchers	1827.5	0.179	
Geography	A.2.10: Include interdisciplinary researchers	2301.5	0.157	
Positionality	A.3.1: Attend each other's meetings	1751	0.767	**0.017**
Gender	A.3.1: Attend each other's meetings	2365.5	0.114	
Geography	A.3.1: Attend each other's meetings	1914	0.467	
Positionality	A.3.2: Explore different knowledge	1925	0.217	**0.017**
Gender	A.3.2: Explore different knowledge	2101	0.893	
Geography	A.3.2: Explore different knowledge	1892	0.428	
Positionality	A.3.3: Express mutual respect	1729.5	0.870	**0.017**
Gender	A.3.3: Express mutual respect	1707	0.057	
Geography	A.3.3: Express mutual respect	2099	0.801	
Positionality	A.3.4: Share experiences	1240	0.013	**0.017**
Gender	A.3.4: Share experiences	1854	0.272	
Geography	A.3.4: Share experiences	2116.5	0.742	
Positionality	A.3.5: Accommodate learning processes	1861	0.393	**0.017**
Gender	A.3.5: Accommodate learning processes	2211	0.503	
Geography	A.3.5: Accommodate learning processes	2202	0.459	
Positionality	A.4.1: Define issue	1718	0.922	**0.017**
Gender	A.4.1: Define issue	2129	0.779	

Geography	A.4.1: Define issue	2008.5	0.833	
Positionality	A.4.2: Develop data collection protocols	1866	0.321	**0.017**
Gender	A.4.2: Develop data collection protocols	2012.5	0.735	
Geography	A.4.2: Develop data collection protocols	2115.5	0.724	
Positionality	A.4.3: Develop project goals	1772	0.696	**0.017**
Gender	A.4.3: Develop project goals	1938	0.495	
Geography	A.4.3: Develop project goals	2176	0.530	
Positionality	A.4.4: Develop research questions	1437	0.155	**0.017**
Gender	A.4.4: Develop research questions	1965.5	0.590	
Geography	A.4.4: Develop research questions	1822	0.257	
Positionality	A.5.1: Analyze data	1929	0.192	**0.017**
Gender	A.5.1: Analyze data	2389.5	0.098	
Geography	A.5.1: Analyze data	1856	0.314	
Positionality	A.5.2: Develop outputs/outcomes	1074.5	0.001	**0.017**
Gender	A.5.2: Develop outputs/outcomes	2271	0.336	
Geography	A.5.2: Develop outputs/outcomes	1854	0.341	
Positionality	A.5.3: Interpret results	1424	0.144	**0.017**
Gender	A.5.3: Interpret results	1539.5	0.009	
Geography	A.5.3: Interpret results	1999.5	0.808	
Positionality	A.5.4: Distribute responsibilities	1946.5	0.176	**0.017**
Gender	A.5.4: Distribute responsibilities	1903	0.384	
Geography	A.5.4: Distribute responsibilities	2318	0.177	

Positionality	A.5.5: Foster capacity	1902	0.276	**0.017**
Gender	A.5.5: Foster capacity	2094	0.923	
Geography	A.5.5: Foster capacity	2273	0.270	
Positionality	A.6.1: Communicate results to practitioners	1371.5	0.080	**0.017**
Gender	A.6.1: Communicate results to practitioners	1837	0.245	
Geography	A.6.1: Communicate results to practitioners	2025	0.904	
Positionality	A.6.2: Communicate results to academics	1705	0.975	**0.017**
Gender	A.6.2: Communicate results to academics	2083.5	0.954	
Geography	A.6.2: Communicate results to academics	2097	0.766	
Positionality	A.6.3: Communicate results to public	1949	0.140	**0.017**
Gender	A.6.3: Communicate results to public	2275	0.272	
Geography	A.6.3: Communicate results to public	2121.5	0.703	
Positionality	A.6.4: High profile group	1619.5	0.628	**0.017**
Gender	A.6.4: High profile group	2131	0.753	
Geography	A.6.4: High profile group	1826.5	0.211	
Positionality	A.6.5: Discuss expanding learning	1617.5	0.649	**0.017**
Gender	A.6.5: Discuss expanding learning	1982.5	0.642	
Geography	A.6.5: Discuss expanding learning	2290.5	0.224	
Positionality	A.6.6: Hold workshops	1654.5	0.808	**0.017**
Gender	A.6.6: Hold workshops	1874	0.322	
Geography	A.6.6: Hold workshops	1781.5	0.187	
Positionality	A.7.1: Assess learning	2090.5	0.015	**0.017**

Gender	A.7.1: Assess learning	2006.5	0.697	
Geography	A.7.1: Assess learning	2072	0.902	
Positionality	A.7.2: Discuss opportunities	1949	0.168	**0.017**
Gender	A.7.2: Discuss opportunities	1957.5	0.552	
Geography	A.7.2: Discuss opportunities	1916	0.499	
Positionality	A.7.3: Reflect on quality	1075	0.001	**0.017**
Gender	A.7.3: Reflect on quality	2310	0.247	
Geography	A.7.3: Reflect on quality	2417	0.072	
Positionality	A.7.4: Reflect on strengths/weaknesses	1900	0.289	**0.017**
Gender	A.7.4: Reflect on strengths/weaknesses	1392.5	0.001	
Geography	A.7.4: Reflect on strengths/weaknesses	1646.5	0.049	
Positionality	A.7.5: Reflect on usefulness	1479	0.243	**0.017**
Gender	A.7.5: Reflect on usefulness	2707	0.002	
Geography	A.7.5: Reflect on usefulness	2145.5	0.645	

APPENDIX C

Table C1. We calculated the weighted mean for academics and non-academics, internal and external respondents, and women and men. We used these values to rank each activity in order of importance. We tested for significant differences in how each respondent type ranked individual activities using Wilcoxon rank sum tests; those activities are marked in bold (indicating $p \leq 0.05$) and which group considered the activity more important (A = academic, NA = non-academic, I = internal, W=women, M=men).

Step 1: Exploration	Academic	Non-Academic	Internal	External	Women	Men
A.1.1 Assess the context, history, or on-going initiatives surrounding this place or problem [NA, W]	3	2	3	2	2	3
A.1.2 Attend meetings of the different groups involved	6	6	5	6	6	6
A.1.3 Connect with individuals who are well-informed, helpful, or who have extensive networks [A]	1	3	1	3	3	1
A.1.4 Connect with stakeholders who are often marginalized	5	5	6	5	5	5
A.1.5 Identify activities to build credibility across participants	4	4	4	4	4	4
A.1.6 Identify concerns of the different groups involved	2	1	2	1	1	2
A.1.7 Learn a locally-spoken language	7	7	7	7	7	7
Step 2: Partnership Formation & Design						
A.2.1 Check the credentials or history of key participants	10	10	10	10	10	10
A.2.2 Conduct a smaller, preliminary project [M]	7	6	7	8	9	7
A.2.3 Define the roles and duties of everyone involved	4	8	5	4	4	5
A.2.4 Engage face-to-face outside of project meetings	8	7	9	6	7	9
A.2.5 Hold regular meetings with diverse participant groups	5	9	6	7	5	6
A.2.6 Identify a diverse core leadership team	2	2	2	2	2	2
A.2.7 Identify mutually appropriate spaces for interactions	9	3	8	9	8	8
A.2.8 Identify shared interests among participant groups	1	1	1	1	1	1
A.2.9 Include individuals with experience working with these participant groups or in this location	3	5	3	3	3	3
A.2.10 Include researchers who are interdisciplinary	6	4	4	5	6	4
Step 3: Draw on Multiple Knowledge Systems						
A.3.1 Attend each other's meetings and events	5	4	5	5	5	3
A.3.2 Explore how you will use different types of knowledge	4	3	4	4	4	5
A.3.3 Express mutual respect for one another's knowledge, experiences, or worldviews	1	1	1	1	1	1
A.3.4 Share experiences with each other [A]	3	5	3	3	3	4
A.3.5 Try to accommodate different processes for learning, understanding, or decision-making	2	2	2	2	2	2
Step 4: Co-Design Research & Action						
A.4.1 Collaboratively define the specific issue(s) being addressed	1	1	1	1	2	1
A.4.2 Collaboratively develop data collection methods	4	4	4	4	4	4
A.4.3 Collaboratively develop project goals for both research and action	2	2	2	2	1	2
A.4.4 Collaboratively develop research questions or hypotheses	3	3	3	3	3	3
Step 5: Co-Produce Research & Action						
A.5.1 Collaboratively analyze data collected	5	4	5	5	5	5
A.5.2 Collaboratively develop outputs or outcomes [A]	1	5	1	4	4	1
A.5.3 Collaboratively interpret results [W]	2	3	2	3	1	3
A.5.4 Distribute responsibilities among participants	4	2	4	2	3	4
A.5.5 Foster capacity to conduct agreed upon methods	3	1	3	1	2	2
Step 6: Communicate & Act						
A.6.1 Communicate results to practitioners outside the project	2	2	2	2	2	2
A.6.2 Communicate results to the academic community	6	6	6	6	6	6
A.6.3 Communicate results to the broader public	5	4	5	4	5	5
A.6.4 Create a group of high profile individuals with power to impact the issue of interest	4	5	4	5	4	4
A.6.5 Discuss how to expand upon learning from project	3	3	3	3	3	3
A.6.6 Hold workshops or meetings to exchange feedback with decision makers	1	1	1	1	1	1
Step 7: Co-Develop Future Opportunities						
A.7.1 Assess participants' learning [NA]	5	4	5	5	5	5
A.7.2 Discuss opportunities for the next collaboration	4	2	4	4	4	4
A.7.3 Reflect on the quality of outcomes and outputs [A]	2	5	3	1	2	3
A.7.4 Reflect on the strengths and weaknesses of the collaborative process [I, W]	1	1	1	3	1	2
A.7.5 Reflect on the usefulness of outcomes and outputs [M]	3	3	2	2	3	1

Table C2. We tested for differences in whether respondent types were associated with the presence of individual activities conducted in their most successful TDW project; those activities are marked in bold (indicating $p \leq 0.017$) and which group was more likely to conduct the activity (A = academic, NA = non-academic, E = external, W=women, M=men). Percent of total projects that conducted each activity is listed.

Step 1: Exploration	Occurred in Most Successful Project
A.1.1 Assess the context, history, or on-going initiatives surrounding this place or problem	76 %
A.1.2 Attend meetings of the different groups involved	53 %
A.1.3 Connect with individuals who are well-informed, helpful, or who have extensive networks	76 %
A.1.4 Connect with stakeholders who are often marginalized	37 %
A.1.5 Identify activities to build credibility across participants	46 %
A.1.6 Identify concerns of the different groups involved	75 %
A.1.7 Learn a locally-spoken language	16 %
Step 2: Partnership Formation & Design	
A.2.1 Check the credentials or history of key participants	13 %
A.2.2 Conduct a smaller, preliminary project	24 %
A.2.3 Define the roles and duties of everyone involved	43 %
A.2.4 Engage face-to-face outside of project meetings	45 %
A.2.5 Hold regular meetings with diverse participant groups	58 %
A.2.6 Identify a diverse core leadership team	47 %
A.2.7 Identify mutually appropriate spaces for interactions	46 %
A.2.8 Identify shared interests among participant groups	77 %
A.2.9 Include individuals with experience working with these participant groups or in this location	64 %
A.2.10 Include researchers who are interdisciplinary [M]	58 %
Step 3: Draw on Multiple Knowledge Systems	
A.3.1 Attend each other's meetings and events	47 %
A.3.2 Explore how you will use different types of knowledge	45 %
A.3.3 Express mutual respect for one another's knowledge, experiences, or worldviews	83 %
A.3.4 Share experiences with each other	67 %
A.3.5 Try to accommodate different processes for learning, understanding, or decision-making	54 %
Step 4: Co-Design Research & Action	
A.4.1 Collaboratively define the specific issue(s) being addressed	78 %
A.4.2 Collaboratively develop data collection methods	54 %
A.4.3 Collaboratively develop project goals for both research and action	67 %
A.4.4 Collaboratively develop research questions or hypotheses	54 %
Step 5: Co-Produce Research & Action	
A.5.1 Collaboratively analyze data collected	48 %
A.5.2 Collaboratively develop outputs or outcomes	65 %
A.5.3 Collaboratively interpret results	64 %
A.5.4 Distribute responsibilities among participants	53 %
A.5.5 Foster capacity to conduct agreed upon methods	47 %
Step 6: Communicate & Act	
A.6.1 Communicate results to practitioners outside the project	68 %
A.6.2 Communicate results to the academic community [A]	72 %
A.6.3 Communicate results to the broader public	57 %
A.6.4 Create a group of high-profile individuals with power to impact the issue of interest	23 %
A.6.5 Discuss how to expand upon learning from project	58 %
A.6.6 Hold workshops or meetings to exchange feedback with decision makers	75 %
Step 7: Co-Develop Future Opportunities	
A.7.1 Assess participants' learning	35 %
A.7.2 Discuss opportunities for the next collaboration	60 %
A.7.3 Reflect on the quality of outcomes and outputs	67 %
A.7.4 Reflect on the strengths and weaknesses of the collaborative process	55 %
A.7.5 Reflect on the usefulness of outcomes and outputs	68 %

APPENDIX D

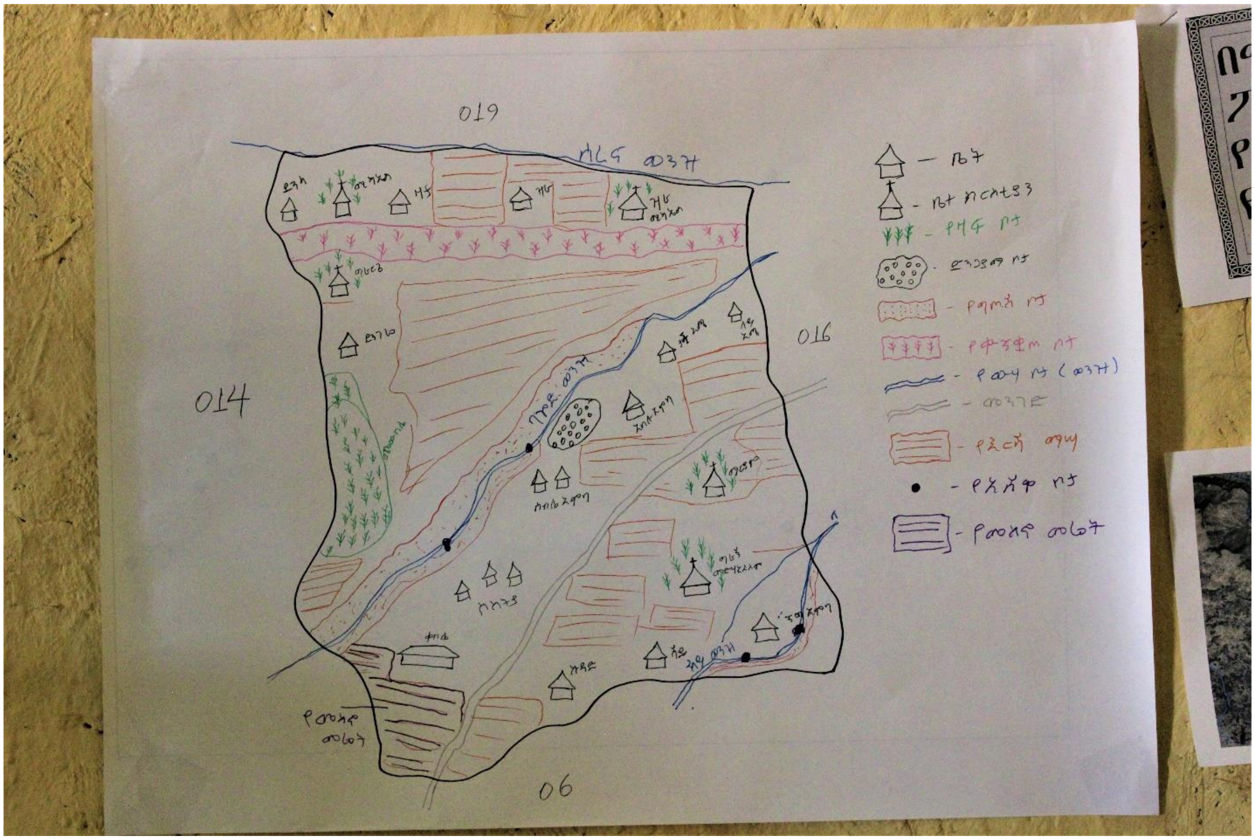


Figure D1. Participatory map drawn by residents of kebele 15 (Gragne).

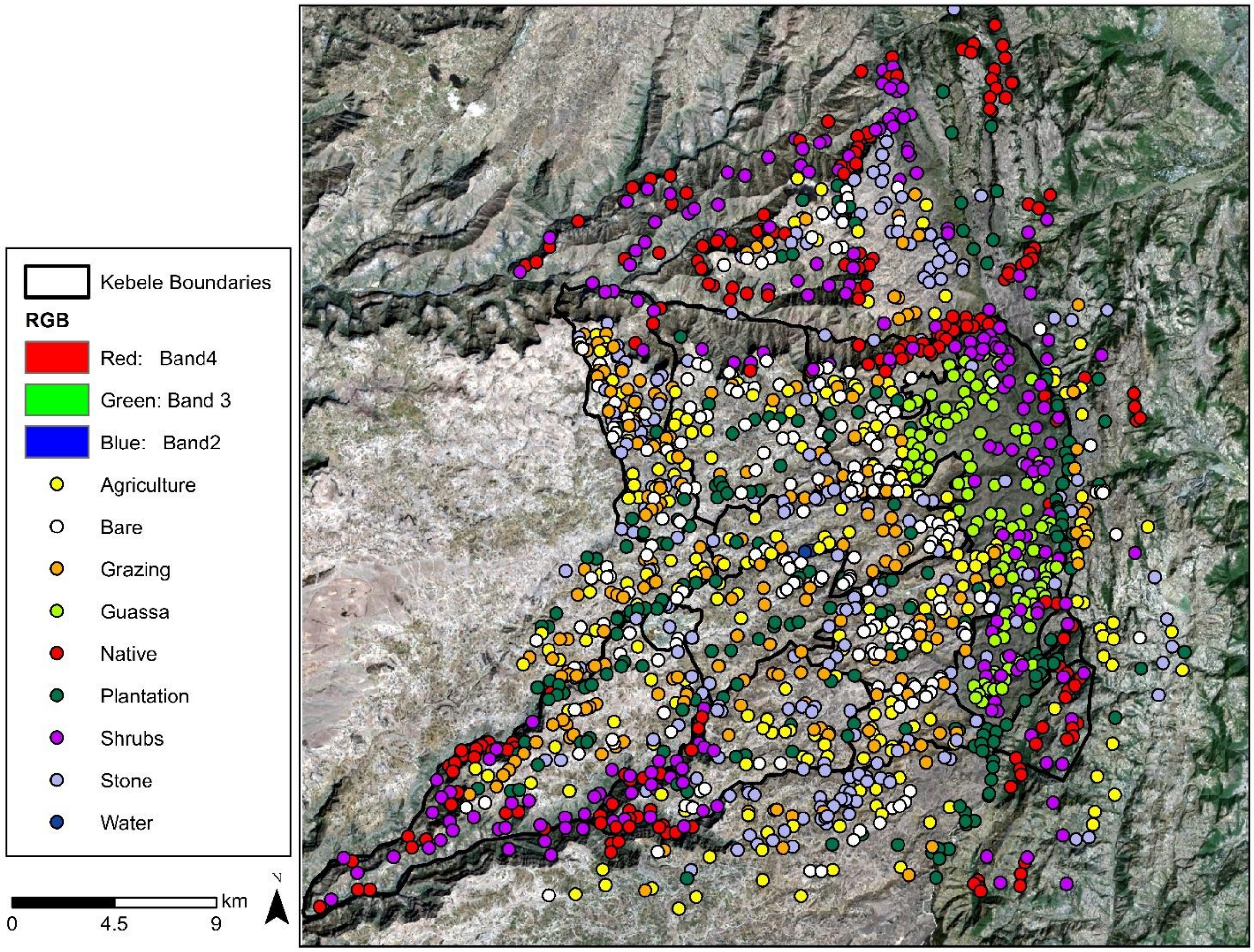


Figure D2. Map displaying the distribution of training points used for each land class in the random forest classifier.

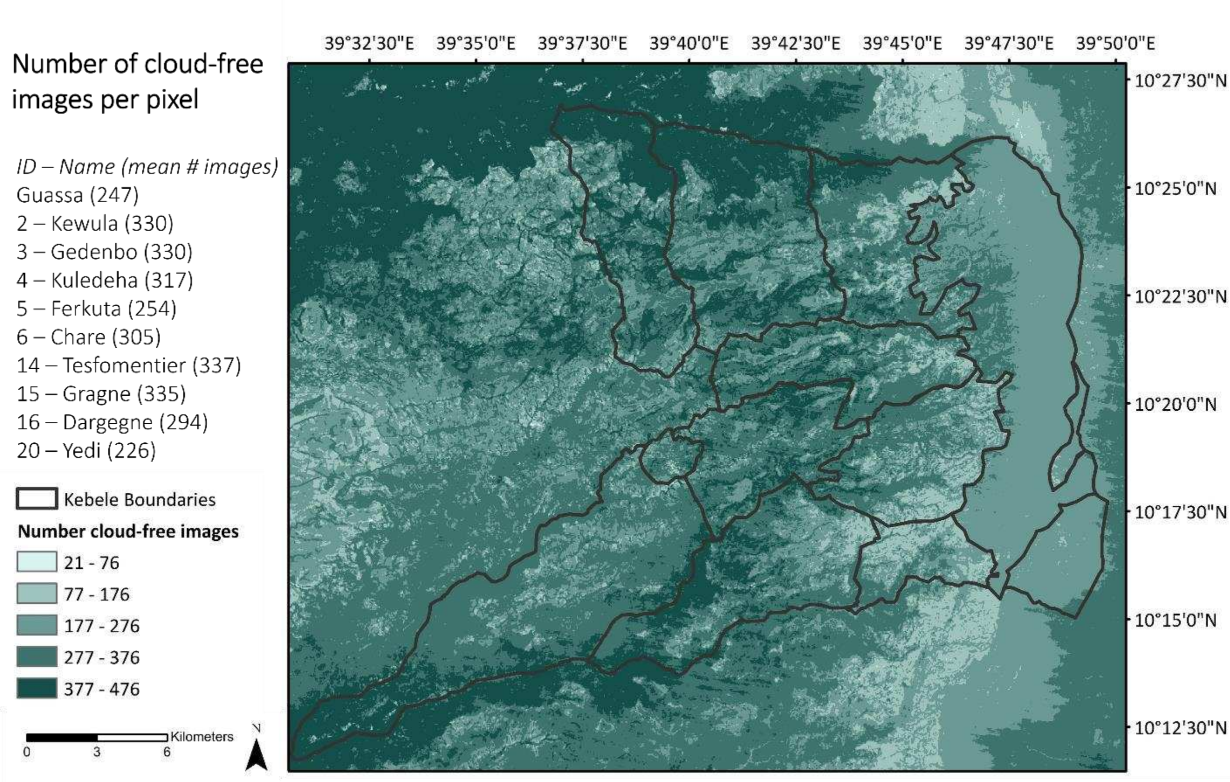


Figure D3. The number of cloud-free images per pixel across the study area.

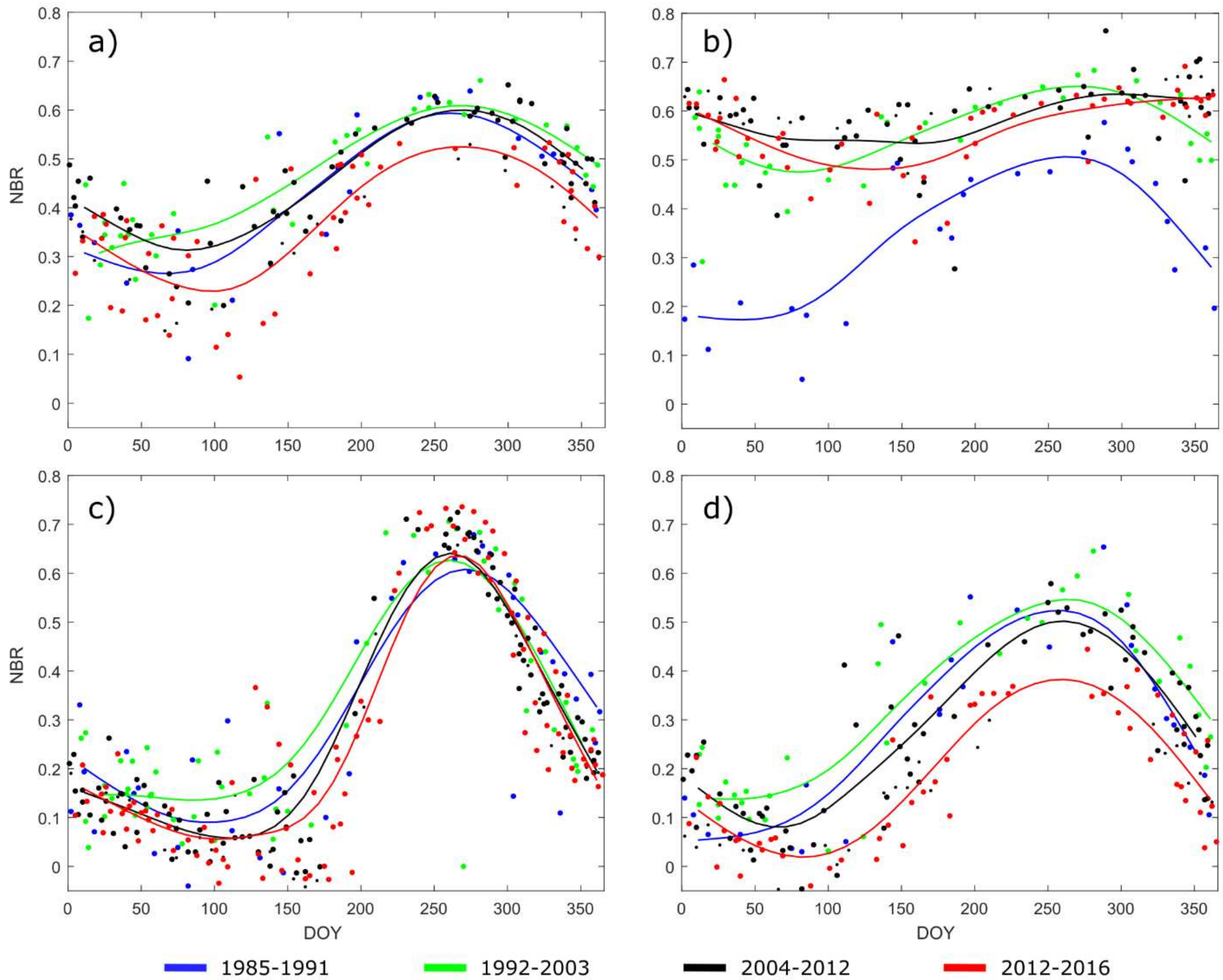


Figure D4. Spline interpolation results for four pixels in our study area showing changes across political and management periods in a) shrublands, b) plantation forest, c) grazing land, and d) protected grassland. For example, the blue line (Derg period) demonstrates the seasonal pattern of the vegetation prior to the establishment of a plantation forest, while the green, black, and red lines are showing the seasonal pattern of the plantation forest in subsequent periods, which is far less variable. There are 70 images in the Derg period (44 with <50% cloud cover), 148 images in the Transition period (87 with <50% cloud cover), 147 images in the NGO period (86 with <50% cloud cover), and 232 in the Co-management period (135 with <50% cloud cover).

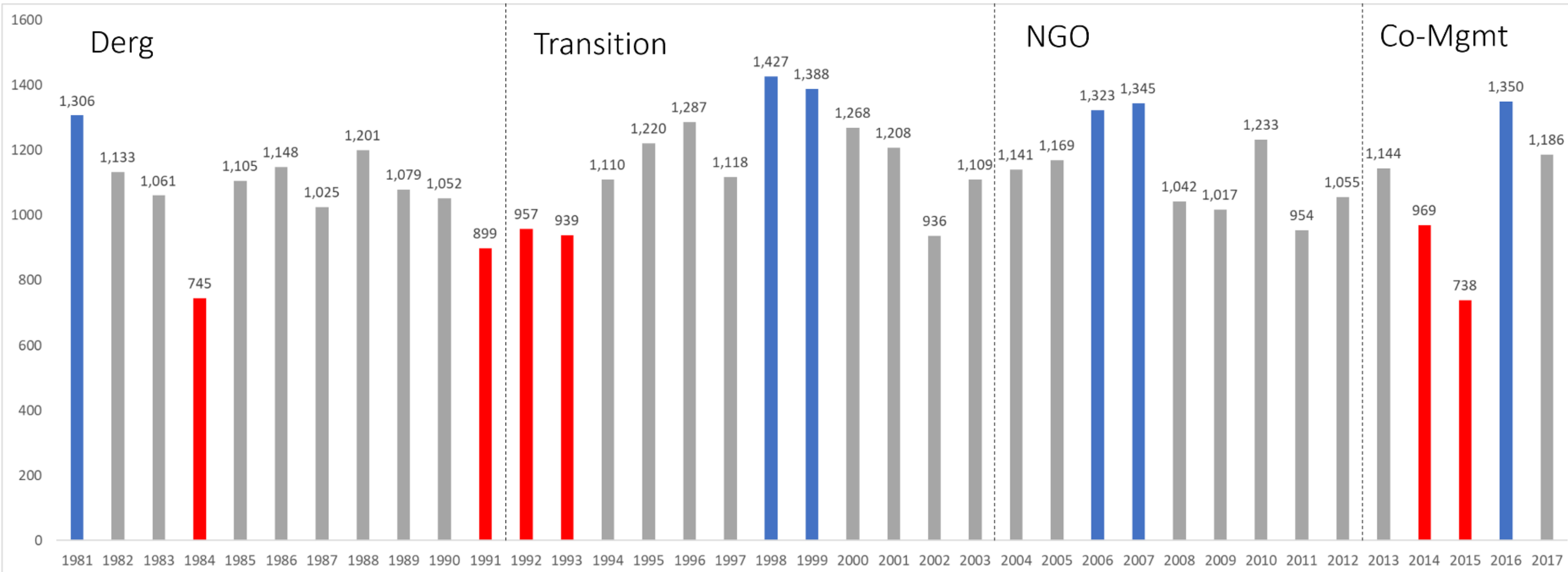


Figure D5. Total annual precipitation (from CHIRPS). Wet years (in blue, precip > 1300 mm) and dry years (in red, precip < 1000 mm) were fairly evenly distributed throughout the study period except for the NGO period.

Table D1. The confusion matrix for the supervised classification demonstrates the ability of the model to correctly classify a set of training points for each land class using a cross-validation approach. The kappa value for this classification was 0.85.

		Actual Class										
Predicted Class		Water	Plantation Forest	Grazing Land	Farmland	Stone	Bare Land	Shrubland	Native Forest	Protected Grassland	Total	User's Accuracy
	Water	2	0	0	0	0	0	0	0	0	2	100.0%
	Plantation Forest	0	201	0	0	0	0	3	6	0	210	95.7%
	Grazing Land	0	0	178	6	6	13	0	0	7	210	84.8%
	Farmland	0	0	5	205	11	3	1	0	0	225	80.4%
	Stone	0	0	2	16	179	23	3	0	2	225	79.6%
	Bare Land	0	0	13	2	14	181	0	0	0	210	86.2%
	Shrubland	0	3	0	0	2	0	173	30	2	210	82.4%
	Native Forest	0	3	0	0	0	0	24	183	0	210	87.1%
	Protected Grassland	0	0	4	0	3	0	3	0	110	120	91.7%
	Total	2	207	202	229	215	220	207	219	121	1622	
	Producer's Accuracy	100.0%	97.1%	88.1%	89.5%	83.3%	82.3%	83.6%	83.6%	90.9%		

Table D2. Top panel shows square kilometers of each land class, separated according to kebele and the Guassa area. Bottom panel shows the percent of land area occupied by each land class for each kebele and the Guassa area.

	Guassa	Chare	Dargegne	Ferkuta	Gedenbo	Gragne	Kewula	Kuledeha	Tesfomentier	Yedi
Farmland	1.3	16.2	15.8	19.3	17.4	25.8	21.6	19.4	15	9.4
Stone	3.2	9.4	6.7	5.9	7.1	10.2	9.5	8.1	6.7	2.3
Shrubland	21.8	0.1	3.7	1.6	0.1	7.2	17.2	5.7	4.9	6.9
Protected Grassland	45.5	0.4	0.6	1.3	0	0	0	0.1	0	0.8
Grazing Land	2	2.4	2.5	4.1	1.8	3.9	10.4	4.5	3.8	4.3
Bare Land	0	2.1	2.5	2	2.2	5	8.8	3.3	6.3	0.8
Native Forest	1.7	0	2.4	0.1	0	0.7	4.5	2.8	0.6	3.1
Plantation Forest	2.7	0.4	0.3	1.1	0.8	0.8	1.7	0.5	0.4	0.4
Urban	0	0	0.2	0.1	0	0	0	0	0	0.1
Water	0	0.04	0	0	0.04	0	0	0	0	0

	Guassa	Chare	Dargegne	Ferkuta	Gedenbo	Gragne	Kewula	Kuledeha	Tesfomentier	Yedi
Farmland	1.7%	52.2%	45.5%	54.4%	59.1%	48.1%	29.3%	43.7%	39.8%	33.5%
Stone	4.1%	30.3%	19.3%	16.6%	24.1%	19.0%	12.9%	18.2%	17.8%	8.2%
Shrubland	27.9%	0.3%	10.7%	4.5%	0.3%	13.4%	23.3%	12.8%	13.0%	24.6%
Protected Grassland	58.2%	1.3%	1.7%	3.7%	0.0%	0.0%	0.0%	0.2%	0.0%	2.8%
Grazing Land	2.6%	7.7%	7.2%	11.5%	6.1%	7.3%	14.1%	10.1%	10.1%	15.3%
Bare Land	0.0%	6.8%	7.2%	5.6%	7.5%	9.3%	11.9%	7.4%	16.7%	2.8%
Native Forest	2.2%	0.0%	6.9%	0.3%	0.0%	1.3%	6.1%	6.3%	1.6%	11.0%
Plantation Forest	3.5%	1.3%	0.9%	3.1%	2.7%	1.5%	2.3%	1.1%	1.1%	1.4%
City	0.0%	0.0%	0.6%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.4%
Water	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%

Table D3. The percent of land area and direction of vegetation change (from NBR values) for each kebele and the Guassa area across each period of political and management history (wet season).

	NBR	Guassa	Chare	Dargegne	Ferkuta	Gedenbo	Gragne	Kewula	Kuledeha	Tesfomentier	Yedi
Transition - Derg	High Increase	0.1%	0.5%	0.2%	1.2%	0.8%	0.4%	0.5%	0.7%	0.2%	0.5%
	Low Increase	69.2%	65.7%	46.2%	72.3%	67.6%	40.6%	70.3%	74.0%	48.6%	50.7%
	No Change	30.5%	33.2%	51.5%	25.8%	31.1%	56.5%	28.9%	24.8%	50.1%	47.3%
	Low Decrease	0.2%	0.7%	2.1%	0.6%	0.5%	2.5%	0.3%	0.6%	1.1%	1.5%
	High Decrease	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
NGO - Transition	High Increase	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.0%	0.0%	0.7%	0.0%
	Low Increase	0.4%	6.4%	1.7%	2.7%	11.5%	16.1%	4.8%	4.4%	15.2%	2.0%
	No Change	66.8%	63.7%	61.1%	59.9%	70.3%	70.9%	61.9%	65.8%	72.6%	71.4%
	Low Decrease	32.8%	29.8%	37.1%	37.3%	18.1%	12.8%	33.3%	29.8%	11.4%	26.6%
	High Decrease	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
Co-Managed - NGO	High Increase	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.0%	0.0%
	Low Increase	2.9%	16.9%	19.8%	10.2%	15.3%	18.3%	9.3%	7.7%	7.6%	5.4%
	No Change	73.8%	80.5%	77.7%	81.6%	79.5%	74.0%	83.5%	83.7%	81.5%	82.0%
	Low Decrease	23.3%	2.5%	2.5%	8.1%	5.1%	7.5%	7.2%	8.5%	10.9%	12.5%
	High Decrease	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%

Table D4. The percent of land area and direction of vegetation change (from NBR values) for each kebele and the Guassa area across each period of political and management history (dry season).

	NBR	Guassa	Chare	Dargegne	Ferkuta	Gedenbo	Gragne	Kewula	Kuledeha	Tesfomentier	Yedi
Transition - Derg	High Increase	1.5%	0.1%	0.1%	0.1%	0.0%	0.3%	0.2%	0.1%	0.0%	0.4%
	Low Increase	29.0%	3.2%	7.0%	3.8%	6.1%	7.2%	10.4%	11.1%	3.8%	14.4%
	No Change	68.9%	95.8%	91.1%	92.1%	93.8%	91.3%	87.7%	88.2%	95.0%	75.5%
	Low Decrease	0.7%	1.0%	1.8%	4.1%	0.0%	1.2%	1.7%	0.6%	1.2%	9.3%
	High Decrease	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.4%
NGO - Transition	High Increase	0.1%	0.0%	0.1%	0.2%	0.0%	0.1%	0.2%	0.0%	0.1%	0.0%
	Low Increase	4.7%	1.0%	0.8%	2.9%	1.6%	1.3%	2.0%	1.0%	1.6%	2.3%
	No Change	91.2%	96.6%	86.4%	90.0%	95.0%	90.5%	83.2%	92.4%	93.6%	79.1%
	Low Decrease	4.0%	2.4%	12.5%	6.9%	3.4%	8.0%	14.2%	6.6%	4.8%	18.4%
	High Decrease	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.4%	0.0%	0.0%	0.2%
Co-Managed - NGO	High Increase	0.1%	0.1%	0.0%	0.1%	0.2%	0.0%	0.0%	0.1%	0.0%	0.1%
	Low Increase	1.4%	2.1%	1.5%	2.2%	4.0%	2.7%	2.1%	1.0%	2.4%	4.0%
	No Change	76.8%	97.5%	95.8%	94.2%	95.6%	95.4%	93.3%	92.1%	95.8%	90.1%
	Low Decrease	21.8%	0.2%	2.5%	3.4%	0.2%	1.9%	4.5%	6.8%	1.8%	5.7%
	High Decrease	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%

Table D5. Relative variable importance (calculated by mean decrease in accuracy) for each predictor variable. Variables are presented in mean decreasing importance across all land classes.

Variable	Water	Plantation Forest	Grazing Land	Farmland	Stone	Bare Land	Shrubland	Native Forest	Guassa	Mean Decrease Accuracy
elevation	8.5	55.2	42.2	65.5	36.0	45.6	52.1	64.2	138.5	158.7
CoMgmt_DOY253	12.5	43.6	53.4	61.4	134.9	38.4	34.9	25.5	52.3	130.8
Derg_DOY40	8.6	61.2	38.1	54.6	39.9	30.4	61.2	90.2	44.8	110.7
greenness	17.2	59.3	47.9	86.2	75.3	30.4	53.6	14.0	72.8	106.4
Band 4	21.6	49.6	46.8	56.5	53.9	90.4	78.5	64.3	69.5	94.5
Band 3	21.7	49.5	40.8	56.4	31.8	87.8	40.5	31.5	59.9	88.3
slope	8.8	26.3	44.4	47.6	28.5	15.2	67.1	28.8	29.3	87.9
Band 5	14.5	28.3	54.9	56.5	61.9	43.6	37.9	17.2	43.6	87.0
CoMgmt_DOY40	19.4	66.5	36.5	73.9	61.0	37.0	50.2	59.0	58.2	85.3
NGO_Trans_DOY253	-4.1	34.2	20.3	53.2	44.8	13.8	32.5	37.7	38.9	84.6
NGO_Trans_DOY40	-0.5	63.1	13.2	24.2	33.6	29.2	21.5	27.6	24.3	83.4
Band 6	12.9	44.4	64.9	53.3	42.6	32.1	50.4	37.6	60.3	83.2
NGO_DOY253	5.9	31.8	43.3	24.4	61.0	35.8	25.9	15.8	44.2	83.1
Trans_Derg_DOY40	2.2	58.4	12.9	17.2	37.6	15.3	22.1	45.9	25.1	83.0
Derg_DOY253	10.9	51.3	39.5	19.9	44.2	29.2	44.8	33.8	48.7	82.4
Transition_DOY253	4.5	34.7	48.9	31.8	52.6	24.5	25.8	15.0	54.1	80.1
Transition_DOY40	2.9	37.2	33.8	48.9	33.8	23.0	38.1	53.0	41.9	80.1
CoMgmt_NGO_DOY253	13.7	37.9	16.8	29.7	56.8	10.3	23.7	33.8	21.1	77.3
CoMgmt_NGO_DOY40	16.0	55.2	15.8	17.6	27.2	26.0	12.0	16.7	38.2	75.9
Trans_Derg_DOY253	-1.0	50.8	21.0	5.8	29.4	8.1	28.1	43.6	26.3	72.2
NGO_DOY40	6.3	43.6	30.0	48.8	38.2	29.4	34.0	58.6	36.4	72.0
Band 2	16.4	40.5	41.5	46.8	39.7	56.6	43.2	34.1	52.3	63.9
wetness	14.8	38.5	30.7	26.8	26.7	18.1	35.2	33.8	36.6	62.5
brightness	9.7	28.1	42.9	36.0	28.5	36.1	33.3	26.5	37.3	61.7
Band 1	12.5	33.9	27.0	36.8	22.7	45.3	26.9	24.0	43.1	56.1
Band 7	15.0	38.1	40.2	32.0	26.1	36.4	35.3	38.4	38.2	55.1
aspect	-2.4	-1.7	6.0	4.1	1.5	9.0	13.1	7.9	14.1	20.1

Table D6. Mean NBR change values from Derg to the Co-management period, by land class.

Dry Season	Bare Land	Farmland	Grazing Land	Native Forest	Plantation Forest	Protected Grassland	Shrubland	Stone	Water
Chare	0.0	0.0	0.0		0.2	0.0	0.0	0.0	0.4
Dergagne	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	
Ferkuta	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	
Gedenbo	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.3
Gragne	0.0	0.0	0.0	-0.1	0.2	0.0	0.0	0.0	
Guassa	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	
Kewula	0.0	0.0	0.0	-0.1	0.2	0.0	0.0	0.0	
Kuledeha	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	
Tesfomentier	0.0	0.0	0.0	-0.1	0.1	0.0	0.0	0.0	
Yedi	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	

Wet Season	Bare Land	Farmland	Grazing Land	Native Forest	Plantation Forest	Protected Grassland	Shrubland	Stone	Water
Chare	0.0	0.1	0.0		0.1	0.0	0.0	0.0	0.2
Dergagne	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	
Ferkuta	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	
Gedenbo	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.2
Gragne	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	
Guassa	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	
Kewula	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	
Kuledeha	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	
Tesfomentier	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	
Yedi	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	

APPENDIX E

Table E1. Key uncertainties identified by each group involved in the mental modeling process (i.e., relationships marked with "I don't know").

Scientists	
The impact of …	On …
human population	invasive plants
rainfall	plant diseases
rainfall	animal diseases
unemployment	human population
unemployment	leadership
illegal users	community awareness
illegal users	leadership
temperature	wildlife population
invasive plants	community awareness
invasive plants	uncoordinated protection
invasive plants	agricultural expansion
invasive plants	guassa grasses
fire	uncoordinated protection
fire	guassa grasses
deforestation	income
regime change	community awareness
regime change	unemployment
regime change	illegal users
regime change	uncoordinated protection
regime change	wildlife population
guassa grasses	illegal users
guassa grasses	plant diseases
wildlife population	community awareness
wildlife population	illegal users
wildlife population	livestock population
tourism	wildlife population

Women Farmers	
The impact of …	On …
fire	community awareness
plant disease	livestock population
Men Farmers (far from Guassa)	
The impact of …	On …
temperature	political instability
temperature	firewood consumption
temperature	uncoordinated protection
temperature	agricultural expansion
temperature	deforestation
temperature	leadership
temperature	regime change
firewood consumption	livestock population
firewood consumption	leadership
firewood consumption	regime change
firewood consumption	research
Men Farmers (near Guassa)	
The impact of …	On …
animal disease	freshwater
plant disease	regime change
wildlife population	deforestation
tourism	wildlife population

APPENDIX F

Table F1. Confusion matrix for the supervised classification of the study area, resulting in an overall accuracy of 77.4% and kappa of 0.73.

	Asta	Cheranfi	Mixed grassland	Forest	Guassa	Helichrysum	Stone	Wetland	Row Total		User's accuracy
Asta	113	11	0	3	0	1	0	2	130		86.9%
Cheranfi	16	64	6	0	2	1	0	19	108		59.3%
Mixed grassland	2	3	43	0	0	0	5	11	64		67.2%
Forest	2	0	0	89	0	0	0	0	91		97.8%
Guassa	2	4	0	0	13	2	1	4	26		50.0%
Helichrysum	2	2	2	0	0	18	4	0	28		64.3%
Stone	2	1	4	0	0	3	79	0	89		88.8%
Wetland	1	13	7	0	1	1	1	64	88		72.7%
Column Total	140	98	62	92	16	26	90	100	**624**		
Producer's accuracy	80.7%	65.3%	69.4%	96.7%	81.3%	69.2%	87.8%	64.0%			

Table F2. Variables listed according to decreasing impact on overall model accuracy, with mean decrease in accuracy given for each land cover class and variable combination.

	Asta	Cheranfi	Cheranfi_Grassland	Forest	Guassa	Helichrysum	Stone	Wetland	Mean Decrease Accuracy
x-coordinate	37.13	34.65	38.39	68.93	21.75	12.42	26.03	38.25	85.61
Band8	58.05	38.35	42.58	35.17	29.11	28.26	47.01	42.60	67.39
elevation	20.01	25.12	21.19	5.20	16.12	8.81	37.16	23.70	54.52
Band1	23.46	22.43	23.21	30.76	15.51	30.55	37.36	28.69	50.81
greenness	25.22	7.15	22.12	12.04	14.68	15.24	19.56	17.11	44.26
wetness	17.10	5.60	22.10	26.53	8.65	10.27	15.09	26.91	37.92
Band5	24.35	-1.39	21.75	2.80	12.34	6.91	6.21	14.51	35.64
Band6	22.67	5.72	30.11	16.71	5.21	12.26	14.28	32.30	33.47
Band2	13.02	11.86	5.42	16.57	8.60	15.56	22.29	18.68	30.59
Band4	19.69	10.83	19.11	17.29	8.93	10.13	19.34	20.37	29.33
brightness	20.71	7.83	20.77	9.35	7.62	8.84	9.86	20.22	29.05
topowet	14.77	13.32	1.83	2.63	1.61	1.48	6.77	21.13	28.40
Band7	13.50	8.66	17.12	13.57	1.41	10.88	15.40	14.74	25.82
Band9	12.31	11.50	7.56	5.74	7.19	3.73	13.66	8.42	25.74
slope	14.54	2.87	-0.75	2.74	-2.91	2.71	10.15	23.73	25.39
Band3	13.60	7.87	13.03	13.13	8.61	6.99	20.02	12.46	24.35
aspect	10.84	13.37	2.33	12.45	5.93	7.07	1.82	6.78	21.92

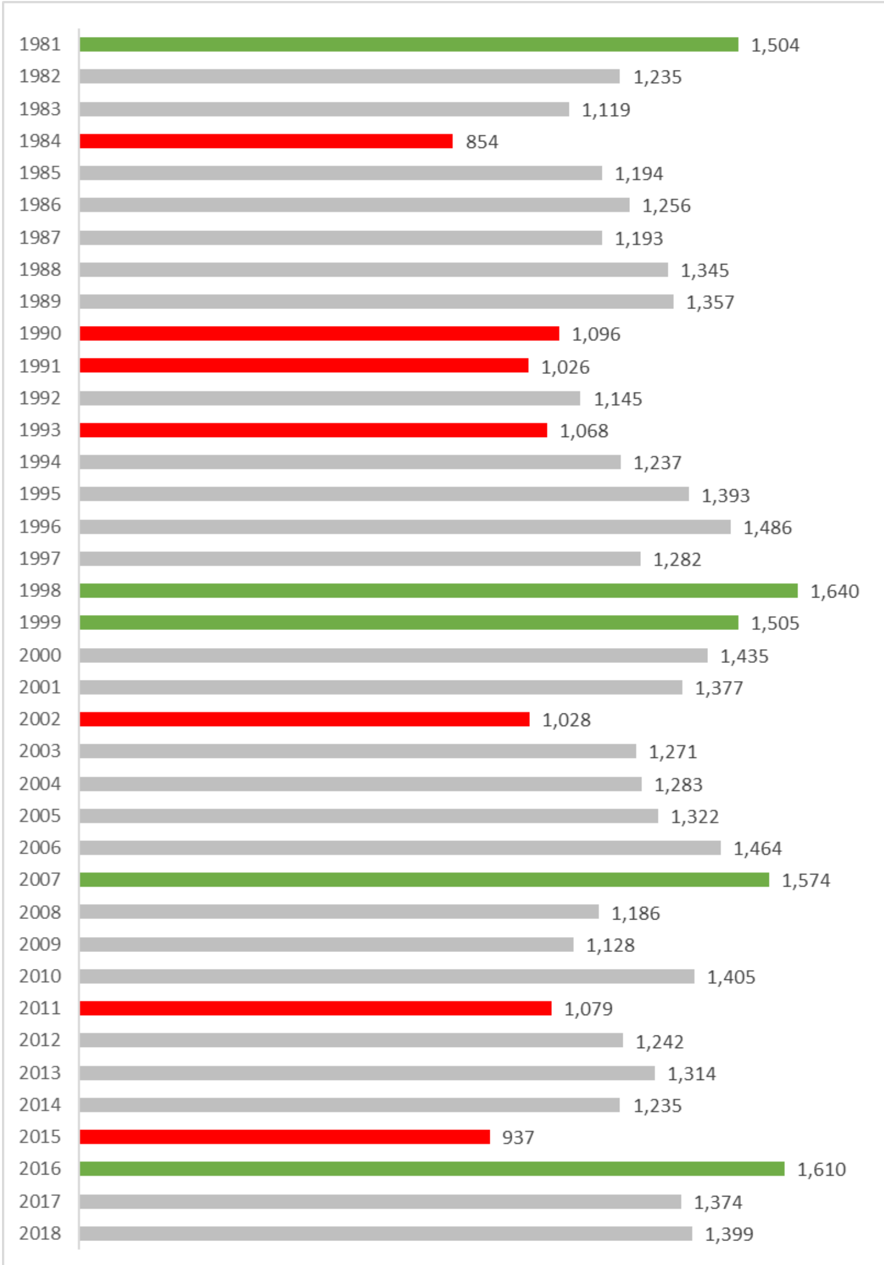


Figure F1. Total annual precipitation (from CHIRPS) over just the Guassa conservation area. Average precipitation over all years is 1,280mm +/- 180mm. Therefore, we are considering anything over 1,500mm to be a wet year (shown in green), and anything under 1,100mm to be a dry year (shown in red).

Sensitivity Analysis

We used sensitivity analysis to refine our model parameterization. Our results revealed that growth rates were very sensitive – for example, an addition of only 0.001 kg/m2/week was enough to cause Erica to outcompete Euryops across the 30 years we simulated (Figure S1). Therefore, we selected a growth rate for Erica that was > 0.005 kg/m2/week as we consider this a more conservative estimation. We also discovered that unless guassa grasses and Helichrysum shrubs had the same growth rate, guassa would expand over a much larger expanse of the landscape – which did not match local perceptions that in fact it was Helichrysum shrubs expanding (Figure S2). Therefore, we gave Helichrysum and guassa grasses the same growth rate of 0.017 kg/m2/week.

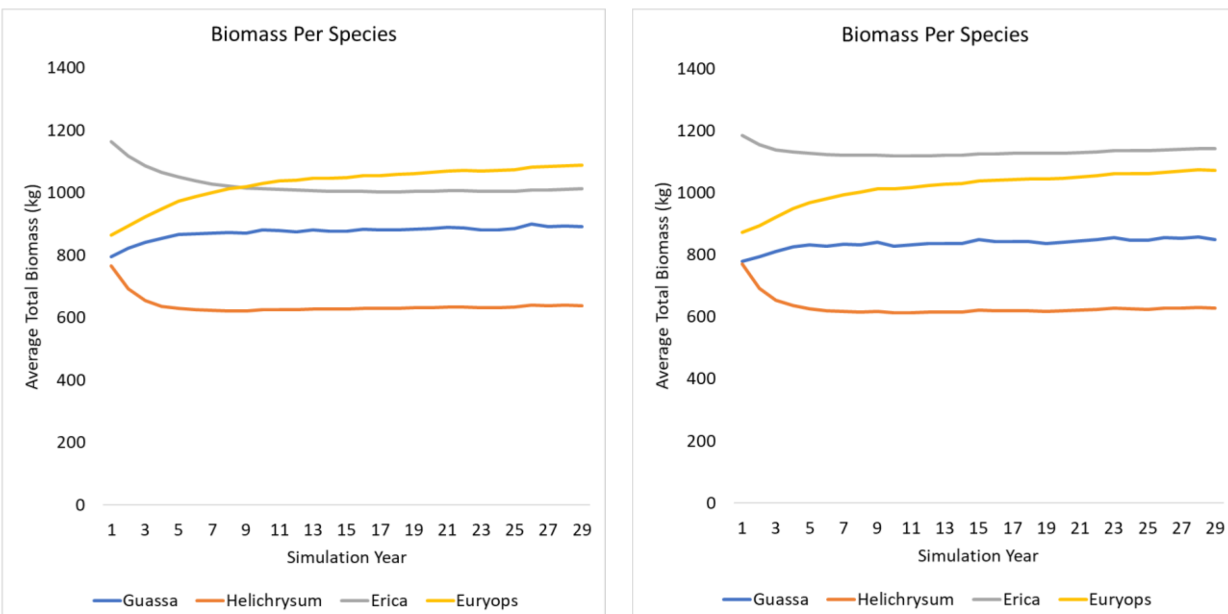


Figure F2. On the left, Erica shrubs had a growth rate of 0.005 kg/m2/week. An increase to 0.006 kg/m2/week (right) caused them to outcompete Euryops shrubs.

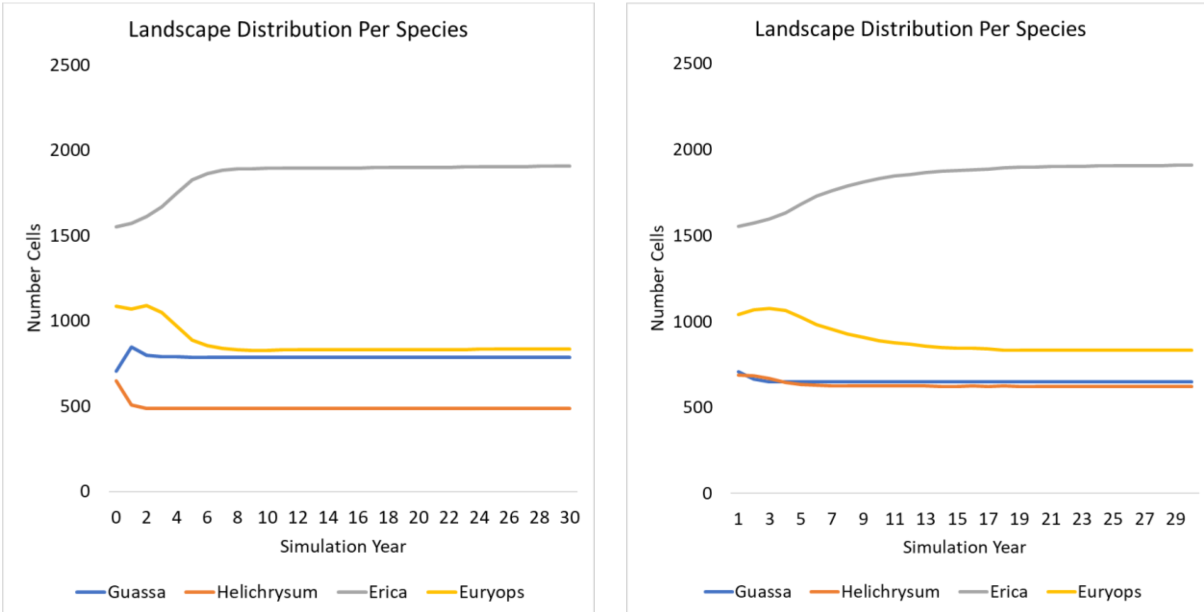


Figure F3. On the left, guassa had a growth rate of 0.019 kg/m2/week while Helichrysum had a growth rate of 0.01 kg/m2/week. Only when growth rates were equal (0.017 kg/m2/week) did we see them occupy equal proportions of the landscape (right). When Helichrysum shrubs had a higher growth rate, they had both higher biomass and higher expansion, but we did not think it was ecologically likely that shrubs would have a higher growth rate than grasses.

We also used sensitivity analysis to isolate which mechanism was likely driving Helichrysum expansion and competition with guassa grasses. We set each parameter for Helichrysum to an extreme value and evaluated how this impacted both biomass and the number of cells where Helichrysum and guassa were dominant. We found that decreasing senescence rates even a small amount (from 60% biomass retained to 70% retained) caused a large increase in Helichrysum biomass over time but did not change the proportion of cells where Helichrysum was dominant (Figure S3). Changing the proportion of seeds that stay in the cell they are produced (i.e., reducing the number of seeds spread to other cells - from 70% to 20%) caused a slight increase in Helichrysum biomass but also did not impact the proportion of cells where Helichrysum was dominant (Figure S4). However, increasing the proportion of Helichrysum biomass devoted to seed production (from 9% to 14%) caused both a decline in biomass over time and a decrease in the proportion of cells where Helichrysum was dominant (Figure S5). Therefore, while all parameters appear to influence biomass, only seed production and growth rates appear to influence the spread of the shrubs to any significant degree, and we encourage further research into these two important components.

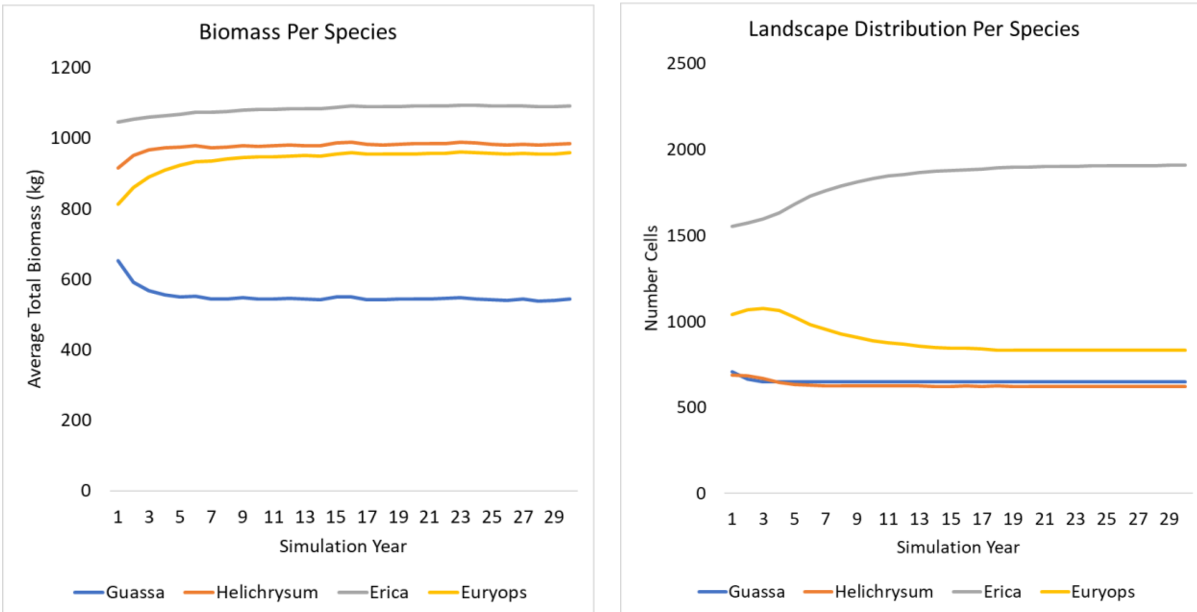


Figure F4. Retaining larger amounts of the previous year's biomass (70% instead of 60%) caused Helichrysum shrubs to outcompete Euryops shrubs in terms of average total biomass (left). However, there was no observed change to the proportion of cells where Helichrysum was dominant (right).

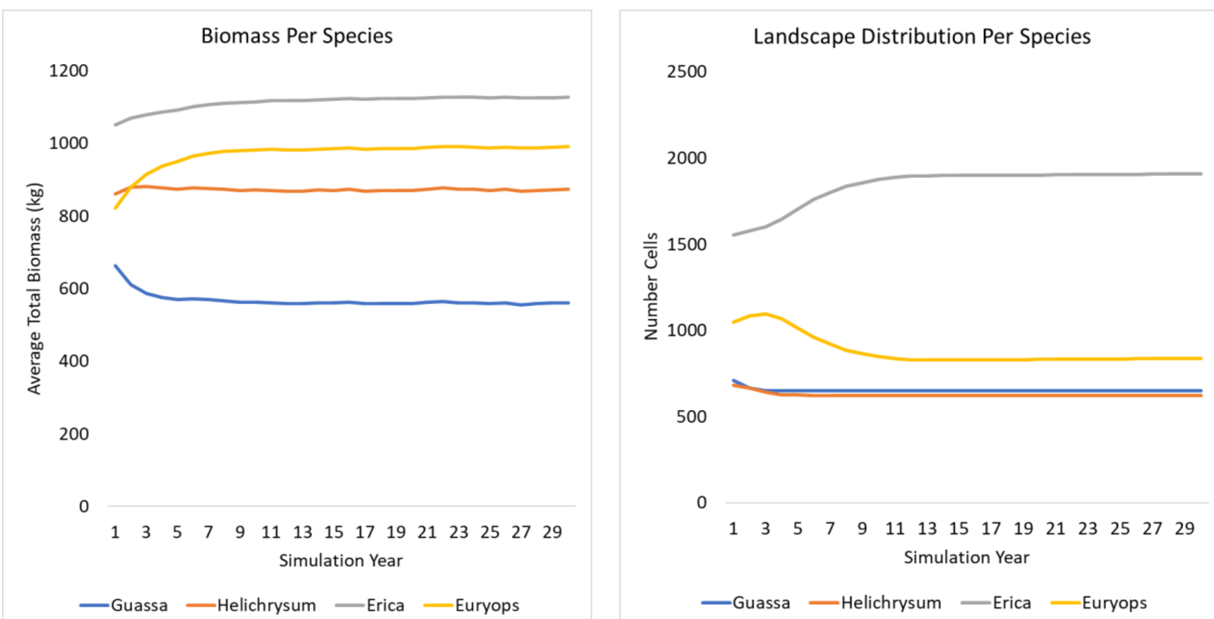
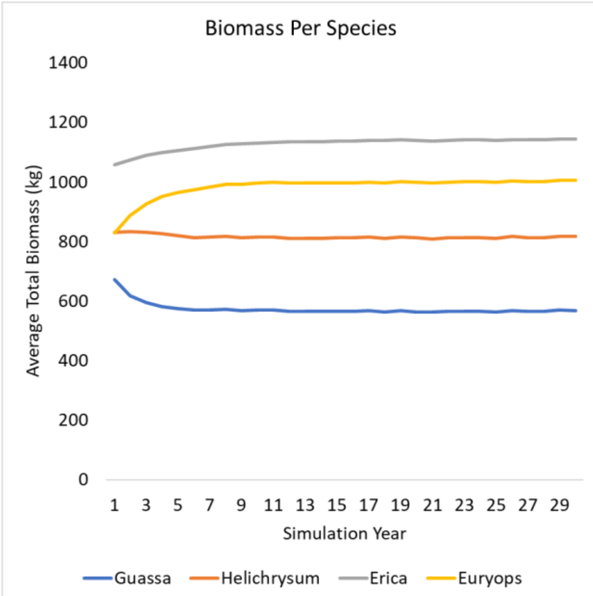


Figure F5. Retaining larger amounts of seeds in the same cell they are produced (80% instead of 20%) caused Helichrysum shrubs to increase their total average biomass very slightly (left). However, there was no observed change to the proportion of cells where Helichrysum was dominant (right).



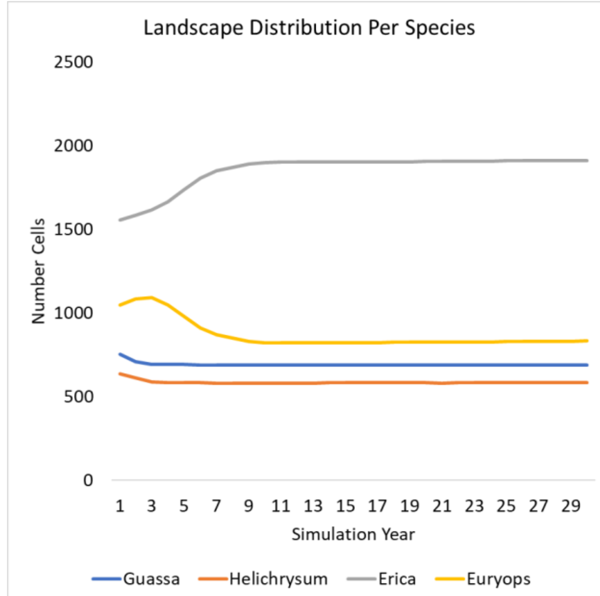
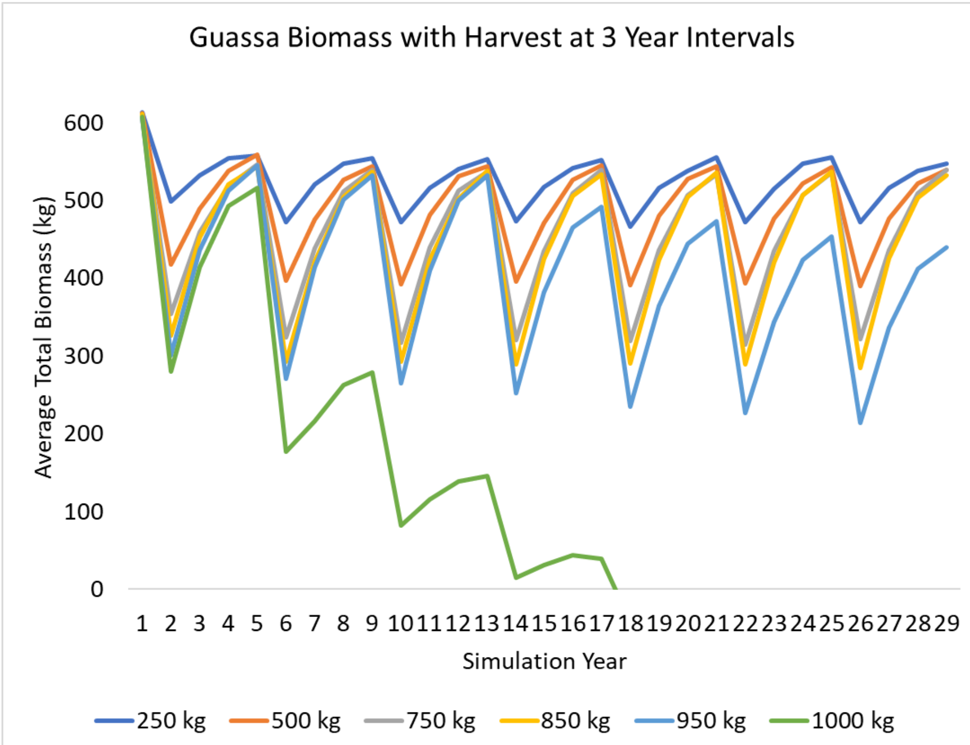


Figure F6. Increasing the proportion of biomass devoted to seed production (from 9% to 14%) caused a slight decrease in total average biomass (left), and a similar decline in the proportion of cells where Helichrysum was dominant (right).

We used the sensitivity analysis to determine the optimal harvest limit per person for the guassa grasses under each climate scenario. Workshop participants estimated a range of guassa harvest per person of 6 – 30 shekams (200 – 990 kg). We tested this range of harvest limits to see if we could discover an optimal harvest rate using the baseline conditions of harvesting every three years. For the average climate, we found that per person guassa harvests remained high through 950 kg harvest limits (Figure S6). However, guassa biomass was unable to recover at this rate, leading to lower average biomass over time. Similarly, guassa range started to contract at a 950 kg harvest limit. Above this limit, declines dropped precipitously. We therefore selected 850 kg as the per person harvest limit for guassa grasses. We used the same process to determine the optimal harvest rate under other climate conditions: 450 kg for the no belg climate, 650 kg for the dry climate, and 1050 kg for the wet climate.



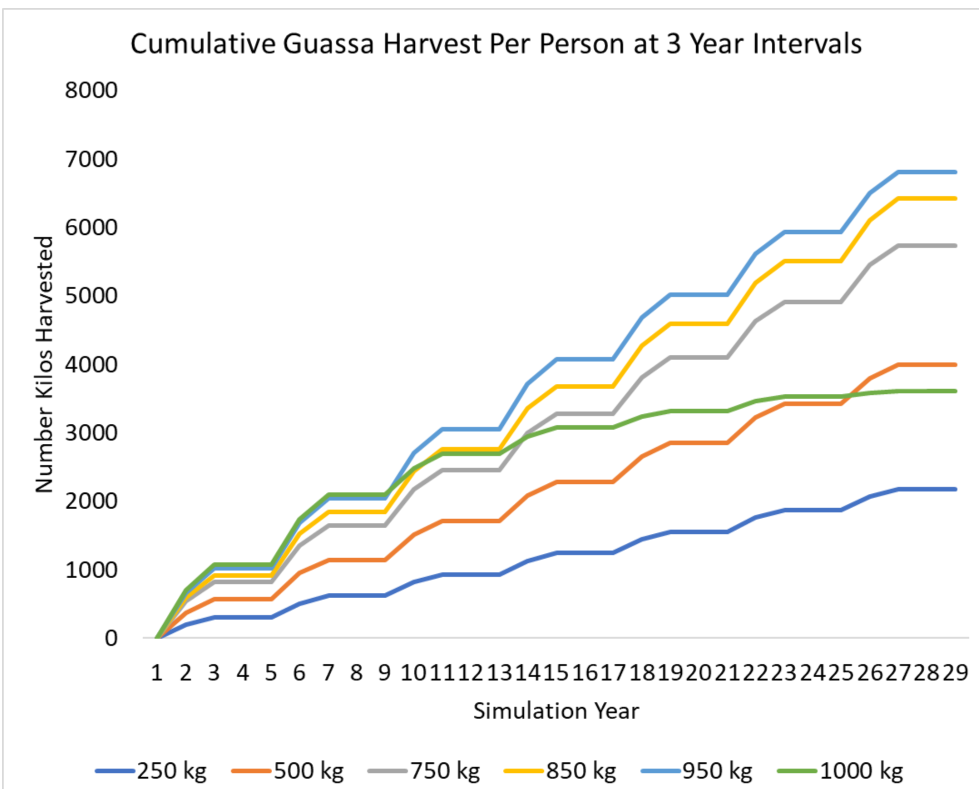


Figure F7. Under an average climate, optimal harvest rates were 850 kg/person/harvest.

Table F3. Landscape distribution (percent of all cells) of all species across scenarios.

	Percent of Landscape Per Species			
	Guassa	Helichrysum	Erica	Euryops
Baseline Scenario	7%	7%	21%	9%
Scenario 1: No belg climate	7%	7%	21%	9%
Scenario 1: Dry climate	7%	7%	21%	9%
Scenario 1: Average climate	7%	7%	21%	9%
Scenario 1: Wet climate	7%	7%	21%	9%
Scenario 2: No belg climate, 2 year harvest cycle	7%	7%	21%	9%
Scenario 2: Dry climate, 2 year harvest cycle	5%	9%	21%	9%
Scenario 2: Average climate, 2 year harvest cycle	5%	9%	21%	9%
Scenario 2: Wet climate, 2 year harvest cycle	5%	9%	21%	9%
Scenario 2: No belg climate, 3 year harvest cycle	7%	7%	21%	9%
Scenario 2: Dry climate, 3 year harvest cycle	7%	7%	21%	9%
Scenario 2: Average climate, 3 year harvest cycle	7%	7%	21%	9%
Scenario 2: Wet climate, 3 year harvest cycle	7%	7%	21%	9%
Scenario 2: No belg climate, 4 year harvest cycle	7%	7%	21%	9%
Scenario 2: Dry climate, 4 year harvest cycle	7%	7%	21%	9%
Scenario 2: Average climate, 4 year harvest cycle	7%	7%	21%	9%
Scenario 2: Wet climate, 4 year harvest cycle	7%	7%	21%	9%
Scenario 3: No belg climate, 2 year removal cycle	2%	2%	36%	5%
Scenario 3: Dry climate, 2 year removal cycle	2%	2%	35%	7%
Scenario 3: Average climate, 2 year removal cycle	2%	2%	34%	7%
Scenario 3: Wet climate, 2 year removal cycle	2%	2%	34%	7%
Scenario 3: No belg climate, 3 year removal cycle	2%	2%	34%	5%
Scenario 3: Dry climate, 3 year removal cycle	2%	2%	35%	5%
Scenario 3: Average climate, 3 year removal cycle	3%	2%	34%	5%
Scenario 3: Wet climate, 3 year removal cycle	3%	2%	34%	5%
Scenario 3: No belg climate, 4 year removal cycle	3%	3%	32%	6%
Scenario 3: Dry climate, 4 year removal cycle	3%	3%	32%	7%
Scenario 3: Average climate, 4 year removal cycle	3%	3%	31%	8%
Scenario 3: Wet climate, 4 year removal cycle	3%	3%	31%	8%

Overview, Design concepts, and Details for Guassa-Helichrysum Model

By: Cara Steger (Cara.Steger@gmail.com)

Purpose

The purpose of this model is to enable people involved in managing a community conservation area in the Ethiopian highlands to explore the individual and combined effects - as well as tradeoffs - of social and ecological factors controlling the spread of native shrubs (*Helichrysum splendidum*) in an Afro-alpine grassland. The model was created to facilitate participatory rural land use planning, and as a research tool for understanding how people learn through models. While there is some level of realism in the landscape and parameterization, we do not intend to produce highly accurate predictions of the future of this area. Rather, we seek to explore potential futures and use these to facilitate discussion among land use planners.

State Variables and Scales

The landscape is represented by 95 x 95 cells, each approximately 30m x 30m, which together represent an 812ha landscape. The eight dominant vegetation types are: Erica shrubs (*Erica arborea*), Euryops shrubs (*Euryops pinifolius*), grassland/shrub mix (not including our target species), guassa grasses (*Festuca macrophylla*), Helichrysum shrubs (*Helichrysum splendidum*), forest (mainly *Eucalyptus globulus* and *Cupressus lusitanica*), stone, and wetlands (mainly *Carex* and *Cyperus* species). Forests, stone, and wetlands do not change in the virtual world; they do not spread and they are unable to be invaded. The grassland/shrub mix also does not spread, but it is able to be invaded by the four vegetation types that do: guassa grasses, Helichrysum shrubs, Erica shrubs, and Euryops shrubs. We initialize patches containing these four vegetation types so that each cell contains some biomass (kg/m2) of each type, following a random normal distribution. For example, Erica shrubs are initialized with 0.5 kg/m2 of dry biomass (+/- 0.2 kg/m2), with 0.1kg/m2 (+/- 0.1 kg/m2) of the other three species.

One time step represents one week in the virtual world. The landscape is modeled after the area surrounding the Guassa lodge in the Guassa Community Conservation Area. The user selects which climate regime to explore in a given simulation: dry (1300 mm ± SD 200 mm), average(1600 mm ± SD 200 mm), wet (1900 mm ± SD 200 mm), or no belg (absence of spring rains, 24% lower than average). Local farmers are the only agent group in this model. Farmers harvest the guassa grasses according to a user-defined frequency and intensity. Farmers also remove the invasive Helichrysum shrubs, again using a user-defined frequency and intensity.

Process Overview and Scheduling

With each tick, the model carries out the following operations:

(1) Set annual rainfall. The annual rainfall is determined at the start of the year following the precipitation values observed using CHIRPS remote sensing products (Funk et al. 2015) and a private rain gauge in the conservation area (Fashing et al. 2014).

(2) Distribute rainfall. Each week receives a proportion of the annual rainfall, again determined using the seasonal patterns observed in the CHIRPS data, as well as local observations. We introduce some variation across the cells, with each cell receiving 90-100% of the weekly rain portion.

(3) Set carrying capacity. We use the maximum biomass estimates from the literature to define the carrying capacity for guassa grasses at 0.8 kg/m2, for Euryops shrubs and Helichrysum shrubs at 1 kg/m2, and for Erica shrubs at 1.2 kg/m2. Following Fryxell et al. (2005), we linked the carrying capacity of these vegetation types to precipitation using a coefficient (ψ). We divided each carrying capacity by the average weekly precipitation in the Guassa area (24.5 mm), yielding estimates of $\psi_{\text{guassa grass}} = 0.0327$, $\psi_{\text{Helichrysum shrubs}} = 0.0408$, $\psi_{\text{Euryops shrubs}} = 0.0408$, and $\psi_{\text{Erica shrubs}} = 0.0490$. In the stochastic simulations, ψ is multiplied by the weekly precipitation.

(4) Grow vegetation. We represent the growth of these four vegetation types through individual modified logistic growth equations. We assume weekly growth rates are at a maximum when vegetation biomass is low, as at the beginning of the rainy season or after a disturbance event (Parsons et al. 2001, Fryxell et al. 2005). Therefore, we include a factor that relates the growth rate to standing biomass and precipitation. We further assume that competition for resources influences both grass and shrub dynamics, and we modify the logistic growth equation to reflect that total biomass from all species restricts growth dynamics in each species equation (D'Odorico et al. 2012). For example, the growth of guassa grass can be represented:

$$\frac{dB_{guassa}}{dt} = r_{max} \times \left[B_{guassa} + \psi(R)\right] \times \left[1 - \frac{B_{guassa} + B_{Helichrysum} + B_{Euryops} + B_{Erica} + \psi(R)}{2 \times \psi(R)}\right]$$

Where B = dry weight biomass (per species), r_{max} = weekly growth rate (per species), and ψ (R) = carrying capacity multiplied by weekly rainfall. This allows both the maximum rate of grass growth and the carrying capacity to rise and fall with rainfall patterns.

Growth rate estimates were derived from MODIS Net Annual Primary Production (NAPP) product (MOD17A3H; Running and Zhao 2015, ORNL DAAC. 2018). First, NAPP was converted from kg Carbon (kgC) to biomass by dividing by 0.5 (0.67 kgC/m2 / 0.5 = 1.34 kg/m2). Based on gross primary productivity curves, maximum growth occurs during the kiremt rainy season, which contains 44.4% of the precipitation over a twelve week period. Given that precipitation is a well-established driver of plant growth in most biomes (O'Connor et al. 2001, Knapp et al. 2002), we assumed that the percent of NAPP during this period was roughly the same as the percent of annual precipitation, yielding a maximum per week growth rate of 0.444*1.34 kg/m2/12 weeks = 0.0496 kg/m2/week. We then divided this maximum growth rate into sections for each vegetation type, assuming that guassa grasses and Helichrysum shrubs are able to grow faster than Euryops shrubs (Everson et al. 2009), which can grow faster than Erica shrubs (Wubie 2018). Due to the highly derivative nature of this parameterization, we tested a range of maximum growth rate estimates in a sensitivity analysis before conducting the management scenarios, and selected growth rates that produce biomass and distribution patterns that match local perspectives.

(5) Produce seeds. Erica seeds are produced in weeks 8-10 of the year, while the other three species produce seeds at the same time in weeks 30-32. Seed production for each vegetation type occurs as a proportion of the aboveground biomass present in each cell, following studies of reproductive allocation and effort (Reekie and Bazzaz 1987). We took the average reproductive allocation (shoots, flowers, and seeds) of three Festuca species in the literature – *F. arundinacea* (7.6%), *F. gigantea* (18.9%), and *F. ovina* (6.9%) (Wilson and Thompson 1989) to estimate that roughly 11% of standing guassa grass biomass is converted to seeds each year. Because reproductive allocation is generally lower in species with low relative growth rates (Bazzaz et al. 1987), we estimate shrub reproductive allocation will be closer to 8% for Euryops shrubs and 7% for Erica shrubs (Vosse et al. 2008). We selected 9% for Helichrysum because our sensitivity analysis revealed larger proportions caused guassa grasses to outcompete Helichrysum, which did not match local perceptions.

(6) Spread seeds. Seeds are spread shortly after production, in weeks 12-14 for Erica and weeks 34-36 for all other species. Due to the absence of aerial dispersal structures (Molinier and Muller 1938), Erica seeds do not typically spread more than 14m from their source plant (Mesléard and Lepart 1991). Therefore, we assume 80% of the seeds produced will stay in the same cell of the model, while 20% will spread to neighboring cells equally. We assume the same distribution for guassa grass seeds, some species of which have been

shown to have highly restricted dispersal distances (Rabinowitz and Rapp 1981). Helichrysum shrubs observed in South Africa have parachute-type seeds that are adapted for long distance dispersal by wind (Shiponeni 2003, Shiponeni and Milton 2006). Helichrysum shrubs have been observed to dominate South African seed banks and become the first shrubs to colonize eroded or overgrazed land, largely due to the papery texture of the seeds and their relative unpalatability (Everson et al. 2009). Therefore, we assume 30% of the seeds produced will stay in the same cell of the model, while 70% will spread to neighboring cells equally. While we were unable to find Euryops seed dispersal observations, research from South Africa (Vosse et al. 2008) shows similar Euryops and Helichrysum seed densities in the soil seedbank. Based on this limited information, we assume 50% of the Euryops seeds produced will stay in the same cell of the model, while 50% will spread to neighboring cells.

(7) Sprout seeds. Erica seeds sprout the same year they are shed in the main rainy season. Seeds of guassa grasses germinate shortly after being shed in July-August, following evidence from observations of *Festuca arundinacea* and *Festuca bromoides* (Bartolome 1979, Grime et al. 1988, Thompson et al. 1997) and preliminary findings that guassa grass seeds are largely absent from the Guassa seed bank (Wubie 2018). Euryops and Helichrysum seeds sprout the following year in the early rainy season. Each seed that germinates contributes a small amount towards the total biomass (0.5 g). Maximum germination rates of Erica shrubs are 62% under ideal conditions in the laboratory (Mesléard and Lepart 1991), therefore, we assume an average 40% germination rate under field conditions. Published data on germination rates for Helichrysum shrubs, Euryops shrubs, and guassa grasses do not exist; therefore, we used estimates from other species in the same genera. Germination rates for the Mediterranean species *H. stoechas* range between 30-50% (Doussi and Thanos 1997) while South Africa *H. foetidum* (12%) and *H.*

patulum (24%) have much lower rates (Brown et al 2003). We thus assume an average 25% germination rate for *Helichrysum* shrubs. Germination rates for seeds from U.S. *F. arundinacea* were between 97-98% (Rampton and Ching 1966); however, seeds from Canadian *F. hallii* had germination rates between 67 – 85% (Qiu et al. 2010). We assume a conservative average of 80% germination rate for guassa grasses. Finally, we take the average of three species of Euryops from South Africa - *E. linearis* (31%), *E. speciosissimus* (24%), *E. virgineus* (13%) (Brown et al. 2003) – and assume a 23 % germination rate for Euryops shrubs in Guassa.

(8) Vegetation senescence. Senescence occurs during the 10 weeks following the end of the kiremt season rains. Each week, guassa grass biomass declines by 8%, resulting in 20% biomass remaining in each cell at the start of the next belg rains. Helichrysum shrubs senesce at a rate of 4% per week so that 60% of their biomass remains the following year, Euryops shrubs retain 80% of their biomass, and Erica shrubs retain 90% of their biomass in the following year.

(9) Transition vegetation cover. In week 39 (late September), we calculate the biomass dominance in each cell with over 0.1 kg/m2 total biomass across the four spreading vegetation types. We selected this week because it falls after the majority of ecological functions in the model (seed production and spreading), yet biomass is still high at the tail end of the main rainy season. We selected the 0.1 kg/m2 threshold to ensure we did not evaluate cells with only very small concentrations of the species of interest. We assume guassa grasses and Helichrysum shrubs need to occupy 40% of the total cell biomass to be considered dominant, while Erica and Euryops shrubs need to occupy 30% of the total cell biomass to be considered dominant. Because Erica and Euryops shrubs are larger, they can produce higher biomass values than guassa grass or Helichrysum shrubs in the same

amount of space. Therefore, we consider a lower percent cover to be equivalent to the same amount of biomass.

(10) Harvest guassa grass. During weeks 18 and 19, farmers are allowed into the Guassa area to cut the guassa grasses. Each farmer moves to a patch with some amount of guassa biomass, and removes 90% of the biomass of that cell. The next week, farmers evaluate whether they are still below the per person limit, and if so they move to another cell and cut 90% of that cell's biomass.

(11) Cut Helichrysum shrubs. During weeks 37 and 38, farmers are allowed into the Guassa area to cut the Helichrysum shrubs. Each farmer moves to a patch with some amount of shrub biomass, and removes 90% of the biomass of that cell. The next week, farmers evaluate whether they are still below the per person effort, and if so they move to another cell and cut 90% of that cell's biomass.

Table F4. Parameter estimates with supporting literature.

Parameter	Description	Estimate	Citations
precipitation	annual precipitation	average (1600 mm ± SD 200 mm), wet (1900 mm ± SD 200 mm) and dry (1300 mm ± SD 200 mm)	Fashing et al. 2014, Funk et al., 2015
Carrying capacity	Maximum carrying capacity	0.8 kg/m2 (guassa grass); 1 kg/m2 (Helichrysum and Euryops shrubs); 1.2 kg/m2 (Erica shrubs)	Wodaj et al 2016; Ensslin et al. 2015; Anderson et al. 2010
growth rate	Maximum weekly growth rate	0.017 kg/m2/week (guassa grass and Helichrysum shrubs); 0.01 kg/m2/week (Euryops shrubs); 0.007 kg/m2/week (Erica shrubs)	Running and Zhao 2015; ORNL DAAC 2018
seed production	Percent biomass allocation into seed production	11% (guassa grass); 9% (Helichrysum shrubs); 8	Wilson and Thompson 1989; Bazzaz et al.

		% (Euryops shrubs); 7% (Erica shrubs)	1987; Vosse et al. 2008
seed bank	Percent seed biomass that stays in current cell	80% (guassa grass and Erica shrubs); 30% (Helichrysum shrubs); 50% (Euryops shrubs)	Rabinowitz and Rapp 1981; Shiponeni 2003; Shiponeni and Milton 2006; Everson et al. 2009; Molinier and Muller 1938; Mesléard and Lepart 1991; Vosse et al. 2008
germination rate	Percent of seeds that germinate from the soil seedbank	80% (guassa grass); 40% (Erica shrubs); 25% (Helichrysum shrubs); 23% (Euryops shrubs)	Rampton and Ching 1966; Qiu et al. 2010; Doussi and Thanos 1997; Brown et al. 2003; Molinier and Muller 1938; Mesléard and Lepart 1991; Olano et al. 2002
senescence	Percent biomass that dies back each year by species	80% (guassa grass); 40% (Helichrysum shrubs); 20% (Euryops shrubs); 10% (Erica shrubs)	Expert elicitation

Design Concepts

The ecological principles addressed by this model include the invasion of three shrub species into a grassland, and the potential effectiveness of introducing a new disturbance regime in the form of mechanical removal of shrubs.

Emergence

These basic principles of competition and shrub encroachment play out through the spread of vegetation patches at the landscape scale. Plant growth and spread are impacted by the growth and spread of other plant species, and also by the suppression/release from spatially and temporally stochastic grass and shrub removal.

Adaptation

The farmers do not adapt in the model, but the management options tested with the model were designed to reflect real-world adaptation possibilities for Guassa management.

Objectives and Prediction

The agents within the model do not learn from their actions or the environment, and they are not able to predict. However, this model was built to facilitate learning in the real world.

Agent-environment interaction and observation

Agents do not interact with one another.

Stochasticity

Most of the variables in the model have some degree of stochasticity built into them, from the initialization of patch rainfall to the percent of seeds that germinate in each cell. Additionally, many of the variables in the model are controlled by changing values in the GUI, which can add some randomness to the simulations.

Initialization and Input

The initial vegetation distribution is derived from a supervised random forest classifier of a February 2019 Landsat image, with an overall accuracy of 77.6%. This ASCII file is brought into the model at the beginning of the simulation so that the initial distribution of vegetation is the same each time. However, the amount of biomass initialized in each cell varies with each initialization.