Explaining Climate-Sensitive Decision-Making:

On the Relationship Between Cognitive Logic and Climate-Adaptive Behaviour

by

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Abstract

The harmonization of climate-adaptive behaviour with pre-existing decision-making processes is central to the way climate change adaptation is described in the literature. Yet such behaviour is largely understudied, making it difficult to predict whether and how individuals can integrate (i.e., 'mainstream') climate change with risk management processes for weather and other 'normal' stressors. In this dissertation, I examine the decision-making processes of South Africa's commercial grain farmers, as a uniquely informative case, through five complementary studies of two original datasets. I seek to better understand the relationship between risk perceptions and climate-adaptive behaviour in this group, who are known to be sensitive to weather risks and who are adopting climate-resilient farming practices (i.e., Conservation Agriculture (CA)), but who are nonetheless perceived by local experts to be insensitive to climate change risks. In doing so, I distinguish between weather-sensitive decision-making, in which farmers perceive and react to weather risks in conjunction with other 'normal' risks, and climate-sensitive decision-making, in which they also perceive and react to the anticipated effects of climate change.

Using mental models interviews in the Western Cape province (*N* = 90), I first reconceptualise farmers' risk-based decision-making processes, drawing on theories of risk perception and framing from cognitive psychology and behavioural economics to interpret the empirical evidence. Second, I explain the variation in farmers' adoption of climate-resilient CA practices based on the different cognitive frames (expressed as linguistic frames) that they use to perceive, interpret and respond to weather risks. Third, I use these results to guide the quantitative analysis of a national survey (*N* = 441), with which I assess the utility of the CA concept in promoting, monitoring and evaluating sustainable and climate-resilient farming practices, as envisioned by the Climate-Smart Agriculture and Sustainable Intensification frameworks. Fourth, I use the interview data to evaluate whether and how farmers integrate climate change and weather risks in farm-level decision-making. Fifth, I build on these findings by using the survey data to quantitatively test whether farmers perceive weather and climate change as equivalent risks.

Lay Summary

Climate change will make life harder for farmers around the world, in part by creating worse and more frequent weather extremes. Many experts want to reduce the economic and social harm by helping farmers adapt to these expected changes through improvements in farming practices known as Conservation Agriculture. However, we currently know little about how farmers combine decisions about weather, longer-term climate risks and other goals, like financial security or family legacy. Borrowing methods and insights from cognitive psychology and risk communication, I use five data-rich studies of South African commercial grain farming to show that farmers have unexpected difficulty integrating climate risks into ongoing decisions, making their adaptations less effective. Farmers and experts think and talk about weather, climate and farming practices differently, creating crucial challenges for communication. The concept of 'climate change adaptation' itself seems to create barriers to farmers' responses to climate risks, and may need rethinking.

Preface

This dissertation is my original, unpublished, independent work.

I identified the problem, designed the research program, gathered and analyzed the data, and wrote the papers. My advisors (Drs. Milind Kandlikar, Terre Satterfield, and Simon Donner) provided feedback at each stage.

All of the work presented herein was shaped by expert interviews that I conducted in South Africa in 2012 and 2013. These experts provided information and advice that contributed to my identification of the research problem and subsequent design of the methodology. In particular, Dr. Hendrick Smith (Grain SA) provided feedback on the survey design.

Ethics approval was obtained from the Behavioural Research Ethics Board in 2012, and has been renewed each year and amended as necessary (Certificate Number H12-01408).

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List of Abbreviations

CA	Conservation Agriculture
CC	climate change (used only in tables and figures)
CV	coefficient of variation (a measure of rainfall variability)
CSA	Climate-Smart Agriculture
FAO	Food and Agriculture Organization of the United Nations
IPCC	Intergovernmental Panel on Climate Change
RSA	Republic of South Africa
SI	Sustainable Intensification

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These pages are the product of many minds. I am foremost indebted to all those who gave me a moment, whether for a friendly chat or with a distant click. The warm welcome that I received in so many homes made fieldwork a pleasure.

I would like to thank my advisors, who have given me time, space and wisdom. Milind Kandlikar for his patience, and for his guidance in extrapolating the forest from the trees. Terre Satterfield for her understanding, and for her guidance in finding rigour in a tempestuous ocean of data. Simon Donner for his keenness, and for his encouragement to aim higher. My friends and colleagues at home and abroad, too many to name, for lending a kind ear, a critical eye, a strong shoulder or a steady hand.

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My family for weaving an emotional safety net. My parents for supporting me unequivocally. They are outwardly pragmatic but secretly idealistic. Their quest to make the world around them a better place is tempered only by their devotion to their children. My fierce and formidable sister, Leah, for charging forth and encouraging me to follow.

My friends for their acceptance. Christian for his eternal external optimism. Marshall for always questioning and never judging. Rachel and Ashlee for crushing and ripping.

Lucy for everything. My light before dawn, my shelter from storms, my partner in peril, my flower in sun, my companion by fire, and my inspiration in dreams.

For my family,

past, present and future

Narrative Prologue

In the monumental halls of storied Disciplines, one may find comfort and stability in the Great Works of Great Scholars. But for an interdisciplinarian, the landscape of potentially crucial intellectual unknowns is unbounded, its dominions nebulous. The Great Scholars of one grand school are the Evil Charlatans of another. These giants are to be found at every turn, and must be tiptoed amongst for fear of mortal wounds inflicted by the myriad complex and contradictory traps they have taken lifetimes to carefully lay. The unknowing Integronaut will otherwise be baited, ambushed and pilloried by the Great Scholars' disciples.

As with those of many prior, my journey was ever winding, often harrowing and sometimes filled with Terror. Setting out from a signpost that pointed towards my intended and comfortable destination, I stepped one foot before the other on a long and lonely road. At my side, sprightly days and weeks were quickly shadowed by hulking Months and Years. I whispered through the Forest of Forgotten Figments, tiptoed around the Desert of Disappearing Delight, swam desperately across the Overwhelming Ocean, trudged among the Perilous Pondering Peaks, and shaded my eyes from the Expanse of Ephemeral Epiphanies. Upon raising my gaze, I found myself in an altogether unforeseen and fantastical place, effervescent with Possibility and buzzing with Questions.

Trembling with nerves and coursing with expectation, I raised my net high and drew long arcs, hoping to catch the fluttering wings of Success, with which I might triumphantly return home. Alas, these fickle creatures were but mist, never to be so entrapped. Exhausted but with heart rekindled, I set resolutely to task laying the foundations of a refuge from Things to Come. Five winters passed, the landscape frigid but the hearth warm, a great many new companions drawn briefly to its flame in my unfinished house. Each brought a small gift of stone, wood, iron or thatch. In time, I rhapsodized and soliloquized, hammered and hewed, tinkered and tailored, painted and polished. At the end of the longest day, on the back of the longest year, I sank into my chair, eyelids heavy and fingers raw. And in the flickering firelight, I beheld a New Home.

Chapter 1: Introduction

As greenhouse gas emissions continue apace and global mean temperatures rise (IPCC, 2013), policymakers' attention has steadily pivoted towards governance innovations that will help individuals, institutions and businesses adapt to the impacts of anthropogenic climate change (Bassett & Fogelman, 2013). The ways in which these diverse actors perceive and respond to climate change's anticipated effects will determine in large part the efficacy of these policies and the societal harms ultimately exacted by this epochal event (IPCC, 2014). Climate change's uncertainty, long timescale and incremental rate of change present unique cognitive challenges that are beyond those of more short-term weather and climate variability (Hallegatte, 2009). However, we know very little about how individual actors will actually interpret and respond to climate change risks (Clayton et al., 2015; Dilling et al., 2015; Grothmann and Patt, 2005). Most allied literatures implicitly assume that individual decision-makers who are sensitive to climate change risks will respond to them as an equivalent long-term extension of the processes by which they presently manage risks stemming from weather and climate variability (e.g., Reidsma et al., 2010; Smit & Skinner 2002; Thomas et al., 2007). In this context, commercial farmers are conceptually vital – they are numerous, relatively autonomous actors who are explicitly weather-sensitive. They manage myriad other uncertain risks on multiple overlapping timeframes, related to markets, finance, ecology, technology and society (Eakin et al., 2014). They are thus widely expected to harmonize (i.e., 'mainstream') climate change adaptation into their existing decision-making processes with ease (e.g., Mertz et al., 2009). However, a growing number of empirical case studies suggest that farmers' climate-sensitive decision-making processes are less straightforward and economically rational than previously understood (Eakin et al., 2016; Kenny, 2011). Climate change may thus magnify existing cognitive challenges in decision-making, creating unforeseen barriers to action.

In many ways, South African commercial grain farmers are an archetypal case study, epitomizing the autonomous private actor foundational to the climate change adaptation literature. They have high theoretical adaptive capacity, and receive little support from government. They perform large-scale, high-input, mechanized, rainfed grain farming (Bernstein, 2012) in a variable Mediterranean climate that is physically vulnerable to climate change (RSA, 2011). They are also differentially adopting Conservation Agriculture (CA), a set of principles recognized by the Intergovernmental Panel on Climate Change (IPCC) as contributing simultaneously to food security and climate resilience (Niang et al., 2015), and key to the Food and Agriculture Organization's (FAO) Climate-Smart Agriculture and Sustainable Intensification programs (FAO 2013a; FAO, 2013b).

In this dissertation, I aim to enhance our understanding of climate-adaptive behaviour by studying South African commercial grain farmers. In examining the relationship between risk perceptions and climate-adaptive behaviour, I ask why this group of farmers appears to be sensitive to weather risks and to be adopting climate-resilient farming practices, yet they are nonetheless perceived by local experts to be insensitive to climate change risks (i.e., the farmers are not thinking much about climate change and are unlikely to respond to its effects proactively). The work addresses this puzzle using five interlinked studies derived from two original data sets: (1) mental models interviews with farmers in the Western Cape province ($N = 90$), and (2) a national survey of commercial grain farmers ($N = 441$). Each study addresses an aspect of decision-making that is critical to the 'mainstreaming' of climate-adaptive decisions. To illuminate the urgent and overlapping problems motivating these inquiries, and to contextualize the five empirical chapters that seek to address them, I first describe the broader arc of the relevant literature and the case at hand (Section 1.1), the research goals (Section 1.2) and questions (Section 1.3), and the methods (Section 1.4). I then provide a brief synopsis of each chapter in describing the structure of the dissertation (Section 1.5).

1.1 The arc of knowledge: Literatures relevant to climate-adaptive behaviour

This research seeks to help fill the gap between decision-making as it is conceptualized in cognitive psychology, behavioural economics and decision science, and as it is represented in studies of climate change adaptation, climate-resilient futures and agricultural risk management. Within each chapter, I synthesize the state of knowledge in relevant literatures, including those related to climate change adaptation (e.g., Bassett & Fogelman, 2013), farm-level risk management (e.g., Moschini & Hennessy, 2001), Conservation Agriculture (e.g., Pittelkow et al., 2015), decision-making (e.g., Evans, 2008) and heuristic shortcuts (e.g., Shah & Oppenheimer, 2008), the role of cognitive framing in shaping choices (e.g., Thaler, 1999), social cognition (e.g., Zhang & Patel, 2006) and social learning (e.g., Bandura, 1977), and relationships between weather and climate change risk perceptions (e.g., Dilling et al., 2015). Here, I present an introductory overview of these literatures prior to their in-depth treatment in the relevant chapters.

Anthropogenic climate change is anticipated to exacerbate the risks posed by weather and climate variability (IPCC, 2013). Its effects are expected to cascade through climate-exposed and interconnected systems in ways that we do not yet fully understand (IPCC, 2014). Meanwhile, human systems are constantly shifting – adapting to changes in stressors that evoke overlapping and competing responses. The decision-making processes that determine risk-mitigating responses are strongly shaped by the nature of those risks – their timeframes, magnitudes and uncertainties (Thaler, 2000). Climate change is unique, in part because its effects are uncertain and will tend to manifest incrementally over decades, with the attribution of its impacts challenging at best (Hallegatte, 2009). Therefore, climate change's effects are and will continue to be numerous, multi-faceted and poorly predicted. In this way, it is misaligned with many 'normal' risks, including weather, to which decision-makers are historically used to responding (Kunreuther et al., 2013). This misalignment makes it difficult to integrate (or 'mainstream') climate change into overarching risk management strategies, as is widely recognized to be best practice (Dovers & Hezri, 2010; Howden et al., 2007).

To reconcile this misalignment, the climate change adaptation, climate resilience and allied literatures have promoted numerous adjusted modes of decision-making to enable the 'mainstreaming' of climate change adaptation into policy-level, institutional and business decisions (Kunreuther et al., 2013). Yet there have been few empirical investigations of the behavioural processes by which *individuals* have and will continue to adapt to its effects (Dilling et al., 2015; Grothmann and Patt, 2005). Though psychologists have sought to understand how *broader publics* perceive climate change risks, they have yet to characterize the ways in which individual climate-exposed decision-makers perceive, understand, and respond to specific climate change stressors (Clayton et al., 2015). Meanwhile, in the subfield known as judgment and decision-making, researchers influenced by cognitive psychology and behavioural economics have clearly demonstrated that human decision-making processes are constrained by limited information, time and cognitive power, as distinct from earlier presumptions regarding models of rational actors and utility maximization (Levine et al., 2015; Lichtenstein & Slovic, 2006; Thaler, 2000).[1] However, these evolving theories of individual decision-making are underrepresented in the literatures relevant to climate-adaptive behaviour.

Motivated by this gap in knowledge, I seek to better understand the challenges faced by individuals in undertaking climate-sensitive decisions (i.e., those that harmonize, or 'mainstream', climate change with broader decision-making processes). In doing so, I argue that South African commercial grain farmers, as a group of climate-sensitive decision-makers, are highly informative. Commercial farmers are conceptually unique – they are an abundant, global population of decision-makers who are explicitly sensitive to weather risks and have relatively abundant resources compared with their subsistence counterparts (Eakin et al., 2014). They operate in diverse environments, managing many interconnected risks related to climate, markets, technology, agronomy, ecology and society (Eakin et al., 2016; Ellis & Ramankutty, 2008). Their careers are devoted to the explicit management of these diverse risks – most of which are highly uncertain and some of which are long term – supported by the field of agricultural economics (Moschini & Hennessy, 2001). Yet they are hybrid actors, making decisions that range from the explicitly rational choices of a small business (e.g., calculating a maximum budget for inputs using expected crop yields and market prices) to the intensely personal choices of the individual (e.g., legacy planning on family farms) (Farmar-Bowers & Lane, 2009; Pannell et al., 2006).

In South Africa, in particular, this large population of small business owners is climate-exposed, with ostensibly high adaptive capacity and the incentive to address uncertain long-term risks. They perform large-scale, mechanized, high-input, rainfed grain farming (Bernstein, 2012) in a variable Mediterranean climate that is physically vulnerable to climate change (RSA, 2011), and are immersed in a culture that reveres multi-generational farming heritage (Devarenne, 2009). They are relatively well educated, with good access to financial, informational and institutional resources. Yet since most are white beneficiaries of South Africa's apartheid past, they receive little support from government (e.g., the subsidies enjoyed by commercial farmers in higher-

[1] The literatures relevant to climate-adaptive behaviours, including psychology and behavioural economics, are reviewed in depth in Chapter 2.

income countries) (Bernstein, 2012). Though some characteristics of the sector are thus unique to South Africa, most are not. Their methods of farming are very similar to those of their better-known brethren in the United States, Canada, Europe and Australia, often with identical implements imported from these countries (Wilk et al., 2013). In sum, they epitomize the autonomous private actor foundational to the climate change adaptation and allied literatures.

Further, they are differentially adopting Conservation Agriculture (CA) (RSA, 2013c)[2] – a set of three principles (permanent soil cover, minimum soil disturbance and advanced crop rotations) promoted by the FAO as a key part of their Climate-Smart Agriculture (CSA) and Sustainable Intensification (SI) foci (FAO 2013a; FAO, 2013b). The IPCC has affirmed that CA has the potential to simultaneously contribute to food security and climate resilience (Niang et al., 2015). Recent meta-analyses have found that comprehensive CA adoption can improve average crop yields and reduce yield variability in dry climates like that of South Africa (Pittelkow et al., 2015; Rusinamhodzi et al., 2011; Van den Putte, 2010). However, these same analyses suggest that when adopted incompletely, these benefits are sharply curtailed or even reversed, particularly when minimum soil disturbance (also known as no-tillage, low-tillage, or minimum tillage) is applied in the absence of advanced crop rotations and permanent soil cover (Pittelkow et al., 2015). They have long been targeted by risk communications efforts that emphasize the threat of climate change and the need for climate-adaptive responses (RSA, 2013c), yet in preliminary interviews, local experts were skeptical that farmers were thinking about climate change or were prepared to respond to it.

1.2 Overarching goals

The goal of this dissertation is to contribute to the better understanding of individuals' climate-adaptive behaviours. To pursue this goal, I undertake two analytical branches using the case of South African commercial grain farmers. First, I seek to better understand how farmers presently perceive and respond to weather and other 'normal' risks (i.e., their weather-sensitive decision-making). Second, I seek to understand how farmers' perceptions of and responses to climate change (i.e., their climate-sensitive decision-making) are related to normal risk management.

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[2] Patterns of CA adoption are explored in depth in Chapters 3 and 4, which each contain a deeper review of the CA literature.

Each chapter of the dissertation is intended to stand alone,[3] but the sum is greater than its parts. The specific goals, objectives and hypotheses of each chapter are summarized in Table 1.1.

The problem identification and study designs were crucially informed by a set of semi-structured expert interviews that I conducted in 2012. Over the course of four months in South Africa, I explored the juncture of climate change, food, water and energy in individual meetings with more than a hundred different local experts in the fields of climate science, water governance, ecology, economics, energy policy, soil science, climate change adaptation, mechanical engineering and remote sensing, along with six outspoken and engaging commercial farmers in the Western Cape province.[4] Throughout these conversations, many of them wide-ranging on the topics of climate change, energy, development and food security, I asked about the most important challenges facing South African agriculture in the coming decades: How would climate change, growing inequality, the national energy crisis, limited and highly variable water resources, and South Africa's apartheid legacy converge in the 21st century with the constitutionally recognized need for a strong, fair and sustainable food system?[5]

In these conversations, as rich and diverse as they were, among the countless pressing issues, intersections and intriguing cruxes, many of my participants noted the same phenomenon with a mixture of hope and skepticism. They had heard or had themselves observed that commercial grain farmers, particularly those in the Western Cape province, were shifting towards more sustainable and climate-resilient methods of food production, largely of their own initiative and with little guidance or support from government and private extension services. However, most of these experts did not think that these farmers were actually responding to climate signals.

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[3] I anticipate submitting the chapters to peer-reviewed journals. They are thus each written to stand alone, and contain some measure of overlapping content in their introductory and methods sections. The synopsis at the beginning of each chapter is in the form of an abstract for journal submission. Further, these chapters are written in first person plural, in recognition of the broader intellectual contributions of my committee members and local partners who may be included as co-authors at the time of journal submission.
[4] Of these meetings, I sought the participants' consent to record and transcribe 50 as formal expert interviews, as detailed in the methodology in Section 1.4.
[5] South Africa's constitution, arguably the most progressive in the world when it was adopted in 1996, recognizes the rights to food and water (Section 27), and to a healthy environment (Section 24) (RSA, 1996).

Though the farmers were explicitly sensitive to weather risks and adopting climate-resilient farming practices, local experts were skeptical that they were thinking about climate change and were prepared to respond to its effects. I thus set out to understand why experts' perceptions appeared to be misaligned with farmers' behaviours.

Table 1.1: Goals, objectives, hypotheses and datasets by chapter.

Chapter	Dataset	*N*	Thematic Branch	Goal	Objective	Overarching hypothesis
2	Mental models interviews	90	Weather-sensitive	To better understand how farmers presently perceive and respond to weather in concert with other 'normal' risks	Characterize farmers' risk-based decision-making processes	Farmers do not respond to weather risks as maximizers of expected utility.
3	Mental models interviews	90	Weather-sensitive	To better understand why the implementation of weather risk-mitigating responses varies	Measure the effect of cognitive framing on the adoption of Conservation Agriculture	Farmers' cognitive framing of weather risks influences their choice of farming practices.
4	National survey	441	Weather-sensitive	To improve the promotion and monitoring of sustainable and climate-resilient farming practices	Characterize the usefulness of Conservation Agriculture as a framing concept	a. Farmers do not adopt Conservation Agriculture as a package. b. Farmers' idea of conservation farming differs from experts' definition of CA.
5	Mental models interviews	90	Climate-sensitive	To better understand how climate change risk perceptions are different from those of weather	Characterize the relationship between climate change and weather cognition	Farmers do not think about weather and climate change risks in similar ways.
6	National survey	441	Climate-sensitive	To test the assumption of equivalency in farmers' weather and climate change risk perceptions	Measure the relationship between climate change and weather risk perceptions	Farmers prioritize weather and climate change risks differently.

1.3 Overarching question

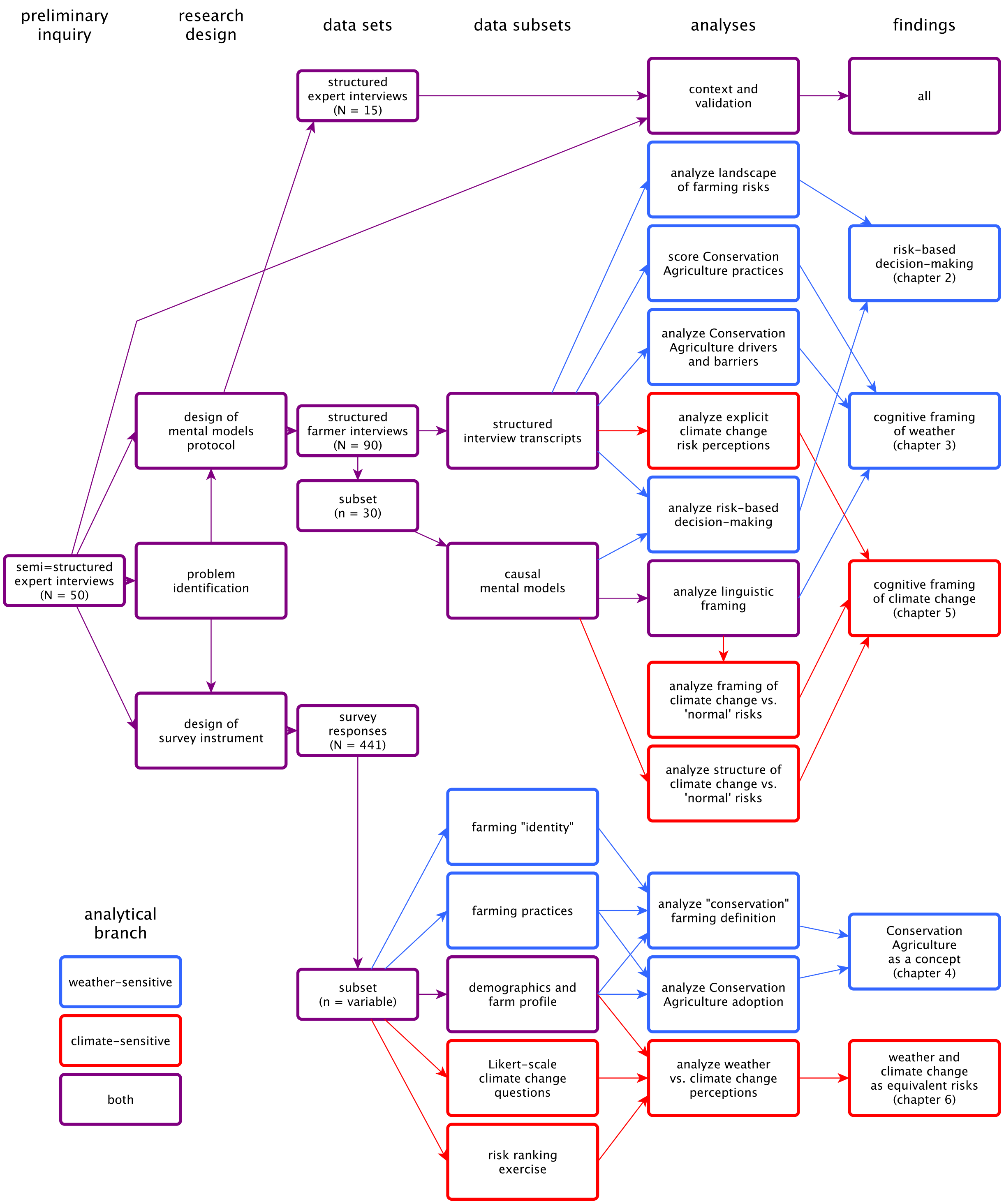
How do risk perceptions influence farmers' climate-adaptive behaviours?

In attempting to answer this question, I distinguish between two different modes of risk management that correspond to distinct branches of inquiry. In the first three chapters, I examine whether and how farmers perceive and respond to weather risks among myriad other 'normal' risks at the farm level (i.e., their weather-sensitive decision-making). In the last two chapters, I then assess whether and how they perceive and respond to climate change risks in concert with weather (i.e., their climate-sensitive decision-making). The specific questions and hypotheses relevant to each chapter are shown in Table 1.1.

1.4 The arc of methodology: Designs, datasets and analyses

This dissertation draws conceptual and policy-oriented conclusions from five problem-centered empirical studies of South African commercial grain farming, using two major data sets: (1) structured mental models interviews with farmers in the Western Cape province ($N = 90$), conducted in 2013; and (2) a national survey of grain farmers ($N = 441$), conducted in 2015. The mental models interviews provide insight into the processes by which individual farmers perceive and respond to weather and climate change risks in conjunction with myriad others at the farm level. This allows for the analysis of cause and effect, as described by participants. In parallel, the survey data provide a larger sample in which to identify statistical relationships among different demographics, farm characteristics, risk perceptions and farming practices, complementing and confirming earlier qualitative findings. Each chapter includes a detailed account of the methods relevant to the analysis therein, but it may be useful to understand the broader arc of the methods that have contributed to this body of work. The data collection and analysis are visualized as a flowchart in Figure 1.1, illustrating the scope and structure of the research program. The five studies are roughly divided into two analytical streams, indicated by their colour: weather-sensitive decision-making (blue) and climate-sensitive decision-making (red). Those steps that contribute equally to both streams are indicated in purple.

Figure 1.1: Flow chart of the data collection and methods contributing to each chapter. The two analytical streams are distinguished by colour: weather-sensitive (blue) and climate-sensitive (red) decision-making. Those steps that contribute equally to both streams are indicated in purple.



As described above, the problem identification and study designs were framed by a set of 50 semi-structured interviews that I conducted in 2012. These suggested that South African commercial grain farmers were explicitly sensitive to weather risks and were differentially adopting climate-resilient farming practices, but that they were perceived not to be sensitive to climate change risks. Following a preliminary analysis of these interviews, I delved into the literatures on climate change adaptation and resilience, agriculture and food security, and judgment and decision-making to better understand the state of knowledge in relevant fields of scholarship. I then designed a program of doctoral research to unravel the conundrum of weather vs. climate change as a contribution to the harmonization of climate-adaptive behaviours with decision-making more broadly.

To better understand farmers' weather-sensitive decision-making and its relationship to climate change, I designed, piloted and implemented a set of structured mental models interviews in late 2013. Mental models attempt to capture the cognitive representations of reality that participants use to perceive, process and respond to a given situation, idea or stimulus (Jones et al., 2011; Morgan et al., 2002). These are visualized as influence diagrams that describe perceived causal relationships. Their contents and structure are then analyzed to provide insights into participants' understanding of the particular processes of interest – in this case, weather and climate change risk management. Each of these interviews included two major components: (1) a risk elicitation exercise in which participants first defined the landscape of risks relevant to their farming enterprises, and (2) mental models sections related to farming practices, weather and climate change. I analyzed the data from these interviews qualitatively and quantitatively, providing the empirical foundations for Chapters 2, 3 and 5.

To complement and confirm the findings from these interviews, I designed, piloted and implemented a national survey of South African commercial grain farmers in 2015. The survey instrument included major sections related to farm characteristics (e.g., farm size, crops grown, profit), farmer demographics (e.g., age, education, political identity), farming practices (e.g., tillage, soil cover, crop rotations, use of cover crops), and risk perceptions (i.e., a broader risk ranking exercise, and Likert-scale questions about climate change). This approach is broadly similar to that used by van Duinen et al. (2015). The data from this survey provide the empirical foundations for Chapters 4 and 6. These chapters comprise quantitative investigations of narrower research questions implied by the earlier studies. The quantitative CA analysis in Chapter 4 builds from the analysis of cognitive framing and CA adoption in Chapter 3, while the quantitative risk ranking analysis in Chapter 6 complements the finding of climate change's cognitive isolation in Chapter 5.

1.5 The arc of inquiry: Structure of the dissertation

In Chapter 2, I examine farmers' risk-based decision-making, and their treatment of weather risks in conjunction with other 'normal' risks. I argue that the climate change adaptation literature is steeped in theories of weather-sensitive decision-making that are inconsistent with real-world risk management behaviours. This has persisted both because its conceptualization is still shaped by rational economic theory, which ignores values, preferences, heuristics, biases and frames (Lichtenstein & Slovic, 2006), and because most research on judgment and decision-making focuses on narrower decisions made within well-controlled environments of limited scope and complexity (Levine et al., 2015). To build a new working theory of farmers' risk-based decision-making, I analyze their in situ thinking about weather within the broader landscape of risks that shape their commercial farming enterprises. I find that their risk management is not the result of a single, cohesive decision-making framework. Instead, farmers make frequent iterative decisions to address multiple competing objectives on different scales and in response to different stressors, a process that is strongly mediated by social and experiential learning. Their behaviours suggest that they are satisficing to ensure "good enough" outcomes under largely unknown risks, rather than optimizing towards the "best" outcome under known and calculable risks. I argue that they use two important decision-making heuristics to make practical trade-offs within and between different domains of uncertain risk, respectively: (1) they use multiple simultaneous risk-mitigating responses that are not necessarily coordinated and may consequently undercut some of the benefits of other concurrent behaviours; and (2) they use "good enough" thresholds rather than precise calculations to make trade-offs among variables measured on uncertain and often incompatible scales. I argue that the predictability of these processes of decision-making is complicated by farmers' use of different cognitive frames to address different risks – such a frame being the set of specific perceptions, preferences, memories and mental models that an individual uses to understand and respond to a particular problem (Thaler, 1999).

In Chapter 3, using the conceptual framework established in the preceding chapter, I study the role of cognitive frames in farmer decision-making. Specifically, I examine the behavioural effects of a suite of cognitive orientations to weather and climate change risks evident among these farmers. Previous studies have established that there are strong linkages between cognitive framing and its linguistic expression (Lakoff, 2012; Porter & Hulme, 2013), and that the use of different cognitive frames can result in choices that differ in their apparent rationality (Thaler, 1999). I thus seek to explain differences in farmers' behaviours by testing the relationship between their linguistic expression of weather and climate change risks and their use of climate-adaptive best practices (exemplified by CA). I find that participants use six "languages" to frame weather and climate change risks: agricultural, cognitive, economic, emotional, political and survival. I show that the prevalence of these languages among those interviewed differs markedly between farmers who are adopting CA in a comprehensive manner and those who are not. High-adopters frame weather risks using "rational" agricultural, economic and cognitive languages. Low-adopters additionally frame weather risks using "irrational" emotional and survival languages. The prevalence of the emotional and survival languages among low-adopters suggests that the investments in knowledge, technology and land necessary for comprehensive CA adoption are inhibited by economic anxiety expressed in terms of the survival of the farm. Short- to medium-term concern for the survival of the farm can therefore impede adaptation to changes in climate that may threaten that very survival in the long term.

In Chapter 4, I build from the findings on CA adoption in the preceding chapter, investigating the concept of CA as a means by which to frame sustainable and climate-resilient farming practices. Meta-analyses of CA's benefits have suggested that comprehensive CA adoption produces crop yield gains in dry climates, but that these are curtailed or even reversed when its principles are applied piecemeal (Pittelkow et al., 2015; Rusinamhodzi et al., 2011; Van den Putte, 2010). This implies that the extent of CA's complete – and therefore beneficial – adoption has been broadly overestimated, because researchers typically use narrow proxies (e.g., the use of minimum-till machinery) to monitor its spread (Knowler & Bradshaw, 2007), rather than by assessing outcomes aligned with its three principles. I analyze patterns of CA adoption in South African grain farming to evaluate the utility of the CA concept in promoting and monitoring the adoption of sustainable agricultural practices in this group, and to compare farmers' shared definition of "conservation" farming with experts' definition of CA. I find that farmers are not adopting CA as a comprehensive package; instead they decide whether and how to adopt its three principles using different rationales, while demonstrating some difficulty in estimating CA outcomes directly. Farmers' definition of "conservation" farming is strongly influenced by older concepts; though related, these are mismatched with the terms used by experts in promoting CA adoption. In combination, these findings suggest that beneficial CA adoption is best promoted, monitored and evaluated using specific bundles of locally tailored practices that contribute to each of its overarching principles. Otherwise, the mismatched definitions of experts and farmers and the piecemeal adoption of CA principles will likely lead both to the underestimation of the agricultural extension challenge and to the overestimation of its results.

In Chapter 5, having gained a better understanding of weather-sensitive decision-making, I revisit farmers' mental models to evaluate the harmonization of climate change with weather and other 'normal' risks (e.g., economic, ecological). The literature holds that farmers ought to integrate (i.e., 'mainstream') their management of climate change risks with 'normal' risks (e.g., Howden et al., 2007), yet the mechanisms by which they might do so are poorly understood (Clayton et al., 2015). To better understand the mainstreaming challenge, I evaluate the extent to which these farmers have integrated climate change risks into the mental models that they use to manage weather risks and to make decisions around farming practices. I find that participants' causal mental models of climate change risks are distinct from their mental models of weather and other 'normal' risks – that is, their stated and implied logic of climate change risk management is linguistically and structurally isolated from that of weather. They frame climate change in different terms, and their proposed responses to climate change are largely novel. Their climate change logic contains more intuitive leaps, where they suggest adaptive responses without describing the intermediate problems and/or effects that these responses are intended to mitigate. I argue that this linguistic and structural isolation is indicative of farmers' use of misaligned cognitive frames in understanding and responding to climate change and weather risks. In turn, such a misalignment will make it more difficult for these farmers to mainstream their climate-adaptive behaviours.

In Chapter 6, I address a complementary and confirmatory question using the broader sample afforded by the national survey. In the literature addressing the mainstreaming of climate change adaptation, commercial farmers are often assumed to have already done so, intuitively treating climate change risks as an equivalent, long-term extension of risks stemming from weather and climate variability (e.g., Mertz et al., 2009). In fact, a small but growing number of in-depth case studies suggest that they do not (e.g., Eakin et al., 2016). Using a risk ranking exercise, I seek to quantitatively test the proposition that farmers treat the two risks as equivalent. I find that individual farmers tend to prioritize one over the other, but which risk they prioritize varies; nearly identical proportions of farmers selected each risk as a high priority and not the other. Further, farmers who selected one were no more or less likely to select the other. The ranks of the two risks were driven by different demographic variables, farm characteristics and farming practices. Furthermore, all of the independent variables that were significantly associated with both weather and climate change ranks had effects on the two that were of opposite sign to each other. The findings suggest that the assumption of equivalence between climate change and weather risks is inaccurate, at best; these farmers do not generally think about climate change risks in the same way that they do weather risks. This implies a major, unrecognized risk communication challenge for climate scientists and policymakers.

Finally, in Chapter 7, I summarize my findings and draw broader conclusions about climate-adaptive behaviours and the cognitive challenge that individuals must overcome in responding to climate change effects. In combination, the findings from the five empirical chapters suggest that farmers will have difficulty mainstreaming climate change adaptation under risk communication regimes that presently assume the integration of weather and climate change in their decision-making. They are therefore less likely than previously thought to respond to climate change risks rationally and proactively, in part because the frames used by farmers and experts are misaligned. I have further identified two specific risk communications challenges that will impair climate-adaptive policies if left unaddressed.

1.6 Final opening remarks

The realization of climate-resilient futures hinges on our ability to perceive, process and respond to climate change risks at many scales. The apparent climate-insensitivity of a group of weather-sensitive and climate-exposed individuals was a riddle in need of an answer. In systematically unraveling this particular conundrum, I hope that I may catalyze in some small way the harmonization of climate change knowledge with our growing understanding of human judgment and decision-making.

Chapter 2: Hazy hedging and bounded trade-offs: Farmers' risk-based decision-making strategies under ubiquitous uncertainty

2.1 Synopsis

The climate change adaptation literature is steeped in theories of weather-sensitive decision-making that are inconsistent with real-world risk management behaviours. To better inform adaptation research and policy, this paper characterizes the messy practice of risk-based decision-making among South African commercial wheat farmers (*N* = 90). Using a mental models approach, we analyze farmers' in situ thinking about weather within the broader landscape of risks that shape the modern commercial farming enterprise. We first assess farmers' direct relationships to weather risks, both in their perception and immediate mitigative responses. We then develop a working theory of farmers' risk-based decision-making by analyzing the ways in which they make trade-offs among different weather risk-mitigating responses, and between weather and other domains of risk. Overall, we find that farmers' decision-making is not rational with respect to standard economic models, but is rational with respect to the ubiquitous uncertainty in their decision environments (i.e., ecologically rational). Risk management, we find, is not the result of a single, cohesive decision-making framework. Farmers instead make frequent iterative decisions to address multiple competing objectives on different scales and in response to different stressors, all of which is strongly mediated by social and experiential learning. Their behaviours suggest that they are satisficing to ensure "good enough" outcomes under largely unknown risks, rather than optimizing towards the "best" outcome under known and calculable risks. They also demonstrate two important decision-making heuristics to make practical trade-offs within and between different domains of uncertain risk, respectively: (1) they use multiple simultaneous risk-mitigating responses that are not necessarily coordinated and may each undercut some of the benefits of the other (i.e., hazy hedging); and (2) "good enough" thresholds rather than precise calculations to make trade-offs among variables measured on uncertain and often incompatible scales (i.e., bounded trade-offs). We illustrate these strategies by analyzing the relationship between two responses – Conservation Agriculture and livestock. These risk-mitigating responses simultaneously complement and compete with one another as concerns weather risk, while both contributing to risk mitigation in other domains. Under pervasive uncertainty, it may be that the heuristics we see are not only "good enough," but that they result in better outcomes than would otherwise be achieved through more exhaustive reasoning.

2.2 Introduction

In the past two decades, humanity's failure to substantially slow emissions of carbon dioxide and other greenhouse gases has prompted the gradual reorientation of global climate change policy from mitigation towards adaptation. The volume of research on climate change adaptation is rapidly expanding (Bassett & Fogelman, 2013), yet its behavioural dimensions remain sorely understudied (Clayton et al., 2015). While policy-level analyses have discerned the need for new decision-making strategies that are robust to uncertainty (Kunreuther et al., 2013), our conceptualization of individual decision-making remains fraught with untested or disproven assumptions. In the absence of an alternative model of climate-adaptive decision-making, the literature on adaptation in commercial agriculture is implicitly founded on three simplifying assumptions: (1) that existing processes of risk management for weather and climate variability are generally rational and therefore predictable; (2) that climate change adaptation will largely be equivalent to a long-term extension of these existing processes; and (3) that farmers will therefore adapt to climate change as it occurs incrementally.

In this paper, we test the first of these assumptions through an empirical study of commercial grain farming in South Africa. We evaluate the processes of decision-making that contribute to the perception and management of weather and climate variability among the diverse risks that shape the commercial farming enterprise. Beginning with risk frameworks defined by each participant, we elicited farmers' causal mental models of weather and climate variability to understand the processes by which multiple stressors produce interconnected risk-mitigating responses. We then developed a working theory of participants' risk-based decision-making by analyzing the ways in which they managed trade-offs among competing responses to weather risk, and between weather and other domains of risk. In turn, this revealed two important heuristics, which we refer to as hazy hedging and bounded trade-offs, that our participants used to make decisions under pervasive uncertainty.

In what follows, we review the literature relevant to weather-sensitive decision-making in agriculture. We begin with a look at risk-based decision-making by individuals as conceptualized in cognitive psychology and behavioural economics, followed by theories of decision-making that are implicit and explicit in climate change adaptation and climate resilience research. In Section 2.3, we describe our study area, sample and methods. In Section 2.4, we present the results of a mental model analysis aimed at elucidating causal relationships among weather-related stressors, risk-mitigating responses, and mediating variables representing other domains of risk. Finally, in Section 2.5, we discuss these findings in conceptualizing a working theory of farmers' risk-based decision-making and two common heuristics.

2.2.1 Theories of decision-making

Rational economic theory, once predominant and still influential (Levine et al., 2015), is premised on the existence of stable preferences that guide optimization processes to maximize the utility of the outcome (Becker, 1976). However, myriad cognitive and environmental factors (e.g., values, preferences, heuristics, biases, frames) pervade working models of individual decision-making (Lichtenstein & Slovic, 2006). Alternative theories of decision-making have instead turned to cognitive psychology and behavioural economics – the study of economic decision-making in which the strong influence of context and framing is explicitly recognized. For a half-century, these fields have been at the forefront of the reimagining of human choice, from the perfectly rational *Homo economicus* to the imperfect and often irrational *Homo sapiens* (Thaler, 2000). Behavioural economists argue that individuals' risk-based decision-making varies in time and space, shaped by cognitive, emotional and social factors, and enabled by cognitive short-cuts (Shah and Oppenheimer, 2008).

Simon (1956) conceived of bounded rationality as a tension between competing behaviours: optimizing, in which utility is maximized, and satisficing (i.e., combining satisfying and sufficing), in which the choices made are "good enough" given limited time, knowledge and cognitive power. In defining prospect theory, Tversky and Kahneman (1981) further established the importance of context and framing. Since the publication of their seminal piece, countless studies have found that the framing of options (e.g., positively or negatively, as defaults or as conscious selections) strongly influences the subsequent choice (Kahneman & Tversky, 1984; Levin et al., 1998). Context and framing in part determine the availability of specific perceptions, preferences, memories and mental models. In aggregate, these represent the cognitive frames, or schema, that individuals use to understand and respond to specific problems. Frame selection is influenced by the nature of the problem, the way in which it is posed, the emotional and physical states of the individual, their recent and past experiences, and their social and physical environments (Goffman, 1974; Lerner et al., 2015; Tversky & Kahneman, 1981). Decisions about risk are imperfect and mutable; for objectively similar tasks, the use of different cognitive frames will result in different decision-making strategies that will differ in their apparent rationality (Thaler, 1999).

Researchers have also experimentally demonstrated dozens of common heuristics (i.e., cognitive shortcuts or rules of thumb) that people subconsciously apply to arrive at "good enough" decisions (Shah & Oppenheimer, 2008). To differentiate between automatic and purposeful reasoning, dual-process theory posits two generalized modes of cognition relevant to decision-making (Evans, 2008), most popularly described by Stanovich and West (2000) as System 1, the intuitive, and System 2, the deliberative. System 1 is automatic, rooted in emotion and experience, and cognitively efficient, whereas System 2 is controlled, analytical, and cognitively taxing. Heuristics are therefore largely within the purview of System 1, serving to facilitate intuitive judgments. Prevailing wisdom holds that, as shortcuts, heuristics usually lead to sub-optimal decisions. However, Goldstein and Gigerenzer (2002) argue that heuristics reflect "ecological" rationality; that they are rational with respect to complex environments that are defined by uncertainty (i.e., unknown risks) rather than by known and calculable risks. They posit that heuristics therefore evolved to help us make better – not simply easier – decisions. Their experimental results suggest that under some circumstances, people (and computers) make better judgments when given less information and less time than they otherwise make with more information and exhaustive reasoning (i.e., less-is-more effects).

Furthermore, social relationships play a crucial role in decision-making. Human cognition is socially distributed, through knowledge-sharing and group norm setting (Zhang & Patel, 2006). Emotions, including peer validation and shame, are strong drivers of behaviour (Lerner et al., 2015; Levine et al., 2015). Learning is contingent on social and institutional relationships (Bandura, 1977; Wenger, 2000) and, by extension, scientific knowledge is socially co-produced (Jasanoff, 2004). Individual agency can be reinforced in both perception and practice through social mechanisms. For instance, Eakin et al. (2016) emphasize the need for farmers to collectively improve their decision-making environment by influencing processes of political action, collaboration across sectors and institutional change. Many recent studies of environmental behaviours (Goldstein et al., 2008; Pahl-Wostl, 2002; Reed et al., 2010) and the co-management of complex systems (Cundill & Rodela, 2012) suggest that public policies should therefore mimic social learning through facilitated knowledge brokerage rather than through conventional educational campaigns.

Theories of cognition and behaviour, largely supported by laboratory or computer-based experiments, have fundamentally changed our understanding of the processes by which individuals make decisions. However, most such research necessarily focuses on narrow decisions made within well-controlled environments of limited scope and complexity. We have much less understanding of the messy processes by which individuals make decisions in situ. Decision-making takes place in complex risk landscapes towards multiple overlapping and competing objectives that require myriad trade-offs using often-incompatible measures. Despite advances in the sophistication of computer simulations and challenges in the interpretation of observational data, field studies remain unmatched in the investigation of naturalistic decision-making within detailed, challenging, and varied cognitive and social environments (Hudson et al., 2012; Levine et al., 2015).

Climate-adaptive behaviours, in particular, are understudied and under-theorized (Clayton et al., 2015; Grothmann & Patt, 2005). Defined as responses that lessen the harms or magnify the benefits of climate change, adaptation has been variously categorized along complementary continua: autonomous or planned; reactive, concurrent or anticipatory; short-term or long-term; localized or widespread; capacity-building or direct action; and soft (flexible and reversible) or hard (inflexible and irreversible) (Adger et al. 2005; Füssel, 2007; Hallegatte, 2009; Smit et al., 2000; Stern, 2007). However, all such frameworks distinguish between responses by policy-makers and those by individual actors. Responses by individual actors are inherently local and context-specific, dependent on such variables as the climate-sensitivity of locally important economic sectors, the broad level of development, and the size and agency of vulnerable groups (Vincent, 2007). Because of the diversity of such responses, adaptation researchers have rarely attempted to relate their findings to the frameworks used by scholars of judgment and decision-making. Few efforts have therefore been made to generalize lessons from empirical studies of climate-adaptive behaviours. The adaptation literature thus typically falls into two distinct categories: (1) policy-oriented lessons and institutionally driven actions based on theories of adaptive capacity, systemic change, transformation, resilience, and vulnerability (e.g., McGinnis & Ostrom, 2014); and (2) detailed case studies of specific instances of adaptation to climate variability by individuals or groups (e.g., Wreford & Adger, 2011).

Within these two adaptation literatures, assumptions about individual decision-making are more often implicit than explicit. Bassett and Fogelman (2013) argue that the vast majority of adaptation studies have adopted the rational language of adjustment or resilience to hazards, the persistence of which political ecologists have long criticized in the natural hazards literature. For agricultural risk management, in particular, theories of decision-making are firmly rooted in agricultural economics as a distinct branch of applied economics (Moschini & Hennessy, 2001). Expected utility theory, foundational to the discipline, conceives of farmers as optimizers with near-perfect information who select rationally from well-constrained but risky choices that will produce predictable outcomes with known probabilities and quantifiable values. Each choice has an expected value based on the probability and value of each possible outcome. The decision-maker can thereby calculate precise trade-offs among responses and between domains of risk. They will then necessarily prefer the option with the higher expected value, contingent on their risk aversion. In the absence of an alternative paradigm, climate change adaptation researchers in the agricultural and resource economics traditions continue to rely on expected utility theory as the default method by which to integrate climate-adaptive behaviours into broader studies (e.g., Rosenzweig et al., 2013). Farmers are therefore conceived as profit-maximizers who will manage climate change risks rationally in conjunction with other important farming risks, as they have always done for weather (Eakin et al., 2016). The development of more realistic alternative theories of farmer decision-making will be crucial to the creation of pragmatic climate change policies that facilitate climate change adaptation not only in theory, but also in practice.

To help better anticipate climate-adaptive behaviours, this paper therefore develops a working theory of farmers' risk-based decision-making through the empirical analysis of South African grain farmers' in situ risk perceptions and responses. South Africa's climate is semi-arid with highly variable rainfall (RSA, 2011), and anthropogenic climate change is expected to reduce mean rainfall in the Western Cape province and to further increase its variability (RSA, 2011). South African commercial grain farmers typically exhibit high adaptive capacity with little explicit support from the government. These farmers generally have good access to education, finance, information and technology, and have demonstrated their responsiveness to evolving external stressors (Wilk et al., 2013). Their farming enterprises are generally large, modern and highly mechanized, with advanced planting and harvesting implements alongside plentiful fertilizer and chemical inputs. These farmers are therefore well positioned to improve our understanding of the likely behaviour of the idealized private actor – autonomous, adaptive and resourceful – that is foundational to the climate change adaptation literature.

While some environmental, social and political factors related to commercial grain farming are unique to South Africa, most are not. Many South African commercial farmers perceive land tenure risks from the ongoing land reform and restitution programs that have followed the end of apartheid (Bernstein, 2012). However, the land reform program remains premised on voluntary participation (i.e., the "willing buyer, willing seller" model), and the relatively low number of land claims pending in the Western Cape (RSA, 2013b) has made the political risks less immediate here than in other provinces. Cultural context is important in shaping judgment and decision-making (Savani et al., 2015), but preferences can vary more within countries than between (Falk et al., 2015). Globalization and subsequent flows of technology and expertise have led to commonalities in the culture and practice of commercial farming (Ellis & Ramankutty, 2008). In practice, the grain farmers who participated in this study greatly resemble their peers in higher-income countries. They practice high-input mechanized farming on large land areas, facilitated by crucial international, intercultural and interlinguistic flows of knowledge and technology through globalized markets, travel and the Internet.

Western Cape grain farming is predominantly rainfed (i.e., dryland), and farmers have long used livestock to mitigate weather risks. They are now also adopting Conservation Agriculture (CA), a set of interlinked climate-resilient crop farming practices (Findlater, 2013). The Intergovernmental Panel on Climate Change has affirmed with "high confidence" that CA has the potential to simultaneously increase food production and climate resilience (Niang et al., 2014). If adopted in concert, CA's three component principles – advanced crop rotations, minimum soil disturbance and permanent soil cover – are expected to improve average crop yields, reduce input costs, and lessen the overall risk of farm failure (Derpsch et al., 2014; Giller et al., 2015; McCarthy et al., 2011). Concurrent benefits include crop yield stability, reduced labour needs, runoff and erosion control, and more moderate soil surface temperatures during hot and dry summers (Hobbs et al., 2008; Knowler & Bradshaw, 2007). This combination has led most grain farmers in the Western Cape to adopt some form of CA, the patterns and drivers of which are further explored in Chapters 3 and 4. In what follows, we use the relationship between livestock and CA to illustrate farmers' risk-based decision-making. These competing and complementary responses to weather (among other) risks are crucial in revealing the heuristics that farmers use to make trade-offs under pervasive uncertainty.

2.3 Methods

In conducting this research, we sought to better understand how farmers presently respond to weather risks in conjunction with other unknown or highly uncertain risks. To this end, we conducted 90 structured interviews with individual South African commercial grain farmers in their normal decision-making environments, capturing their mental models of risks and adaptive responses in situ. The interviews had two major parts: (1) an open-ended risk elicitation exercise, in which the participants framed the conversation by characterizing the risks most important to their farming enterprises; and (2) a structured and indirect mental model elicitation of the processes by which farmers perceived and responded to weather (among other) risks. The sampling strategy and interview protocols were designed and piloted in consultation with partners from the University of Cape Town, Stellenbosch University, and the Western Cape provincial Department of Agriculture. In this section, we explain our data collection and analysis, including descriptions of the sample and sampling strategy, and the theory and practice of mental modeling.

2.3.1 Sample and sampling procedure

Ninety (90) participants were recruited through geographically stratified random sampling in the Western Cape, split evenly between the province's two major grain-growing regions. None were given any material incentive to participate. In keeping with the local farming population, all of the participants were men ranging in age from 25 to 62 years (M = 43.9, SD = 9.3). Their available arable farmland ranged from 250 to 4500 hectares (M = 1443 ha, SD = 880 ha). All participants had finished high school, with the majority (76%) having a university or college degree. A plurality (39%) of participants had completed one- or two-year technical degrees, while one-third (33%) held Bachelor's degrees and a small fraction (3%) held Master's degrees. Though most spoke Afrikaans as their first language, all were conversant in English.

The interviews were conducted over a two-month period in late 2013, shortly before the grain harvest. Participants were recruited with the assistance of liaisons from the four co-operatives and agribusinesses (also formerly co-operatives) that store and market grain produced in the region. From their organizations' contact lists, these liaisons reached out to farmers in randomized order, and recruited willing participants in proportion to the number of farmers within each of their service areas. About 20% of those who were contacted declined to participate; most who did so cited time constraints, though some also expressed discomfort with English. Overall, the sample included approximately 10% of the commercial grain farmers in the province, in each region and in each service area.

Most of the Western Cape's grain farmers grow rainfed wheat during the region's winter wet season (RSA, 2011). Summer rainfall is very low and the vast majority of farms lack irrigation, largely precluding summer crops. By value, wheat is the most important field crop in the Western Cape, and the third most important in the country (RSA, 2013a). Wheat is rotated with other grains (barley, canola, rye, oats, triticale) and legume pastures (lupins, clovers, alfalfa). Nearly all grain farmers in the Western Cape use mixed crop/livestock farming systems – most with sheep, but some with cattle and ostriches. Livestock are kept on pastures or fallow fields during the winter, and graze on crop residues during the summer. These farmers have variably adopted CA: most have implemented crop rotations that include legumes, nearly all have adopted some form of reduced tillage, and many intend to improve their permanent soil cover (Chapter 3).

2.3.2 Mental models

Mental modeling approaches to human cognition and behaviour use methods that attempt to capture the internal representations of reality, stored in memory, which participants use to perceive, process and respond to a given situation, idea or stimulus (Jones et al., 2011). The technique employs a 'broad-to-narrow' question structure to encourage participants to express and explain causal relationships, in particular, which can be understood colloquially as their theories of explanation for a given phenomenon (Jones et al., 2011; Morgan et al., 2002). It does not allow for direct observation of the decision-making process, but rather for the observation of explicit and inferred reasoning. A mental models interview script is designed to avoid introducing concepts not previously raised by the participant. Progressively narrower questions and prompts encourage the participant to elaborate. During the analysis, the interview data are visualized as a network of nodes (concepts) and edges (causal relationships) to provide a rough approximation of the participant's mental model. Its contents and structure are then analyzed to provide insights into the participant's understanding of the overarching process of interest – in this case, weather risk management.

Mental model elicitation can be direct or indirect. In the direct method, the interviewer clearly prescribes the model boundaries and asks the participant to define the model structure (Jones et al., 2011). The participant lists relevant concepts, arranges them, describes their causal relationships, and often weights these relationships to enable quantitative analysis. This simplifies the procedure by compelling the participant to visualize and consciously explore the structure of their mental model, but implies rationality and constrains both the model's scope and the language that the participant uses. In the indirect method, the participant is discreetly prompted to elaborate on causal relationships, but they are not made explicitly aware that the interviewer seeks the overall model structure. The mental model is then derived in subsequent analysis, through the systematic coding of the interview transcripts for explicit and inferred causal statements. During the interview, participants are therefore less likely to consciously rationalize the contents and structure of their mental model, and to identify and resolve redundancies and inconsistencies.

We used the indirect method of mental model elicitation to capture the multi-faceted nature of decision-making. Our interview protocol began with broad questions about the participant's life history, their farming experience, and their farm. These contextual questions allowed for the building of a rapport between the interviewer and the participant. The participant was then asked to list and explain the stressors or risks that they perceived as important to their farming enterprise. As each risk was raised by the participant, the interviewer documented it on a sticky-note in the participant's own words and placed it on a white board. At the end of the section, the participant was asked to organize the risks into 'manageable' and 'unmanageable' categories, and to explain how and to what extent they were each manageable. The risk-listing exercise allowed participants to frame the subsequent mental model elicitation in their own terms, and the discussion of their manageability catalyzed participants' initial explanations of causation. This risk landscape, both physical and metaphorical, guided participants as they answered further questions about their sources of information, their agricultural practices (emphasizing the three CA principles) and, finally, their perceptions of climate change.[6] Each of these more specific sections itself followed the 'broad-to-narrow' structure, beginning with a question in the form, "What comes to mind when you hear the term…."

This indirect, weather-oriented mental modeling technique, which included participant co-construction of the risk framework, is unique as far as we can tell, particularly as it pertains to the analysis of individual decision-making. Otto-Banaszak et al. (2011) used a similar method to study climate change adaptation options among experts in Europe, but at the policy level and with researcher-prescribed boundaries. With an average of only six participants per expert group, they also necessarily focused on the breadth of possible models rather than on the specific mechanics therein. Van Winsen et al. (2013) used an indirect mental modeling approach with five farmers, analyzing their choice of agricultural risk management strategies. However, their approach was not weather-oriented and they only chose the analytical technique after having completed their data collection. Because of our large sample recruited from a relatively homogeneous population, we were able to conduct more extensive analyses than in either of the above papers.

While all 90 structured interviews were coded and analyzed with respect to risk perceptions and farming practices, only 30 were selected for formal modeling because of the time-consuming nature of the process and the diminishing utility of additional mental models (Morgan et al., 2002). The candidates for modeling were selected on the basis of their farming practices, their

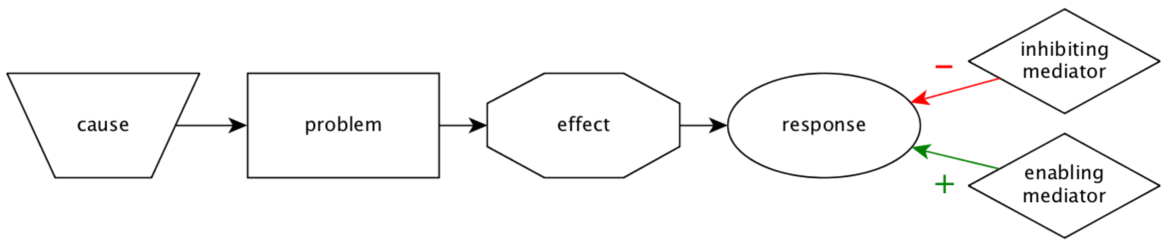
[6] The climate change elements of participants' mental models are analyzed in Chapter 5.

language proficiency, and the extent to which they had elaborated on simple answers (whether prompted or unprompted) as a measure of interview quality. To capture a diverse range of practices, and to enable the subsequent analysis of the patterns and drivers of farming practice in Chapter 3, all 90 participants were scored on the extent to which they practiced CA.[7] Ten participants were then selected for modeling from each of the three resulting categories of CA adoption (low, moderate and high). The language criterion may have led to some bias in the modeled subset, since the English language proficiency of Afrikaans-speaking farmers likely depends in part on their social integration; however, the inference of causal relationships during the analysis was expected to be more precise where participants were comfortable expressing nuance in English.

Transcripts from the selected interviews were carefully coded for causal statements related to risks and risk-mitigating responses. For instance, SA050 said, *"When you really go the minimum [tillage] way, you get more pests like snails that live underneath that material."* Therefore, his mental model showed that minimum tillage causes an increased risk of pests (and specifically snails). Those concepts and relationships that stemmed from weather and climate change problems were then imported into data visualization software and represented graphically as networks of nodes (concepts) connected by edges (relationships) (see Figure 2.1 for a simplified representation and Figure C.1 in Appendix C for a full-scale example). In these network graphs, the nodes were classified by function (causes, problems, effects, responses, and mediators of response), and the edges were directional (left to right, except for mediators). For this paper, the models were not simplified during analysis, nor were they aggregated across participants. This allowed for the analysis of the multiple cascading or divergent effects, and multiple sequential or competing responses that often branched from each effect. The 30 visualized mental models were then qualitatively analyzed in combination with the 90 coded interviews to explicate an overarching theory of farmers' risk-based decision-making, and to describe two heuristics that farmers commonly used to make trade-offs under ubiquitous uncertainty.

[7] The CA scoring method is detailed in Chapter 3:.

Figure 2.1: Simplified representation of the mental model structure. Nodes (concepts) are displayed as shapes, and edges (causal relationships) are displayed as directional arrows. Causes (e.g., climate cycles) lead to problems (e.g., rainfall variability) that create negative effects (e.g., low soil moisture). Participants mitigate these effects through responses (e.g., increasing soil cover) that are mediated by non-weather variables (e.g., inhibited by competition for crop residues as livestock feed).



2.4 Results

By analyzing participants' mental models, we found distinct patterns in their responses to weather that were strongly mediated by factors associated with other uncertain risks. As elaborated below, farmers' risk-based decision-making was multi-faceted, incremental and iterative across domains. Weather risks produced both complementary and competing responses that were constrained by pervasive uncertainty in other domains. These patterns largely resembled satisficing rather than maximizing behaviours. The ways in which the participants described mediating variables suggested that they represented competing processes of risk management. Responses that mitigated weather risks were therefore not part of a comprehensive process of risk management, but rather the result of numerous interlinked decision-making processes. Participants made estimates of "good enough" outcomes for mediating variables in non-weather decision-making processes, largely verbalized as rough estimates or thresholds in place of precise calculations. These were then incorporated as satisficing criteria in undertaking weather-relevant responses. Mediating variables related to access to reliable information played a crucial role in determining the clarity of estimates or thresholds for other mediators, though they themselves did not necessarily represent trade-offs. Participants were very unlikely to adopt new strategies by rapidly changing their practices or reorienting their businesses, relying instead on constant experimentation and incremental change. They continuously updated their decisions as new information became available through multiple channels strongly shaped by social and experiential learning. Because of uncertainty in the predicted outcomes, participants often mitigated specific risks using multiple strategies that were uncoordinated or only loosely coordinated. These strategies were therefore not fully optimized, and in some instances, each compromised the benefits of the other.

In what follows, we elaborate on these observations using the risk-mitigating examples of Conservation Agriculture (CA) and livestock husbandry. These two distinct responses to weather risks simultaneously complemented and competed with each other, requiring trade-offs within and between domains of risk. Using data from 90 risk elicitation exercises, Section 2.4.1 first defines the broader landscape of farming-relevant risks within which weather interacts with other domains. From the 30 mental models, Section 2.4.2 gauges participants' perceptions of weather risks (i.e., their causes, problems and effects (Figure 2.1)). Section 2.4.3 describes participants' direct responses to weather effects, while Section 2.4.4 evaluates the largely external non-weather mediating variables that alternately enable and inhibit these responses (most prominently, information). Drawing from the 30 mental models in the context of the 90 structured interviews, Section 2.4.5 then analyzes emergent patterns of effect, response and mediation as they represent relationships among different weather responses and between weather and non-weather risks. These results provide evidence of the iterative and interconnected nature of participants' risk management processes that we then use in the discussion to extrapolate a working theory of farmers' risk-based decision-making and to elucidate two common decision-making heuristics.

2.4.1 Sketching the landscape of farming risks

During the risk elicitation exercise, participants characterized farm-level risk management as a crucial and continuous process: *"It's easy to plant something; anyone can do that in life. But to manage the risk factors is the crux of any farm system."* [SA107]. They described numerous distinct and overlapping risks. Across all 90 structured interviews, participants introduced 1402 risks (15.6 per interview) that they perceived as important in their farming enterprises in the short to long term. These were iteratively coded and narrowed to 81 unique risks within 10 emergent categories.[8] For each risk category, Table 2.1 indicates the number of unique risks mentioned, the percentage

[8] A full list of unique risks within each category may be found in Table D.1 in Appendix D. Since the data used for this analysis were the sticky notes generated during the risk elicitation exercise, there was little or no information about the attribution of specific environmental problems to weather and climate change causes at this stage of the analysis. Climate change was therefore included within the Weather and Climate category.

of participants who introduced at least one such risk, and examples of specific risks. Economic and weather-related risks were most prevalent, with all participants listing at least one economic risk, and all but one participant listing at least one weather or climate risk. Section 2.4.5 elaborates on patterns of interconnection among these domains of risk management. Crucially, non-weather risks often mediated actions that were also responses to weather and climate problems. For example, high or unstable input costs encouraged farmers to implement advanced crop rotations for natural fertilization. Similarly, difficulty in finding skilled and reliable labourers encouraged mechanization and minimum tillage. Weather was therefore only one among many domains of risk that participants deemed important, and explicitly interacted with other risks in evoking responses.

Table 2.1: Elicited categories of risk and their frequencies. * The risk elicitation centered on grain farming within mixed farming systems. The prevalence of livestock-related risks is therefore not indicative of their importance in the farming business overall.

Risk category	Unique risks within category	Percentage of participants	Examples
Economic	21	100	Input costs, product prices
Weather and Climate	12	98	Drought, climate change
Political	11	93	Rights, services, regulation
Labour (excluding cost)	3	60	Availability, skill, reliability
Crop (excluding weather)	6	59	Weeds, pests, diseases
Technological	8	59	Research, availability
Societal	8	42	Crime, strikes, food security
Personal	5	19	Health, morale, ability
Livestock *	3	12	Mortality, soil compaction
Logistical	2	8	Transport, infrastructure
Other (uncategorized)	2	3	Availability of information

2.4.2 Defining the weather problem

Since weather is implicit in rainfed agriculture, it was often veiled in discussions of risk. Across the 30 interviews for which we constructed mental model diagrams, participants did not often distinguish between weather problems (e.g., variable rainfall or drought) and the causes of those problems (e.g., variable climate). Where they elaborated on such causes, these spanned local and regional climate, climate cycles, and God. Participants expressed a lack of direct agency over weather risks because of the universality of these causes: *"Ask the Father above; He's the only one that knows the weather."* [SA109]. Participants often dismissed weather as being so integral to farming that it was unworthy of much discussion. Only 47% of participants explicitly raised Rainfall (Mean or Variability) during the risk elicitation, though all later spoke of farming challenges stemming from rainfall. In dismissing weather, participants used such phrases as "farming is weather," "we're farming rain," and "weather is everything." SA126 expressed typical indifference: *"The weather is the weather. It changes all the time. We are in the weather business. So you have to adapt to that as it comes."* Favourable weather conditions during the study period potentially contributed to the lower salience of weather risks. Western Cape grain farmers enjoyed near-record wheat yields that year, just shy of the previous year's record tally (RSA, 2013a).

The reported problems stemming directly from weather and climate variability varied little among participants. Descriptions were typically broad, often referring to weather risks in general terms. References to drought and rainfall variability were common, driven primarily by concern for low soil moisture. Temperature and wind problems were secondary, driven by loss of soil biota in the summer and the potential loss of seed during harvest (particularly for canola), respectively. A few participants reported regular or occasional damage from flooding. Erosion (from wind and water) was not generally of acute concern, largely because of historic reductions in tillage. The negative effects created by these weather and climate problems were expressed in various terms, though agricultural and economic effects were most common.[9] Effects expressed in agricultural terms included low mean crop yields, high yield variability, low crop quality, crop failure, and loss of soil resources; those in economic terms included financial insecurity, volatile income and low profit; those in terms of farm survival included loss of the farm due to sudden financial hardship or long-term accumulation of debt; those expressed in terms of decision-making included greater uncertainty, difficulty planning and steep learning curves; those in emotional terms included low morale, stress and anxiety; and those in political terms included the potential failure of the land reform program. For example, SA085 described the emotional effects

[9] See Chapter 3 for an elaboration on the linguistic framing of weather effects.

of drought: *"When it's dry, the farmers are quiet. They don't speak a lot. But as soon as the rain has come, it's like a vibe in the air. Everybody's up and going."* Overall, participants were therefore acutely aware of weather risks and characterized them as integral to farming, but simultaneously downplayed their importance in the broader context of farm-level risk management.

2.4.3 Responding directly to weather

Participants' direct responses to problematic weather effects varied widely and included those framed as potential, planned and performed. Agronomic and economic responses were most common, but participants also described emotional and political responses, alongside adjustments to their planning or decision-making processes. Related or coordinated responses were clustered in participants' mental models; primary responses to weather effects often prefaced secondary and tertiary responses that followed logically. Many participants argued that the most important overarching strategy was to be flexible and to constantly experiment: "*I'm always trying something different and something new…. This whole farming exercise is an experiment. If something doesn't work…I change it."* [SA050]. This allowed them to make incremental and proactive changes over time rather than attempting drastic and reactive changes all at once: *"You can't jump around…. Never in a year must you change more than ten percent."* [SA090]. These incremental changes were described as leading to long-term transformations in farming practice, and were framed as crucial to participants' survival under changeable political, economic and climatic conditions.

Agronomic responses to weather effects were broadly characterized as improving soil health: efforts to improve soil fertility, increase soil water infiltration and retention, safeguard and strengthen preferred ("natural") communities of soil biota, improve the balance of soil nutrients and pH, and manage soil erosion from both wind and water. While the focus on CA late in the interview protocol ensured that each participant discussed soil processes, the stated causal relationships varied. Additionally, CA practices were nearly always introduced first by the participants themselves, rather than by the interviewer. Further agronomic responses included measures to increase mean crop yields, and to reduce yield variability in an effort to forestall crop failures. Such efforts included minimizing evapotranspiration through increased soil cover (either using crop residues or cover crops), adopting new cultivars better suited to local climate and soil conditions, and better managing weeds, pests and plant diseases.

Economic responses included income diversification within and beyond agriculture, the purchase of insurance products (e.g., crop, fire), farm expansion to leverage economies of scale and to broaden soil types, improved cost control and marketing, investment in better machinery or reliance on machinery contractors, and the establishment of cash reserves. Those framed in terms of farm survival included debt avoidance and repayment, farming on a cash basis, and a renewed focus on economic sustainability. Responses described in decision-making terms included changes in planning, flexibility, vigilance, focus, reactivity, learning, experimentation, improvement and adaptation. Those in emotional terms included humility, prayer, positivity, acceptance, love for farming, sense of duty and restrained expectations. Only two responses were indicated in political terms: lobbying and emigration. Direct responses to weather risks were therefore numerous and varied; however, they were strongly mediated by non-weather factors.

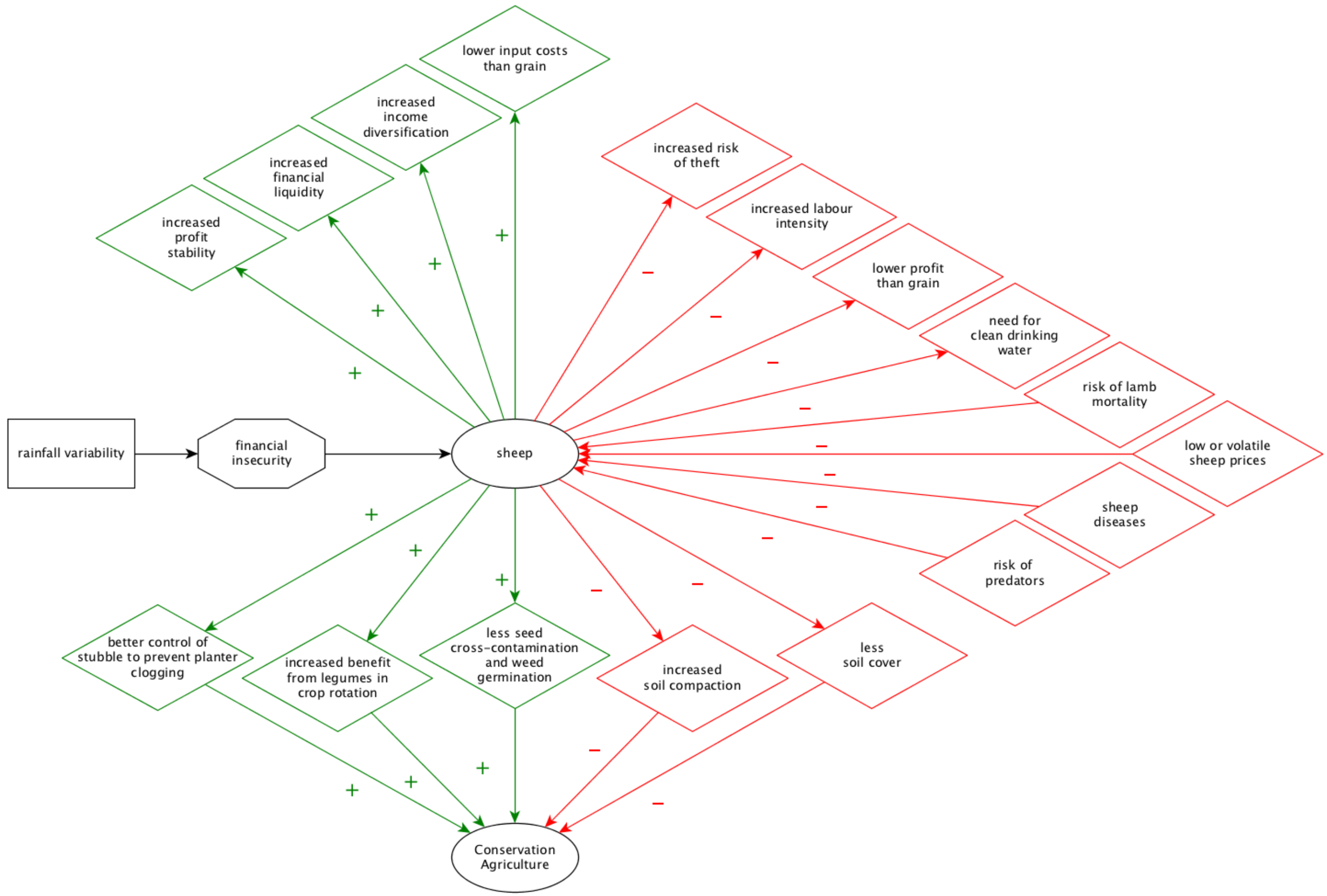
2.4.4 Non-weather factors mediating weather responses

In participants' mental models, direct responses to weather risks were strongly shaped by factors associated with other domains of risk. Mediating variables enabled or inhibited specific weather-related responses, spanning a wide range of endogenous and exogenous elements. These included myriad agricultural and economic factors at various scales; emotional factors related to personal and familial contexts; political factors related to land reform; and decision-making factors crucially dependent on access to reliable information. For instance, SA081 described his faith in God as mediating his decision about whether or not to plant wheat this year, in light of its high input costs and vulnerability to drought: *"I didn't grow grain this year, because I just... I've got a special advantage to other farmers. I can hear God's voice when he speaks to me. So I know when He tells me to sow or not. This year, I asked Him, and He told me that I shouldn't sow."*

Figure 2.2 demonstrates the multi-faceted influence of mediating variables by showing the circumscribed mental model of sheep farming as a response to the financial insecurity caused by rainfall variability. This figure includes all of the non-weather mediators of sheep farming described across the 30 modelled interviews. Some mediators encouraged farmers to have sheep or to increase their number (green), while others discouraged sheep farming or limited the size of the flock (red). For instance, one positive (enabling) non-weather consequence of sheep farming was the increased diversification of farm income in light of volatile market prices for other agricultural products. One negative (inhibiting) non-weather concern was that sheep are vulnerable to natural predation by leopards and jackals.

Mediating variables related to information played a crucial role in defining uncertainty and clarifying trade-offs. Uncertainty was described as pervasive in the commercial farming enterprise, shortening the planning horizon: *"The biggest problem is that uncertainty. We don't know what is going to happen next week, next year, and the next five years."* [SA072]. Participants reported continually updating their risk management strategies based on the availability of trusted information from other farmers (locally and globally), private and public sector experts, and the Internet. They recognized plentiful sources of information in the modern world, but distrusted most and approached them with substantial caution. For instance, SA125 was skeptical of advice from the consultants employed by agribusinesses and preferred to ask other farmers: *"It's difficult. Agronomic-wise, you would talk to your chemical guys. But they're usually biased towards what they want to sell. The more successful farmers – we go look at what they do and chat to them."* In contrast, SA105 distrusted advice from other farmers: *"I think there's most of the time a competition. The one guy wants to be better than the other one, and it's very easy to be better. You just don't tell people about your expenses…. When you start to hide some of your costs you can look very smart."* Reported mediators related to information included the need for diverse sources of information and good on-farm record-keeping; the availability of localized knowledge, from crop trials and leading farmers; distrust of other farmers, experts, salesmen, and agribusiness consultants (employed by chemical, machinery or seed companies); the perceived inaccuracy of weather and climate forecasts; low levels of public investment in research; the long-term decline of agricultural extension services; and the lack of readily available information from neutral third parties.

Figure 2.2: Partial mental model of sheep farming as a response to weather risks. The figure includes all of the factors that participants described as mediating sheep farming, aggregated across the 30 mental models. In particular, this illustrates the multi-faceted relationship between sheep and Conservation Agriculture, involving both trade-offs (e.g., sheep decrease soil cover) and complementarities (e.g., sheep help to prevent cross-contamination and weed germination). Variables that encouraged farmers to have sheep or to increase their number are shown in green (+), while those that discouraged sheep farming or limited the size of the flock are shown in red (-).



Participants generally described themselves as risk averse and therefore cautious in adopting new farming practices. Without strong evidence under agronomic conditions perceived as very similar to their own, many indicated that they were loath to commit to changes in practice: *"Every farm, and every piece of land on this farm, is different…. Let your farm tell you what to do."* [SA049]. For example, SA078 was distrustful of crop yield results from nearby trials: *"The best experimental farm is your own farm."* SA104 emphasized the importance of good record-keeping: *"You must [keep records]. How else do you make tomorrow's decision?"* However, some farmers kept no records of their own inputs and crop yields, and many recorded only the average yield for each year. For instance, SA081 was dismissive of written records: *"I don't normally [keep] a track record of those things. I have it in my head."* SA163 argued that he had more pressing concerns: *"Not too much [in the way of records], no. I'm living from day to day."* Most participants were therefore deficient in storing and accessing reliable information, even when the source was within their immediate control.

Though participants widely described extension services as insufficient, CA programs at the provincial Department of Agriculture, the Agricultural Research Council, Grain SA, agribusinesses, co-operatives, and local farmer associations were reported to have provided valuable information, training and demonstrations. Early adopters of CA were said to have predated publicly financed experiments and outreach; however, subsequent local access to persuasive demonstrations, whether by neighbours or at experimental farms (public or private), was reportedly pivotal in convincing most farmers in the Western Cape to adopt at least some aspects of CA.[10] Agricultural programs at technical schools and universities have also helped to provide a foundation for life-long learning among younger farmers, alongside standard models of practical and theoretical learning about new methods and alternative paradigms. Educational institutions have facilitated changes in the shared definition of "good" farming. SA051 emphasized that norms related to ploughing have changed drastically and may yet change back: *"My dad and them, they fucked up the soil. They ploughed it and they ploughed it. It's crazy. I bet one day my kids are going to tell me, 'Hey, daddy. Why don't you plough this thing? Plough the bloody soil man.'"* SA096 was more contemplative in describing the obsolescence of older farming practices: *"I've got two ploughs*

[10] See Chapters 3 and 4 for quantitative analyses of CA adoption rates in the Western Cape and South Africa, respectively.

there. I've got a nice place for them; they look out on the sun with a nice roof on them. They just look out on the farm; they're never used."

The information seeking behaviours described by farmers were consistent with theories of social learning. These farmers were willing and able to adapt proactively, but they perceived themselves as having only limited access to imperfect knowledge. They defined their own success – what was "optimal" or "good enough" – using normative criteria that were socially constructed. Individual farmers expressed a strong sense of agency, but they relied heavily on social learning for knowledge and validation. By this, we mean that intergenerational flows of knowledge have provided crucial transfers of experience from the older generations and innovations from the younger, both within and between farms. For instance, SA056 emphasized the importance of intergenerational knowledge transfers: *"I trust my dad and his dad before that. Things – technologies – do change, and ways of farming do change…. But just your regular day-to-day crisis, if there's something that you don't know, maybe the guy that's been farming for 30 years knows."* Similarly, SA090 argued that knowledge transfers between farms have become increasingly important among younger farmers: *"When my father was young, they never used to talk about stuff to their neighbours or other farmers, but the younger generation is much different. We talk about stuff, and if we do something right we go and tell our neighbour."* Social learning and access to trusted information have therefore been vital to the adoption of CA practices and other technologies in the Western Cape. Other mediating variables, representing trade-offs with other domains of risk, were similarly crucial in shaping responses to weather risks in farmers' mental models.

2.4.5 Making trade-offs among domains of risk and between alternative responses

Participants' mental models suggested that they mitigated negative weather effects using multiple complementary and competing responses shaped by implicit trade-offs with other domains of risk. As elaborated below, they did not use a single rationale for their choices, but rather combined various overlapping rationales in seeking to mitigate multiple risks simultaneously towards "good enough" outcomes within each domain. The use of rough estimates to make trade-offs among these various objectives allowed them to make constrained decisions within a landscape of pervasive uncertainty stemming from largely incalculable risks. Success and failure were often verbalized in terms of thresholds established through experiential or social learning. The iterative re-calculation of these thresholds over time allowed for some measure of optimization, but participants' rationales were primarily expressed in satisficing terms.

In mitigating each risk, participants often described alternative responses as competing with each other or as mutually incompatible. For instance, to mitigate the long-term risk of bankruptcy during severe droughts, many farmers diversified their financial assets beyond the farm. However, this meant that they had less capital to invest in the new planting equipment needed to improve their crop farming practices and thereby to reduce the vulnerability of their crop production to weather risks. SA107 described his tendency to prioritize off-farm investments as contrasting with his neighbours': *"Put your money many places, that's how I feel about it. Other people don't agree. They try to put everything back in farming."* This tension between competing responses applied equally to non-economic risks. SA140 observed that many farmers had responded to the political risks of land reform by isolating themselves socially, while others had sought instead to improve the societal perception of commercial farmers by better integrating their labourers economically: *"[Since] the big change in South Africa, a lot of people have still not adapted to it. They live in their little corner – not that they're bad. But their circle in which they think is too small."*

CA and livestock have an especially multi-faceted and illustrative relationship as they represent competing responses by which to mitigate the risks of weather and climate variability (Figure 2.2). CA requires the application of three principles – advanced crop rotations, minimum tillage, and permanent soil cover – each of which is enabled or inhibited by livestock production. Participants said that livestock grazing provided supplementary income during the non-cash crop (nitrogen-fixing legume) phases of crop rotations. Grazing also reduced the density of older crop and weed seeds that would otherwise germinate during the following growing season, contaminating the new crop. However, the subsequent soil surface compaction by animal traffic was difficult to resolve without some form of tillage. Grazing also reduced soil cover; therefore, comprehensive CA implementation implied low livestock ratios to ensure that sufficient crop residues remained on the soil surface at the end of the dry season. Paradoxically, livestock were sometimes used to manage excessive residues when participants had difficulty penetrating them with minimum-till tine planters.

Income from crop production was higher but also more variable than that from animal husbandry, and livestock provided insurance against crop failures. Livestock therefore regulated income variability while reducing average income, whereas CA reduced income variability but maintained or improved average income. Low-CA farmers had generally responded to weather risks by increasing livestock and reducing their cropping area, whereas high-CA farmers experiencing the same stimuli had responded by planting more crops and improving their CA practices. During the study period, no participants practiced continuous cropping (i.e., crop rotations that excluded pasture and therefore livestock), but many expressed that preference. For instance, though SA055 still had sheep on his farm, he recognized that they compromised his ability to practice CA comprehensively: *"The really serious no-till farmers, conservation farmers...they don't have sheep on their fields. They know the negative effects of that."* However, most of those who acknowledged this compromise nonetheless felt constrained by the need for livestock during severe droughts. For instance, SA050 emphasized the importance of sheep to the survival of the farm: *"If I let the sheep go, I can go as well, because the sheep keep me here in that drought – in those ugly years."*

Participants tended to describe livestock as immediately beneficial in insuring against severe droughts, whereas they perceived that the maximum benefits of CA – insuring against moderate droughts and frequent rainfall variability, while simultaneously reducing other long-term non-weather risks (e.g., climate, markets, input costs) – were fully realized only after years of careful implementation. Therefore, high-CA farmers seemed to be risk averse in the long term, while low-CA farmers were more risk averse in the short term. For instance, SA107 acknowledged that crop rotations reduced the average area on which he grew lucrative wheat each year, but he argued that CA's long-term risk-mitigating benefits were well worth that foregone profit: *"You can go play the lotto – throw it all at once and see if it's a jackpot – but that's not sustainability. That's my aim: I want sustainability."* However, when decision-making was shared, differences in risk aversion caused conflicting attitudes towards CA and livestock: *"My uncle puts lots of animals on [the fields]. I would like him to stop doing that. I don't think we get any returns from that. I think we should just sell the bloody things."* [SA051]. The simultaneous use of livestock and CA therefore represented a form of 'hedging one's bet'. That is, CA was understood to be most profitable when implemented without livestock, but lingering doubts about its performance during severe droughts were addressed by diversifying with livestock. Each adaptive response was perceived as insufficient alone.

However, farmers rarely characterized comprises between the two strategies as calculated trade-offs. For instance, when balancing CA and sheep, SA049 used time limits and visual thresholds to avoid over-grazing and soil compaction: *"Sheep…. Two weeks [in the field]. Don't put them there and leave them there…. I will say that they mustn't start walking paths. If they start walking paths you must take them out. It's almost too late then."* SA049 expressed his grazing threshold as a ratio: *"You must try to manage it. That's why I say [that the sheep should be in the field only] one week in a month. Don't overdo it. Don't overdo it. Balance; balance is very important. Everything must be in balance."* In contrast, SA050 described his difficulty in finding such a balance: *"You must manage it your way: not disturbing the ground that much with your livestock, not trampling it with your livestock, and not taking away the stubble [by grazing] livestock or baling it. It's a very tricky combination. I definitely don't have the answer."*

Beyond CA and livestock, other mediating variables were also often expressed in satisficing terms (e.g., as "too high", "too much", "too low", "not enough") rather than as precise effects, because they inevitably represented sources of uncertainty. For instance, SA077 was frustrated with the inclination of his past instructors to insist on more precise calculations of input costs and projected crop value, because of the inescapable uncertainty in growing conditions: *"My instructor told me: you must plan for three scenarios – an average scenario, a best scenario, and a worst scenario. Now how the hell do you plan for that? So, in other words, you have to give a little bit of fertiliser, and then when you see it rains, then you give a bit more fertiliser. And how do you know that it's going to keep on raining? In this world of ours, it's not easy…. My best year in production was my worst year in profit."*

Though participants differed in their tendency to maximize or to satisfice, depending on the domain of risk, most decisions were expressed in terms that suggested satisficing. The trade-off between CA and livestock was the most clearly expressed as such, but other trade-offs that were deemed important were similarly described as "good enough" thresholds. For instance, SA087 specified his threshold for input costs as a function of the price of wheat: *"Maximum: we'll never go over 100 [kg of fertilizer per hectare]. But it's one of the things I'm starting to realize. If you want to make a good crop, you need to do that…. My input cost mustn't be more than [the price of] two tonnes of wheat."* Thresholds of success towards narrower goals reflected underlying uncertainties in their achievement. For example, SA084 defined successful yields in reference to the rough average among his peers: *"I can tell you roughly. When I started on my own, [I harvested] 1.5 [tonnes per hectare] for wheat…. That's roughly what you can work on, around here."* SA081 used a rough yield threshold in concluding that a mistake had not cost him too dearly: *"I had a bit of a frost problem, I think I sowed a little bit too late…. But I still did good, I made about two tonnes [per hectare] last year."*

Those farmers who kept poor records had little choice but to satisfice; they tended to use vague estimates of past crop yields and input costs in evaluating their own performance. For example, SA077 explained that he only keeps track of farm-wide average yields from memory: *"I've got it in my head, but I do not specifically say, 'This [field] did this and this one did this....' I don't have a formal set of records."* SA071 expressed a similarly casual attitude towards record keeping: *"I'm a bit lazy in that aspect…. I can tell you more or less what [the yields are] in the area, and what I've had the last few years. And my cost more or less."* SA088 described his exasperation at such poor record keeping practices among his peers: *"If you don't keep records, how can you compare this year to last year? Did you make a profit and how much? My own brothers don't [keep records]. They write on the back of a cigarette box."* However, pervasive uncertainty forced satisficing even by farmers who were very diligent record-keepers. SA087 kept detailed records, but used his worst-ever crop yield as a threshold to limit his input costs rather than trying to optimize them for maximum profit: *"I work it out at the end of the year, every year. The co-op gives us an average [for input costs], and I always try to be underneath that…. My belief about input costs is really easy; my worst year was 2010, and my input costs can't be more than 2010's income. As easy as that. That's on a basis of one tonne [of wheat produced] per hectare."*

Even profit and financial success, firmly in the purview of the rational actor model of decision-making, were often characterized in satisficing terms. For example, SA108 described making a rough estimate of the income he needed to break even each year, as a measure of his financial success: *"My financial record keeping: I'm not good at that, but touch wood, we're doing alright…. I like to make my calculations in such a way that I know what it basically costs me in a month, to live…. I just multiply that by 12, and I know that's the kind of money I need to get at the end of the year; that's easy."* Understanding that he could not manage economic risks in a calculated manner, SA141 tried to establish redundancies and to avoid making explicit trade-offs among his income-generating strategies:

"Like this chair, [there] must be three legs…. There's no subsidy or cross-subsidy. Everything must be on its own…. I steal from all three of them, but it works." Some participants also expressed rough trade-offs between profit and other objectives, including quality of life (e.g., stress, time with family, stability) and the provision of economic opportunities for their labourers. For instance, SA141 warned of the dangers of over-emphasizing profit: *"If you are greedy, greediness kills you. It destroys you. You will make a lot of money if you are greedy, but it will take you five years to make that lot of money, and in one month you will have nothing. That's the thing of greediness." [SA141].*

Overall, participants avoided making explicit and calculated trade-offs within and between multiple uncertain domains of risk in which the criteria for success were often measured on incompatible scales. These trade-offs were rather expressed as thresholds, be they implicit or explicit, illustrating a tension between maximizing and satisficing strategies. With respect to CA alone, farmers tended to optimize their implementation of its three component principles to maximize its benefits. However, the benefits of livestock as a hedge against the risk of severe drought were only roughly weighed against the costs of lost soil cover and increased soil disturbance, in part because the benefits and costs were intractably uncertain. In place of precise trade-offs, participants used rough estimates expressed as boundaries or thresholds that resulted in "good enough" outcomes in concurrent risk management strategies. This tendency to satisfice under pervasive uncertainty resulted in two distinct decision-making heuristics that are elaborated below: (1) multiple simultaneous risk-mitigating strategies that are only loosely coordinated in response to the same risk; and (2) the use of rough thresholds to make trade-offs among parallel decision-making processes towards the same or different objectives.

2.5 Discussion

The messy practice of weather-sensitive decision-making is mismatched with the theories of decision-making and risk management prevalent – implicitly and explicitly – in the climate change adaptation literature. The commercial farming enterprise is primarily defined by pervasive uncertainty rather than by calculable risks. Participants typically highlighted weather or climate as the most important risk in their farming business, but their mental models show that such stimuli do not translate directly into specific responses. Instead, weather permeates the decision-making process, where most responses are undertaken for other proximate reasons. The choice of response is contingent on the perceived importance of the myriad non-weather variables that mediate agricultural practice, as well as on competition among various responses. Trade-offs between alternative responses and among various domains of risk are usually expressed in terms of rough thresholds that represent "good enough" outcomes, rather than as optimized calculations. In what follows, we extrapolate a theory of farmers' risk-based decision-making in the context of weather, and identify two heuristics, one decision-making and one cognitive, that participants use to make intractably uncertain trade-offs among competing risk management strategies and domains of risk, respectively.

2.5.1 Practical decision strategies for a messy world

Family farms are a hybrid of personal and business-oriented decision-making, but farmers are often assumed to make structured decisions in the manner of institutions. In reality, they make many strongly interlinked decisions every day with respect to varied objectives. In general, farmers make frequent, iterative and largely incremental decisions towards multiple competing and complementary objectives on different scales and in response to different stressors. Their risk management is not the result of a single, cohesive decision-making process. It is rather the result of multiple, parallel and continuous processes that are alternately prioritized based on the most salient objective, which is rarely the minimization of weather risk. This produces a combination of decisions that appear economically rational at the micro scale but are not often optimized at the macro scale. Standard models of decision-making may appear to explain farm-level outcomes well for constrained problems, but they mask a multitude of parallel risk management processes that result in networked responses that both compete and cohere, depending on the frame of reference.

Our results imply two satisficing heuristics that farmers use to navigate uncertainty. The first, hazy hedging, appears to be a conscious decision-making strategy to reduce the likelihood of severe loss in the face of diverse and uncertain risks. The second, bounded trade-offs, appears to be a subconscious cognitive heuristic to integrate diverse objectives subject to multiple risks, by simplifying the representation of trade-offs as rough thresholds. The decision-making strategy of hazy hedging is therefore supported by the cognitive heuristic of bounded trade-offs. Levine et al. (2015) suggest that heuristics are the default mode of human cognition, and that exhaustive rationalization occurs only infrequently. Rather than being cognitive shortcuts that systematically cause people to make irrational errors, heuristics can offer methods by which to make better decisions with less information in an uncertain world. As strategies by which farmers make practical decisions under pervasive uncertainty, these two heuristics may reflect the "less-is-more" effects postulated by Gigerenzer and Goldstein (1996; 2002). However, most evidence of such effects is limited to narrow, mutually independent decisions. Further study will be needed to determine whether these heuristics do indeed exhibit "less-is-more" benefits, as implied by the data.

2.5.2 Hazy hedging: risk management strategies under pervasive uncertainty

Farmers are likely to undertake multiple simultaneous responses to the same or similar weather stimuli, because (1) there is uncertainty in the success of each response, (2) farmers make parallel decisions on multiple timescales and in multiple domains, and (3) there is competition between the management of weather risks and progress towards competing objectives (including the economic objectives of yield and profit maximization, and the non-economic objectives of farming lifestyle, stewardship and family legacy). Each response usually provides benefits towards multiple objectives, and each requires trade-offs, either in the allocation of scarce financial, social, institutional or cognitive resources, or in the exacerbation of other risks that may endanger competing objectives.

Multiple simultaneous responses that are explicitly undertaken with respect to the same objective may compete with or complement each other, depending on the frame of reference. For instance, CA and livestock are both used for weather risk management, reducing the damaging impact of rainfall variability on farm profit. However, each requires trade-offs from the other while also providing mutual benefits. During the study period, no participant pursued only one or the other strategy, yet the two were not necessarily coordinated. The chosen balance suggests divergent timescales of risk aversion. Those who are risk averse on shorter timescales tend to invest more heavily in livestock to protect against periodic drought, whereas those who are risk averse on longer timescales tend to invest more systematically in long-term improvements in cropping practices. While they are often explicitly separate choices in risk management, and each undermines the idealized implementation of the other, the combination of CA and livestock is perceived as nearly unavoidable. Overall, farmers are often conscious of the macro-scale inconsistencies in their multiple responses. Individual farmers recognize the apparent irrationality of specific decisions as perceived through other, equally valid, frames of reference.

Hazy hedging is therefore the use of simultaneous risk management strategies that are not necessarily coordinated and that may each undercut some of the benefits of the other. These simultaneous strategies are arrived at through parallel decision-making processes across multiple domains of risk. This produces relatively independent responses that might otherwise be linked if they were to be optimized. It suggests the conscious non-optimization of decision-making in the rational economic sense, and provides evidence of satisficing within domains of uncertain risk. It is ecologically rational because of intractable uncertainty in the success of any particular strategy (i.e., conditions under which strict economic rationality is impossible). An appropriate balance between the multiple strategies is determined through rough trade-offs among domains of risk, described in the following section.

2.5.3 Bounded trade-offs: using satisficing thresholds in place of optimization

Diverse measures of success and pervasive uncertainty suggest that trade-offs between domains of risk are cognitively challenging. Bounded trade-offs are a practical, satisficing-based heuristic approach to trade-offs among variables measured on uncertain and often incompatible scales. Farmers use rough thresholds as stand-ins for calculated costs and benefits. For instance, the extent to which participants kept records of inputs and crop yields was far less than expected on the basis of prior expert interviews, suggesting that most participants were not tracking the precise costs and benefits of fertilizers, chemicals, seeds, fuel, etc. These thresholds are primarily stored in memory, and shaped by social and experiential learning. They are updated iteratively with the accumulation of experience, the evolution of norms, and the cautious adoption of expert advice. This iteration underscores the need for incremental experimentation in modifying agricultural and business practices, since the thresholds are recognized as imperfect.

These thresholds bound the present decision without requiring the precise calculation of effects across multiple domains infused with uncertainty, ensuring "good enough" outcomes for decisions in which optimization is impossible. Because the comprehensive decision environment is large and multi-faceted, farmers appear to use various cognitive frames to parse it into narrower and simpler systems relevant to specific objectives. They thus seem to lose clear focus of competing objectives, and must make trade-offs imprecisely. Thresholds allow for multiple risks to be treated in concert, while most cognitive resources are directed at the immediate problem. More precise trade-offs would imply that farmers had accurate information, and that outcome probabilities were well defined. It may therefore be ecologically rational to represent trade-offs as thresholds in highly risky environments where uncertainties are difficult or impossible to calculate. It is in similar circumstances that Gigerenzer and Goldstein (1996; 2002) have detected less-is-more effects, where simpler decision strategies using less information can perform better than exhaustive strategies incorporating more information.

2.6 Conclusions

The risk-mitigating behaviours of South African commercial grain farmers are rooted in social and experiential learning. Iterative and incremental experimentation drives small but continuous changes in personal, business and agricultural behaviours that result in systemic changes over time. Within a multi-faceted landscape of risk, they use multiple simultaneous risk management processes to narrow their decisions. Each process occurs in its own cognitive frame, with different relevant endogenous and exogenous factors, available information, and coupled experiences and emotions. Farmers are variably risk-averse as individuals, and in reference to different domains of risk. To integrate their risk management approaches more broadly, they imperfectly coordinate and optimize their strategies within and between domains of risk.

Commercial farmers represent a vast and understudied population of naturalistic decision-makers. They are foundational to the climate change adaptation literature, epitomizing the ideal, autonomous, adaptive and resourceful private actor. However, prevalent theories of farmers' climate-adaptive behaviours fail to capture the messy practice of real-world risk management. In practice, weather is rarely the most salient concern in farmers' risk-based decision-making and responses to weather risks are strongly mediated by concerns in other domains. Because of such competing rationales, farmers often choose not to undertake available actions that would reduce their vulnerability to weather risks. The same can be expected for climate change. Naïve theories of decision-making therefore underestimate the individual challenge of adaptation to climate change, and the inaccurate archetype of the economically rational farmer is likely to lead researchers and policy-makers astray.

Chapter 3: Six languages for a risky climate: The cognitive framing of agriculture

3.1 Synopsis

This study examines the behavioural effects of a suite of cognitive orientations to weather and climate change risks evident among commercial grain farmers in South Africa. Previous studies have established that there are strong linkages between cognitive framing and its linguistic expression, and that the use of different cognitive frames can result in choices that differ in their apparent rationality. We thus seek to explain differences in farmers' behaviours by testing the relationship between their linguistic expression of weather and climate change risks and their use of climate-adaptive best practices (exemplified by Conservation Agriculture (CA)). We first use a mental models protocol to evaluate farmers' performance on three CA-related practices and to elicit their understanding of weather and climate change risks – that is, the logics that they use in processing and responding specific problems, ideas or stimuli. We then algorithmically cluster these mental models to illuminate a set of exhaustive and mutually exclusive "languages" with which farmers frame weather and climate change risks. Lastly, we quantitatively analyze the prevalence of these languages in farmers' mental models across three levels of CA adoption (low, moderate and high). Specifically, we find six languages with which participants (n=30) frame weather risks: agricultural, cognitive, economic, emotional, political and survival. We show that the prevalence of these languages among those interviewed differs markedly between farmers who are adopting CA in a comprehensive manner and those who are not. High-adopters frame weather risks using "rational" agricultural, economic and cognitive languages. Low-adopters additionally frame weather risks using "irrational" emotional and survival languages. The prevalence of the emotional and survival languages among low-adopters suggests that the investments in knowledge, technology and land necessary for comprehensive CA adoption are inhibited by economic anxiety expressed in terms of the survival of the farm. Short- to medium-term concern for the survival of the farm can therefore impede adaptation to changes in climate that may threaten that very survival in the long term.

3.2 Introduction

"Adapt or die. If you're stuck to one thing… you're not going to survive." – SA087

Climate change adaptation policies have garnered increasing scholarly attention as greenhouse gas emissions continue apace and global mean temperatures climb (IPCC, 2013). The volume of adaptation research is rapidly expanding (Bassett & Fogelman, 2013), yet its behavioural dimensions are sorely understudied (Clayton et al., 2015). This remains so despite the recognition that climate-adaptive decision-makers face unique cognitive challenges created by long-term climatic uncertainty alongside incremental changes on decadal timescales (Grothmann & Patt, 2005; Pidgeon & Fischhoff, 2011). Many scholars have published conceptual models of adjustments to *institutional* decision-making – robust, iterative, adaptive, mainstreamed (Füssel, 2007; Hallegatte, 2009; Kunreuther et al., 2013; Weaver et al., 2013) – but little empirical work has examined the ways in which *individual* decision-makers filter climate signals within a landscape of multi-causal risks, and with respect to differences in their climate vulnerabilities.

The conceptualization of decision-making on behalf of individuals facing climate change risks (e.g., farmers) thus remains particularly fraught with untested or disproven assumptions. The literature on agricultural adaptation is founded on three such simplifying assumptions: (1) that existing processes of risk management for weather and climate variability are generally rational and therefore predictable; (2) that climate change adaptation will largely be an extension of these existing processes; and (3) that farmers will therefore adapt to climate change as it occurs incrementally. In Chapter 2, we investigated the first assumption by analyzing the structure of the mental models used by South Africa's commercial grain farmers to perceive and respond to weather risks. This group closely resembles the idealized autonomous private actor foundational to the adaptation literature – physically vulnerable to climate change, but relatively well educated and with good access to financial, informational and institutional resources. There we found evidence that farmers' risk-based decision-making is messy and difficult to predict. Pervasive uncertainty causes farmers to satisfice (i.e., undertaking risk-mitigating strategies, and trade-offs among them, that result in "good enough" outcomes) rather than optimizing (i.e., choosing those that will result in the "best" outcome through exhaustive reasoning). The results suggest that farmers may be undertaking parallel risk management processes within different cognitive frames – the set of specific perceptions, preferences, memories and mental models that they use to understand and respond to a particular problem (Thaler, 1999). It has previously been shown that different cognitive frames can trigger different decision-making strategies that vary in their apparent rationality (Lichtenstein & Slovic, 2006).

In the present paper, we extend this analysis by identifying those cognitive frames that have explicit implications for climate-resilient behaviours. Specifically, we test the relationship between linguistic expressions of weather risks[11] and the adoption of Conservation Agriculture (CA) – an important measure of climate-resilient best practice. We first score our participants on the extent to which they have adopted CA, and qualitatively assess the drivers and barriers of this major change in practice. Using a mental models interview protocol, we then show that farmers use various cognitive frames for weather and climate change risks, as evidenced by their use of six different languages to describe those risks. We finally combine the quantitative analysis of these languages with farmers' CA scores to identify key frames that enable or inhibit CA adoption. We close by inferring a set of recommendations for how public policy might best address the barriers to CA adoption in these and equivalent contexts.

3.2.1 Climate change adaptation and the archetype of the rational commercial farmer

Research on proactive and reactive responses to climate change impacts has focussed heavily on broad theories that might help explain adaptation, maladaptation, transformation, resilience, thresholds and limits (Adger et al., 2009; Barnett & O'Neill, 2010; Dessai et al., 2009; New et al., 2011; O'Brien, 2012). Such highly conceptual contributions are in part a function of the decadal rate of change and the challenge of differentiating climatic stressors from myriad others drivers of change. Together, these make strongly empirical work difficult and time-consuming. Empirical work has thus generally been limited to small case studies of highly vulnerable groups under marginal climatic conditions (Tschakert, 2007), the examination of pre-emptive policy changes

[11] Though climate change risks were included in the mental models and in the identification of the six languages, their implications are assessed separately in Chapter 5. The smaller size and greater variability of the climate change branches of farmers' mental models made the quantitative analysis of their cognitive framing more challenging.

explicitly addressing climate change adaptation (Berrang-Ford et al., 2011), cross-sectional studies of implicit adaptation to variable climates using Ricardian methods (Seo & Mendelsohn, 2008), or studies of historical cases (Orlove, 2005). Fewer scholars have examined the relationships between stressors and responses in situ – i.e., the effects of weather and climate variables within pre-existing and multi-faceted decision-making processes (Eakin et al., 2014; Eakin et al., 2016; Risbey et al., 1999).

These foci have led to some failure to illuminate the challenging *practice* of adaptation, enmeshed as it is in messy webs of attributed causation (Chapter 2) that are further complicated by decision-making and information processing governed by human irrationalities (Lichtenstein & Slovic, 2006; Thaler, 2000). Consequently, the logic of the economically rational actor persists (e.g., Anton et al., 2012; Menapace et al., 2013) despite decades of social science research to the contrary (Levine et al., 2015). Many public policy processes are implicitly shaped by the rational actor model, and so fail to tailor policies to real-world human responses to climate change impacts at the global, regional, national, provincial/state, municipal, community, household and individual scales. Instead, such policies are premised on the ability of individual decision-makers, at each scale, to systematically incorporate changing climatic conditions into their existing decision-making processes. At the individual scale, this idealized decision-maker is autonomous, flexible, knowledgeable, resourceful and rational, making full and efficient use of available technologies and institutional support. In what follows, we critique this assumption as evidenced by the thinking and behaviours of commercial grain farmers, whom we argue are numerous, autonomous and deeply climate-sensitive. They thus represent a vast and underutilized source of information about individual decision-making and human-environment relationships.

Commercial grain farming is conducted using broadly similar techniques worldwide, despite enormously variable socioeconomic and environmental contexts (Ellis & Ramankutty, 2008). Agricultural economists conceive of commercial farming enterprises as small businesses that are economically rational (Moschini & Hennessy, 2001). However, their management is contingent on the many and varied irrational facets of individual decision-making, which we know are deeply embedded in social and cultural systems that introduce myriad non-economic considerations, particularly for those farms that are family-owned (Eakin et al., 2014).

Commercial farmers are more accurately understood as hybrid actors, combining explicitly rational and inherently human models of decision-making. Seemingly dispassionate agricultural or economic decisions about the future of the farming business become acutely personal (and often shared) when enmeshed in complex identities of family, culture and place (Pannell et al., 2006). For instance, many farmers have an emotional attachment (whether personal or familial) to their farms that makes them reluctant to sell unprofitable land, and may lead to seemingly uneconomical investments in stewardship and conservation measures (Farmar-Bowers & Lane, 2009). Some farmers even anthropomorphize their land, speaking of it as if it were a family member (Sullivan et al., 1996). Similarly, farming practices may be shaped by undercurrents of social performance and social symbolism (Burton, 2004).

South Africa, in particular, provides a uniquely informative environment – climatically, agriculturally, politically, culturally and developmentally – within which to examine climate-adaptive responses. The country has a semi-arid climate with highly variable rainfall and scarce water resources (RSA, 2011). Its commercial grain sector is well developed and highly mechanized, but without the subsidies common in other industrialized agricultural systems. However, grain farming in the Western Cape province, where this work is located, is overwhelmingly rainfed and the use of crop insurance is uncommon, implying that these farmers are less buffered against weather risk than some others (e.g., the irrigation farmers studied by Eakin et al. (2016)). These agronomic conditions are overlain upon a dynamic socioeconomic environment in which post-apartheid programs of land restitution and land reform aim to create and nurture a new generation of emerging farmers (Bernstein, 2012). Though no emerging farmers were included in the present study because of their scarcity in the Western Cape, the challenges of commercial farming will be amplified for this group, who generally have less farming experience and less access to external resources. The largely white, Afrikaans-speaking commercial farmers of the Western Cape are also steeped in a culture that reveres multigenerational farming heritage (Devarenne, 2009), which encourages them to plan for long-term risks (Chapter 2). The Western Cape case, as presented herein, therefore combines climatic vulnerability, individual adaptive capacity, broader social imperatives, and cultural obligations.

Over the past two decades, the sweeping deregulation of South Africa's agricultural sector has introduced considerable financial insecurity, not unlike that which is also expected to result from climate change risks. Following the end of apartheid, in 1994, the newly democratic government eliminated agricultural subsidies, including price floors linked to variable crop production costs (Bernstein, 2012). Consequently, South African commercial farmers became less buffered against the economic impacts of weather extremes, and the high and variable costs of wheat production. This increased their sensitivity to climate variability and made it riskier to plant wheat on climatically marginal lands. Farming, including wheat production in the Western Cape, therefore shifted to better account for the underlying climate variables. From 1994 to 2012, the total area planted with wheat declined by half, though total production remained flat as technologies, and therefore crop yields per hectare, improved (RSA, 2013a). This policy change exposed commercial grain farmers to greater risks of farm failure during wet and dry years, making farmers more sensitive to weather and climate stimuli. It also forced those that survived to adopt weather risk-mitigating practices that would help them to avoid future yield losses (Chapter 2).

3.2.2 Conservation Agriculture as climate change adaptation in the Western Cape

The ongoing adoption of Conservation Agriculture (CA) in the Western Cape grain sector is among the most prominent transitions towards weather- and climate-resilient agricultural practices in South Africa (RSA, 2013c). CA consists of three principles – advanced crop rotations, minimum soil disturbance and permanent soil cover – that are strongly promoted by the Food and Agriculture Organization of the United Nations (FAO) as part of the Climate-Smart Agriculture and Sustainable Intensification frameworks (Giller et al., 2015; FAO, 2011). When adopted in concert, they are considered best practices in maintaining soil health and soil moisture (Hobbs et al., 2008). CA aims to make crop production less sensitive to climate variability and weather extremes, especially short- and long-term droughts, primarily by moderating soil moisture (improving both water-logging and drought performance) and by reducing planting times (requiring a smaller window of good weather) (Holland, 2004; Thierfelder & Wall, 2010). Overall, the Intergovernmental Panel on Climate Change affirms with "high confidence" that CA has the potential to simultaneously increase food production and climate resilience (Niang et al., 2014).

Though no-till or minimum-till planting techniques have been promoted as methods of soil erosion control since the 1930s “dust bowl” in the United States (Hobbs et al., 2008), recent advances in crop cultivar research, crop rotation planning and chemical pest control (enabled by herbicide-resistant transgenic cultivars) have prompted the spread of more comprehensive CA adoption (Bolliger et al., 2006). Major global drivers of CA uptake have been reported to include soil degradation, soil erosion, water scarcity, rising input costs, globalized markets and low profit margins (Findlater, 2013; Hardy et al., 2011; Knowler & Bradshaw, 2007). Further benefits include runoff and erosion control, moderate soil surface temperatures, lower labour requirements and long-term improvements in soil fertility, soil structure, nutrient cycling, natural pest control, input costs and crop yield stability (Hobbs et al., 2008; Knowler & Bradshaw, 2007).

The dilemma for farmers is that the inconsistent adoption of the three CA principles may jeopardize their long-term benefits (Giller et al., 2015). For instance, farmers’ use of livestock (another weather risk management strategy) can inhibit the comprehensive implementation of CA (Chapter 2). Livestock compete for the crop residues that are needed to maintain permanent soil cover. The presence of livestock also encourages farmers to perform periodic soil disturbance to reduce soil surface compaction. Such disturbance can lead to rapid nutrient mineralization and soil carbon loss (Jat et al., 2012). CA’s incomplete application may therefore lead to crop yield losses relative to conventional techniques (Hobbs et al., 2008; Knowler & Bradshaw, 2007; Pittelkow et al., 2015). Other barriers to full adoption include the high capital costs of the precision planting equipment necessary for CA, the potential for temporary yield reductions following its initial implementation, the foregone ability to control weeds through mechanical tillage and residue burning, and the need to improve drainage when implementing CA with some soil types (Giller et al., 2009; Hobbs et al., 2008; Jat et al., 2012; Knowler & Bradshaw, 2007).

In Chapter 2, and as detailed above, patterns in farmers’ risk-based decision-making suggested that they may be undertaking parallel risk management processes in different cognitive frames. To better understand the effect of cognitive framing on climate-adaptive behaviour, we here use the same set of structured interviews with South African commercial grain farmers to reveal the cognitive frames that they apply to weather and climate risks, in particular. We argue that these frames are evident in the words (or languages) that they use to describe these risks, as scholars have previously found in other contexts (Goffman, 1974; Lakoff, 2012; Porter & Hulme, 2013; Werner & Cornelissen, 2014). These farmers' mental models of the problems, effects, responses and mediators of response stemming from weather risks are then mapped and analyzed quantitatively in reference to six languages that are representative of identifiably different problem framings. Finally, we analyze the prevalence of each of these languages across different levels of CA adoption, as an example of climate-adaptive behaviour.

3.3 Methods

To evaluate the relationship between cognitive framing and climate-resilient behaviours, we interviewed 90 grain farmers in South Africa's Western Cape province (Section 3.3.1). In doing so, we used a mental models protocol to elicit their farming behaviours and cognitive logic (Section 3.3.2). We then conducted a multi-stage analysis, each step of which is elaborated in Section 3.3.3:

1. We scored each of the 90 participants on the extent to which they had adopted CA practices, assigning them to three groups (i.e., low, moderate and high adopters).
2. We qualitatively analyzed their stated and inferred drivers and barriers to CA adoption.
3. We coded 30 participants' causal statements stemming from weather and climate change risks.
4. We used these causal statements to construct influence diagrams showing weather and climate change problems, their negative effects, farmers' risk-mitigating responses, and the non-weather variables that mediated those responses (see simplified example in Figure 2.1).
5. We used an automated clustering algorithm to identify groups of mental model elements that were well connected and thus formed natural "communities". We used these groups to identify six exhaustive and mutually exclusive "languages" with which participants expressed logic related to weather and climate change risks.
6. We coded each element of each participant's mental model into one of these six languages.

7. We counted the instances of each language within each participant's mental model as captured in both the number of nodes (concepts) assigned to each language, as well as the number of directional edges (causal relationships) originating from each of those nodes.
8. We quantitatively analyzed these counts (both in absolute terms and in proportion to the size of the mental model) against participants' CA scores and the CA adoption groups from (1).

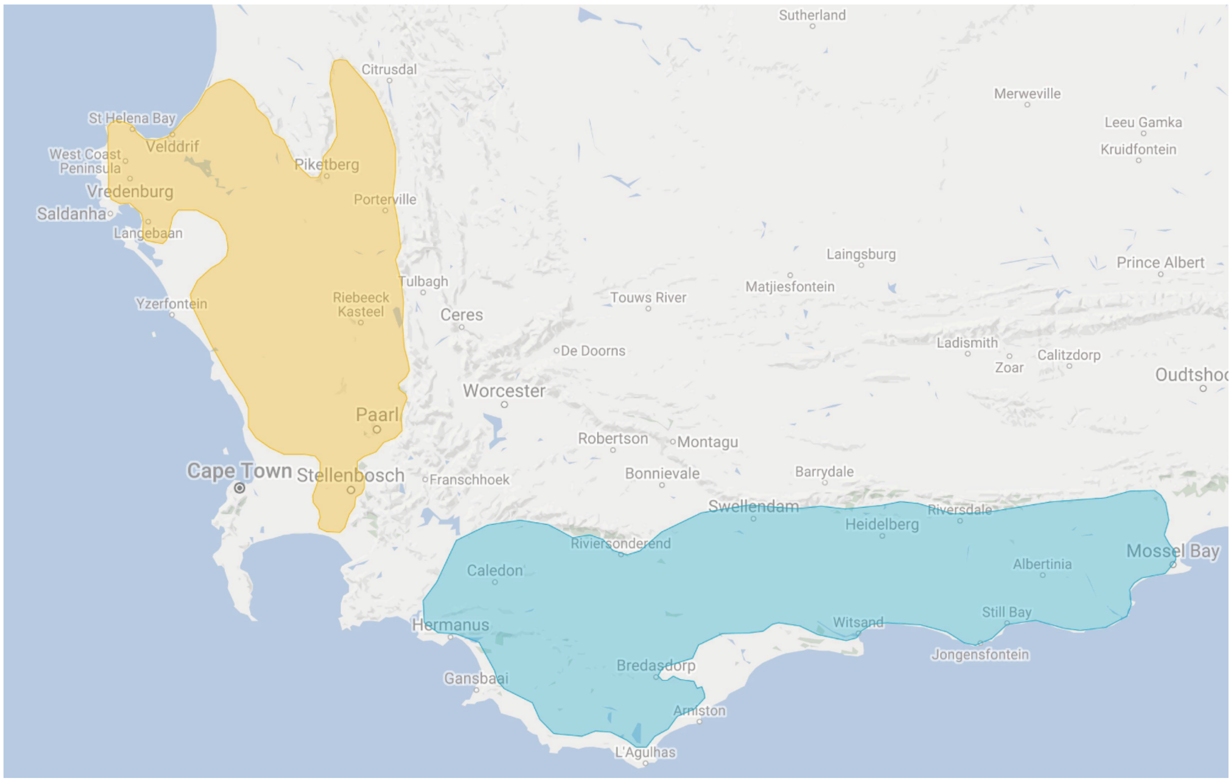
The study protocols were designed, piloted and implemented in consultation with partners at the University of Cape Town, Stellenbosch University and the Western Cape Department of Agriculture.

3.3.1 Sample and sampling procedure

The recruitment procedure was designed to produce a random but geographically representative sample of commercial grain farmers in the two major grain-growing regions of South Africa's Western Cape province (

Figure 3.1). The Western Cape grain sector is anchored by wheat production but includes barley, canola, rye, oats, triticale, lupines, medics (clover) and lucerne (alfalfa). By total value, wheat is the most important field crop in the Western Cape, and third-most in the country (RSA, 2013a). Most grain farmers raise livestock – commonly sheep but also cattle and ostriches. Farmers in both regions have been adopting CA step-wise over the past decade, though adoption in the Southern region is more advanced. Farmers in the Southern region are largely on long-term crop rotations with lucerne (for five to seven years), often including wheat, barley, canola, oats and lupines during the cash-cropping phase. Those in the Western region mainly use short rotations of biennial clovers (medics) and wheat, with some incorporating other annual crops (e.g., canola, oats or lupines) or eschewing clovers.

Figure 3.1: Map of the two study regions. For the purposes of this study, the Southern study region (blue) broadly corresponds to the Overberg District Municipality and part of the Eden District Municipality, bordered to the west by the Hottentots-Holland Mountains, to the south by the Atlantic and Indian Oceans, to the north by the Cape Fold Mountains, and extending east to the town of Mossel Bay. The Western study region (orange) broadly corresponds to the Saldanha Bay, Swartland and Bergrivier local municipalities, bordered to the east by the Boland Mountains, to the west by the Atlantic Ocean, to the south by the City of Cape Town, and extending north to the town of Eendekuil. Map data ©2017 AfriGIS (Pty) Ltd, Google.



Ninety (90) structured interviews sought to capture the breadth of current agricultural practices across varied farm sizes, with equal representation from each of the two climatically distinct grain-growing regions. Generally, 30 interviews are considered adequate to capture the breadth of thinking in a homogenous group (Morgan et al., 2002). We added to that to ensure representation in the two primary regions; however, as described below, we used a subset of 30 interviews for the more intensive analyses. In keeping with demographic trends in the local farming population, all of the participants were male, ranging in age from 25 to 62 years (*M* = 43.9, *SD* = 9.3). Their available arable farmland ranged from 250 to 4500 hectares (*M* = 1443 ha, *SD* = 880 ha). All participants had finished high school, with the majority (76%) having a university or college degree. A plurality (39%) of participants had completed one- or two-year technical degrees, while one-third (33%) held Bachelor's degrees and a small fraction (3%) held

Master's degrees. Though most spoke Afrikaans as their first language, all were conversant in English. None were given any material incentive to participate.

The interviews were conducted over a period of two months in late 2013, prior to the start of the grain harvest. Participants were recruited with the help of the four local co-operatives and agribusinesses that store and market the grain produced in the province. Within each organization's operational area, a liaison recruited a randomized sample of willing participants by phone, in proportion to the number of farmers assigned to each grain depot. All interviews were conducted in English. Approximately 20% of those contacted declined to participate, most frequently citing time constraints, but with some suggesting a discomfort with English. Fifteen agricultural experts from the co-operatives/agribusinesses, universities and the provincial Department of Agriculture were also interviewed to provide contextual data.

3.3.2 Mental models elicitation

Participants' behaviours and cognitive logic were elicited using a mental modeling protocol, an approach that attempts to depict the internal representations of reality that participants use to perceive, interpret and respond to environmental stimuli (Jones et al., 2011; Morgan et al., 2002) – in this case, weather and climate change risks. The approach can either be direct or indirect (Jones et al., 2011), where the direct method involves the explicit co-construction of an influence diagram by the interviewer and participant, showing concepts interconnected by causal relationships (e.g., drought causes low soil moisture, which causes low crop yields, which cause financial insecurity). The interviewer prescribes the model boundaries, and the participant is encouraged to identify and resolve inconsistencies. By contrast, using the indirect technique, the participant is not made aware that the interviewer seeks their mental model. The interview script follows a 'broad-to-narrow' question structure (e.g., beginning with the form, "What comes to mind when you hear the term…."), and standardized prompts encourage participants to elaborate on causal relationships. The participant determines the boundaries of the discussion and is less likely to identify and resolve inconsistencies than with direct elicitation.

In this study, the interview script was indirect both with respect to the technique (i.e., mental modeling) and the topic (i.e., weather and climate change risks). The interview began with an open-ended elicitation of the risks that participants perceived as being important in their farming enterprises. This allowed each participant to frame the conversation in their own terms, which enabled the subsequent analysis of the linguistic framing of weather and climate change risks. Because of the time-intensive nature of the indirect mental modeling analysis and the diminishing marginal benefit of each additional model, only 30 of the 90 participants were selected for modeling – ten from each CA index group, split evenly at each CA index level between the two study regions. To ensure that these structured mental models captured the complexity and nuance of participants' understanding of cause and effect, interviews were selected for modeling based on the participants' English language proficiency and the extent to which they had elaborated on simple answers when prompted. The language criterion may have led to some bias in the modelled subset, since English proficiency among Afrikaans-speaking farmers likely depends in part on their social integration. However, the inference of causal relationships during the analysis was expected to be more precise where participants were more comfortable expressing nuance in English.

3.3.3 Data analysis

As briefly introduced above, we conducted a multi-stage analysis to assess the relationship between participants' climate-adaptive behaviours (as represented by CA adoption) and their linguistic expression of weather risks:

1. <u>Quantifying Conservation Agriculture adoption:</u> We first provided an aggregate score of each of the 90 participants' CA practices by developing an CA index based on scoring criteria for each of its three components – advanced crop rotations, minimum soil disturbance, and permanent soil cover (results in Section 3.4.1). These criteria (listed in Table E.1 in Appendix E) were created in collaboration with local agricultural experts on the basis of the FAO guidelines and relevant peer-reviewed scientific literature. The CA index score was then calculated as the un-weighted sum of the three component scores. To allow for the clear comparison of different levels of CA implementation, the participants were separated into three groups corresponding to low, moderate and high scores. The grouping thresholds were established independently for each of the two study regions to control for broad differences in local climate, as well as differential access to

public and private agricultural extension services. Multiplying, rather than adding, the component scores resulted in no change in group membership. These CA index groups were later used to analyze variability in the linguistic framing of weather risks (in the final stage below) across different behavioural outcomes (as indicated by group membership).

2. Assessing the drivers and barriers of CA adoption: We conducted a qualitative analysis of the stated and inferred drivers and barriers to CA adoption across all 90 participants (results in Section 3.4.2). To that end, the interview script contained 'broad-to-narrow' sections specific to each of the three CA principles (advanced crop rotations, minimum soil disturbance and permanent soil cover). These sections sought to elicit participants' logic of adoption or non-adoption of CA without alerting them explicitly to the overarching CA theme, though many inferred this.
3. Coding for statements of cause and effect: The full transcripts of 30 interviews were coded for causal statements (i.e., those that implied cause and effect) related to weather and climate change risks. For example, a participant might have made the following statements (whether sequentially or at various points in the interview) linking back to rainfall variability: climate cycles cause rainfall variability (problem); rainfall variability often leads to low soil moisture (effect); soil moisture can be improved by increasing soil cover using crop residues (response); and the use of crop residues for soil cover is mediated (or in this case inhibited) by the competing need to use them as livestock feed.
4. Re-constructing participants' mental models of weather and climate change risks: For each participant, these causal statements were visualized as an influence diagram with nodes (concepts) connected by directional edges (causal relationships). They were then structured left-to-right from causes to problems, effects, risk-mitigating responses and mediators of response (see Figure 2.1 for a simplified example and Figure C.1 in Appendix C for a full-scale example). Participants' mental models, as re-constructed in this manner, ranged in size from 26 to 87 nodes (M = 52.48, SD = 12.96), and in interconnectedness from 2.05 to 3.61 edges per node (M = 2.81, SD = .34). To preserve nuance in the mental models, we did not limit the set of possible nodes or aggregate them across participants at this stage; each participant's mental model was re-constructed from their interview transcript in isolation of the others.

5. Developing codes for linguistic framing: We used a clustering algorithm to identify groups of nodes within each participant's mental model that were structurally related, forming natural "communities". Beginning with these clusters, we then iteratively categorized the nodes until we had identified an exhaustive and mutually exclusive set of "languages" that represented distinct linguistic framings of weather and climate change risks. The clustering was conducted using an automated algorithm embedded in the yEd network graphing software – "natural clustering" based on edge "betweenness", proposed by Girvan and Newman (2002) (see Figure C.2 in Appendix C for an example of a clustered model).
6. Coding the mental models for language: We coded each node in each participant's mental model into one of the six languages. The edges originating from each node were coded into the same language as that node. For example, periodic droughts (problem) might lead to multi-year crop failures (agricultural effect), creating serious financial harm (economic effect), which can be mitigated through better planning processes (cognitive response) mediated by a lack of access to reliable information about crop markets (cognitive mediator). In this case, the edge between crop failure and financial harm was coded as "agricultural", while the edge between financial harm and better planning was coded as "economic". Care was taken to ensure consistent coding for nodes that fell at the boundary between two or more languages (e.g., access to reliable information (cognitive) about markets (economic) was coded as cognitive). Such decisions were made in consideration of the original context of the statement.
7. Quantifying participants' linguistic framing of weather risks: Within each participant's mental model of weather risks,[12] we counted the number of nodes of each language and the number of edges originating from those nodes.
8. Quantitatively analyzing patterns of language and behaviour: Lastly, we quantitatively analyzed these language counts (both in absolute terms and in proportion to mental model size) with respect to the three CA adoption groups established in the first stage above. In analyzing node counts for each language across participants and groups, we referred to them as language "frequencies" (Section 3.4.3.1). Similarly, in analyzing the

[12] Though climate change risks were included in the identification of the six languages, they are analyzed separately in Chapter 5.

number of edges linking different mental model sections (i.e., effects, responses, mediators), we referred to them as language "flows" (Section 3.4.3.2). We then used the results from the qualitative second stage (barriers and drivers of CA adoption) to contextualize these quantitative findings.

3.4 Results

Overall, we found strong relationships between agricultural practice and the linguistic framing of weather risks. Specifically, we identified six languages that participants used to frame the effects, responses and mediators of response stemming from problems of weather and climate variability: agricultural, cognitive, economic, emotional, political and survival. We found statistically significant and meaningful relationships between the presence of particular languages in participants' mental models and their performance towards CA best practices. In particular, emotional and survival languages were strongly and negatively correlated with CA adoption.

3.4.1 Conservation Agriculture performance ($N = 90$)

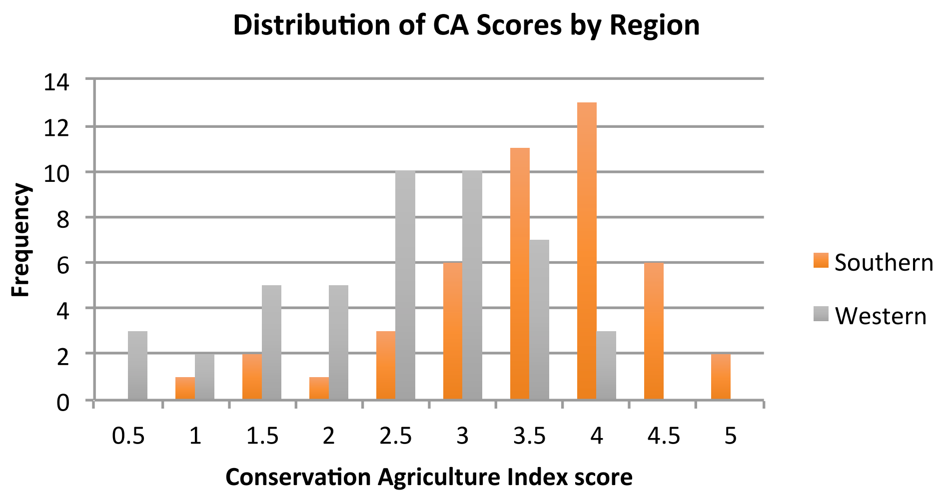
We found significant differences in the adoption of all CA practices in the two study regions, driven by climate variability, soil type and access to extension services. The mean CA index score for participants in the south ($M = 3.53$, $SD = .89$) was significantly higher than for those in the west ($M = 2.50$, $SD = .94$), $t(88) = 5.356$, $p < .001$ (Table 3.1). Differences in soil type and climate encouraged the earlier adoption of advanced crop rotations in the southern region and have deterred certain CA-related techniques in parts of the western region. For instance, southern farmers predominantly use five- to seven-year periods of lucerne (alfalfa) pasture to incorporate nitrogen-fixing legumes into their crop rotations, while western farmers rely on the alternate-year growth of biennial medics (clover) because lucerne performs poorly due in part to the region's hotter and drier summers. The unique characteristics of each rotation system imply differential grades when scored on the same definitions of practice. As described in the methods (Section 3.3.3), different grouping thresholds were therefore applied in each region when designating participants as low, moderate or high adopters.

The CA scores were approximately normally distributed (Figure 3.2), overall and within each region, as indicated by the Shapiro-Wilk test. On average, southern participants scored higher on each component than their western counterparts. Their crop rotation scores showed the greatest mean difference, $t(85.416) = 7.784$, $p < .001$, but the difference in soil cover was also significant, $t(88) = 2.890$, $p = .005$. No statistically significant correlations were found between CA index group and age or farm size. Regardless of their CA scores, participants commonly expressed their intent to improve their CA practices in the upcoming season. Many of those who owned the necessary equipment for CA continued to intersperse older methods with newer CA techniques (e.g., using a precision planter but still ripping or ploughing every few years). Participants' self-perception of their CA practice therefore often differed markedly from their CA index scores; low-scoring participants often provided optimistic assessments when asked to broadly evaluate their own CA practices, while high-scoring participants qualified their successes.

Table 3.1: Mean Conservation Agriculture (CA) scores for each study region. Mean scores are shown for the composite CA index and each of its components, as well as the author-defined CA index ranges for low, medium and high adopters in each region. Other than for minimum soil disturbance, all mean scores were significantly higher ($p < .05$) in the southern region than in the west.

	Mean Scores by Region	
Category/Group	**Southern (n = 45)**	**Western (n = 45)**
Advanced crop rotation	1.64	0.97
Minimum soil disturbance	1.06	0.96
Permanent soil cover	0.83	0.58
Total CA index score	3.53	2.50
Low adopters (range)	1.0 - 3.0 (n = 13)	0.5 - 1.5 (n = 10)
Moderate adopters (range)	3.5 - 4.0 (n = 24)	2.0 - 3.0 (n = 25)
High adopters (range)	4.5 - 5.0 (n = 8)	3.5 - 4.0 (n = 10)

Figure 3.2: Distribution of participants' CA index scores in each region (*N* = 90). The full index range was 0 to 6 at intervals of 0.5. No participants scored less than 0.5 or greater than 5.0. The Shapiro-Wilk test statistics, overall and for each region, were not significant, indicating that the distributions were approximately normal.



3.4.2 Qualitative drivers and barriers of CA adoption (*N* = 90)

> *" Farmers may seem to be very conservative, but I think we're very adaptable to changes in our environment. "*
> – *SA094*

The reported drivers of CA adoption were diverse, spanning many domains of risk (e.g., agronomic, economic, climatic). These included lower risks of farm failure because of reduced crop yield variability; lower economic risks due better income diversification and reduced inputs of seeds, fuel and fertilizer; lower labour risks due to mechanization; lower weather risks because of better soil moisture conservation; lower risk of pests because of improved soil biota communities; lower technological risks (i.e., weed resistance to chemicals) because of the capacity to cycle through a variety of herbicides; lower societal risks due to improved food security; and lower political risks because of potential improvements in farmers' reputations as responsible stewards of their land. Recent technological advances have also accelerated CA adoption. The advent of locally-built or locally-customized minimum-till tine planters, with their simultaneous and precise application of seeds, fertilizer and herbicide, has reportedly improved performance and reduced input costs compared with older planters. Many participants expressed cautious optimism in the ongoing trials of locally customized no-till disc planters that are more commonly used in South America. Canola was cited for many benefits in crop rotations, including weed and disease control, improved soil structure through natural tillage, and access to new markets. However, previous efforts to promote canola in the Western Cape were hampered by the poor performance of older varieties. The development of better cultivars has been crucial to its adoption and therefore to the improvement of crop rotations.

In contrast, the major *barriers* to adoption were centred on the large and risky investments in knowledge, technology and land necessary for CA's comprehensive implementation. These included the need to invest in costly equipment (e.g., minimum-till planters, larger tractors), and the need for large farm sizes to achieve economies of scale and to enable incremental experimentation without jeopardizing farm survival. While localized minimum-till planters have been integral to CA adoption, they tended to clog when crop residues became too thick. Many participants said that they therefore needed to modify their combine harvesters by purchasing equipment to shred crop residues. Others reported that their harvesting equipment was inadequate in handling canola's small seeds, with substantial proportions scattered and lost. Low-scoring participants expressed a greater sense of isolation and a mistrust of the lessons learned by others, making them skeptical of evidence from other farms or experiments. They largely understood and believed in the benefits of CA, but felt that they had constraints that high-scoring participants did not: unique local climates, soil types, personal conditions, risk aversion, unwillingness to take on debt, small farm sizes and difficulty controlling weeds by non-mechanical means. Since participants with small arable land areas needed to set aside a larger proportion of their land or capital to experiment with new technologies, they reported that such experimentation posed greater risks for them.

The vast majority of participants – even those in the low-scoring CA group – perceived CA to be an appropriate way to mitigate the risks of weather, climate variability and climate change. Of the 90 participants, only one argued that CA adoption was generally a bad idea, though others had misgivings specific to their own farms. When asked what measures they might take in response to future climate change, even those who expressed skepticism in the science of climate change suggested that CA would be a likely method by which to adapt if it were to occur. Many participants cited droughts in 2003, 2004 and 2005 as crucial in driving farm failures, subsequent farm consolidations, and broad changes in agricultural practices.

Participants reported many available options in responding to weather risks. Their choice of risk-mitigating responses was contingent on the myriad non-weather variables that mediated their agricultural practices, as well as on competition between responses. As previously described in Chapter 2, CA most directly competes with animal husbandry as an alternative response to weather risks. At the time of the interviews, all participants practiced mixed farming with both grain and livestock, though many suggested a preference for one or the other. The participants and experts alike agreed that livestock made it more difficult to maintain permanent soil cover (because of competition for crop residues as feed) and to practice minimum soil disturbance (because of soil surface compaction). Participants perceived livestock as necessary to protect against severe droughts that would otherwise threaten the immediate survival of the farm. In contrast, CA was perceived improve crop yields during more moderate droughts and to improve long-term economic sustainability.

Though participants strongly recognized the weather and climate change risk-mitigating benefits of CA, many of the proximate drivers of CA adoption were unrelated to weather – mechanization to reduce labour risks, precision and natural fertilization to reduce input costs, and crop rotations to increase economic diversification and to ease the management of pests, weeds and crop diseases. CA has therefore encouraged the conscious integration of risk management processes that were previously only loosely coordinated through farm budgeting. For example, SA077 described the need to change his mindset: *"I must talk to myself when I hear it. It's self-discipline that you must try every day. It's a total mind-shift away from conventional tillage to a minimum tillage system, where as much stubble as possible is kept on the soil, with a good rotation crop in which grass weeds are being destroyed."*

It represents a paradigm shift in the way that farmers approach risk, requiring systems thinking, long-term planning, continual learning, and the integration of risk management across domains. For instance, in describing his adoption of CA, SA085 argued for a steady, long-term perspective: *"You must change your perception of farming…. [You] must start with Conservation Agriculture…. It's [all]* *unpredictable, so you must stick to your original plan. You will make more money than if you're just responding to short-term market [fluctuations].''* SA100 similarly emphasized the long-term implications of his present CA practices: *"The decisions that I make in the next 10 years will determine the future for the people who cultivate the land after me."* SA141 emphasized the role of each component within the CA system: *"I work this [system] like a bicycle wheel with these spokes. You can say that the ring forms the unit, but if you touch one spoke, the whole thing must not fall apart. The wheel must still turn. If you remove one spoke, the thing must still keep going until you have time to put in the next spoke."* CA's largely autonomous adoption in South Africa therefore demonstrates that farmers are willing and able to adapt proactively to uncertain long-term risks.

3.4.3 Six languages of weather and climate change risks (*n* = 30)

Using automated clustering and iterative coding (described in the methods), we identified six major languages that participants used to frame weather and climate change risks: agricultural, cognitive, economic, emotional, political and survival (Table 3.2). For instance, periodic droughts (problem) might lead to multi-year crop failures (agricultural effect), creating serious financial harm (economic effect), which can be mitigated through better planning processes (cognitive response) mediated by a lack of access to reliable information about crop markets (cognitive mediator). In what follows, we show that there were clear patterns between participants' CA scores and the prevalence of these six languages in their mental models of weather risk.

3.4.3.1 Nodes: Language frequencies

The frequencies of these six languages within participants' mental models varied widely, but broad patterns within and between groups were nonetheless evident. Table 3.2 lists definitions for each language, with key examples of an effect, a risk-mitigating response, and a mediator of response. It also shows important intersections between languages, which are elaborated below. Agricultural language dominated the mental models across all three CA index groups, both because farming is an agricultural activity and because the interview protocol prompted extensive discussion of agricultural practices as they related to major risks at the farm level. Economic language was secondary to agricultural language, reflecting the nature of the commercial farm as a small business. Cognitive, emotional and survival languages varied the most between groups. Cognitive language was used to describe challenges in cognition, decision-making, uncertainty and access to information. Emotional language was used to describe challenges in motivation and morality. Survival language occurred at the intersection of economic and emotional languages, describing the fear of farm failure. It was indicative of economic anxiety expressed in terms of the farm's survival. For instance, it was often used to describe the threat of long-term debt, though not necessarily because the participant presently carried such debt. Participants instead cited their fathers' or their own past errors in overcapitalization or borrowing that threatened bankruptcy, or examples of acquaintances who were forced to leave farming during historical droughts. Political language was the least used in these mental models of weather risk, most often in reference to the role of land reform in mediating farm expansion as a response, or in describing the absence of political support for agricultural programs that might improve agricultural innovation.

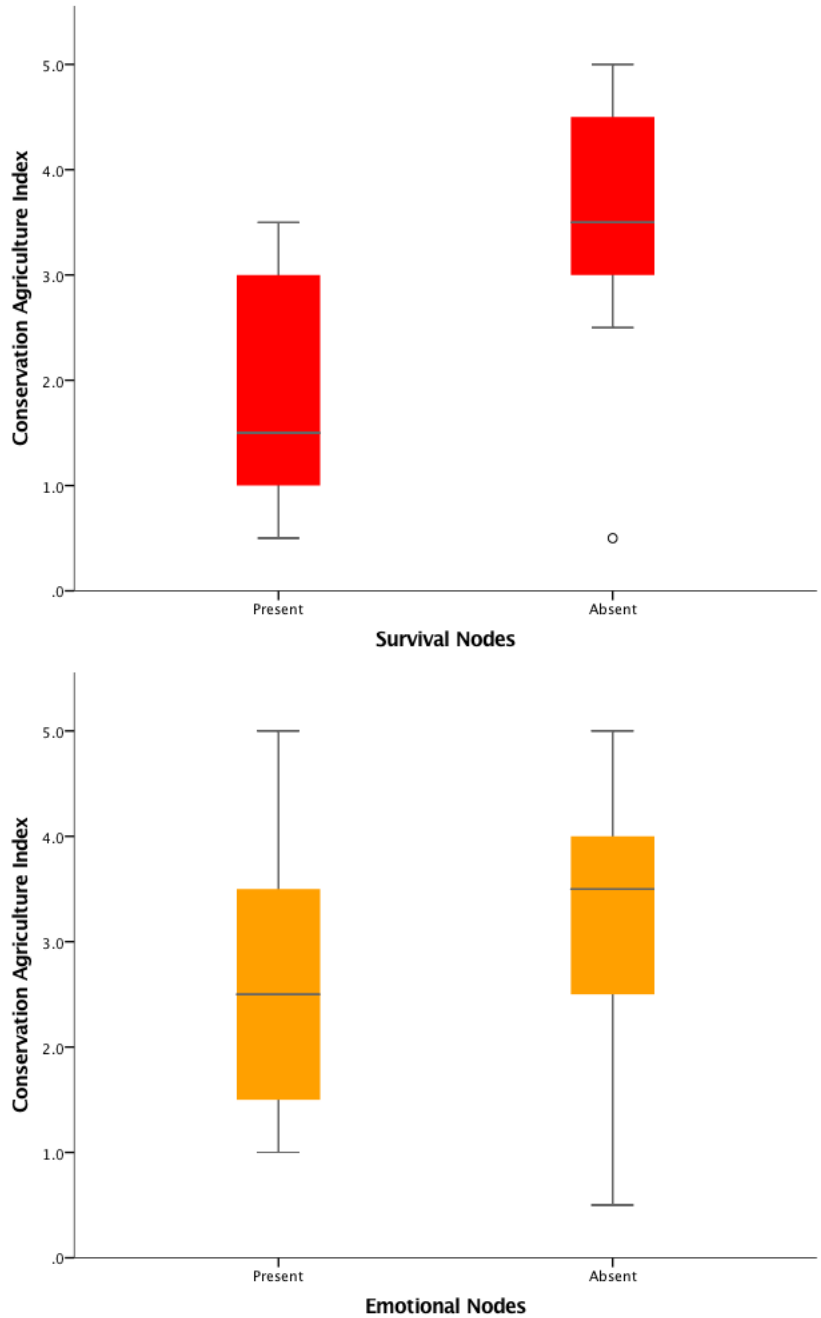
Table 3.2: Six languages of weather and climate risks, as evident in participants' mental models. No mediators were expressed in survival language, and thus no example of such is listed.

Language	Definition	Key Examples (Effect, Response, Mediator)	Intersecting Languages
Agricultural	Related to the practice of agriculture	Crop failure; Minimum tillage; Weeds	
Cognitive	Related to human cognition, decision-making or problem-solving	Increased uncertainty; Better planning; Lack of reliable information	
Economic	Related to farm-level, national or global economic processes	Financial hardship; Diversification beyond farming; Product prices	
Emotional	Related to human emotion, motivation or values	Anxiety; Faith in God; Distrust of others	Survival
Survival	Related to the threat of farm failure	Loss of farm; Sell farm; N/A	Survival
Political	Related to local, provincial or national politics	Increased political support for farmers; Lobbying for support; Land reform measures	Economic, Emotional

There was a clear inverse relationship between CA practice and the presence of survival language in the mental models of weather risk. Among low-scoring participants, nine of ten had survival nodes, whereas only one of ten high-scoring participants had such a node. For those with moderate CA scores, four had survival nodes. There was therefore a strong, negative and statistically significant correlation between CA index group and the presence of survival language (Spearman's rank-order correlation: $r_s(28) = -.570$, $p = .001$). The relationship between CA group and the *number* of survival nodes per participant was nearly as strong ($r_s(28) = -.545$, $p = .002$). The same held for the relationships between the more variable CA index score and the presence of survival language ($r_s(28) = -.575$, $p = .001$), and between CA index score and survival node count ($r_s(28) = -.526$, $p = .002$).

As an alternative approach, independent-samples t-tests were conducted to compare the CA index scores of participants with and without survival and emotional nodes (Figure 3.3). There was a significant difference in the scores of participants with survival nodes ($M = 2.00$, $SD = 1.08$) and those without ($M = 3.53$, $SD = 1.10$), $t(28) = 3.84$, $p < .001$. Levene's test indicated equal variances ($F = .24$, $p = .627$). For those with ($M = 2.62$, $SD = 1.26$) and without ($M = 3.08$, $SD = 1.36$) emotional nodes, the difference was not found to be significant, $t(28) = .97$, $p = .339$. However, in the following section, we show that emotional nodes nonetheless had a broader, statistically significant effect in their interconnections with other languages. No statistically significant differences were found between CA groups for the frequencies of the other languages (see Appendix F for supplementary figures).

Figure 3.3: Boxplots of CA index score by presence/absence of survival and emotional nodes. These were derived from participants' mental models of weather and climate variability risk (N = 30), and do not include climate change risks. The single point in the Survival figure represents a statistical outlier.



3.4.3.2 Edges: Language flows

The CA index groups also exhibited meaningful differences in the broader influence of each language within participants' mental models, as evidenced by the number of edges (causal relationships) originating from the nodes of each language. Using modified Sankey diagrams, Figure 3.4, Figure 3.5 and Figure 3.6 illustrate the flows of the six languages through the aggregate mental models of the low, moderate and high CA groups, respectively. These figures show the number of edges connecting different model sections (i.e., causes, problems, effects, responses, and mediators of response), and the transitions between language that occurred in logical sequences of cause and effect. For instance, in the low-CA group (Figure 3.4), survival effects in red (e.g., potential farm failure) are connected to agricultural (green), economic (blue), survival (red) and cognitive (yellow) responses. The width of each connection is proportionate to the number of edges it represents. Though most nodes were connected to others of the same language, connections between languages were important in showing participants' logic. For instance SA061 (low CA) indicated that rainfall variability (weather problem) created a risk of crop failure (agricultural effect) and unstable income (economic effect), which could be mitigated through off-farm diversification (economic response), further encouraged by his children's disinterest in farming (emotional mediator of response). These figures thereby show how the different linguistic framings of weather risk were related to one another.

All CA groups had predominantly agricultural, economic and cognitive edges. However, taking emotional, survival and political edges in aggregate, participants in the low-scoring CA group had significantly more such edges as a proportion of total edges in their mental models (M = .084, SD = .054) than did those in the high-scoring CA group (M = .024, SD = .024), $t(12.493)$ = 3.190, p = .007. The moderate CA group had correspondingly moderate contributions from these languages. In absolute terms, high-scoring participants had significantly more agricultural edges (M = 88.70, SD = 23.61) than low-scoring participants (M = 69.90, SD = 14.57), $t(18)$ = -2.143, p = .046, which corresponded to a significant positive correlation between CA score and the number of agricultural edges ($r_s(28)$ = .434, p = .015). This implies that high-CA participants spoke of more causal relationships stemming from agricultural effects, responses and mediators of response than did low-CA participants.

The emotional and survival languages each clearly exhibited more influence in the low-CA group. Figure 3.7 shows the differences between CA groups in the number of edges stemming from survival and emotional nodes as a proportion of total edges in participants' mental models.

The low-CA group had significantly larger proportions of their edges coded as survival (M = .041, SD = .051; $t(9.524) = 2.330$, $p = .043$) and emotional (M = .029, SD = .029; $t(11.602)$ = 2.457, $p = .031$) than did the high-CA group: survival (M = .003, SD = .009) and emotional (M = .005, SD = .011). There were correspondingly strong and significant negative correlations between CA score and the number of survival ($r_s(28) = -.466$, $p = .008$) and emotional ($r_s(28) = -.433$, $p = .015$) connections.

Figure 3.4: Flows of language through farmers' causal mental models of weather risk for those with low CA scores (*n* = 10). The figure shows the aggregate number of edges (causal relationships) of each language that connect different mental model sections (i.e., problems, effects, responses, mediators of response), as well as transitions between these languages in the logical sequences of cause and effect. The width of each connection is proportionate to the number of connections it represents. This shows the interconnectedness of each language as evidenced by the number of nodes (concepts) that it influences. For example, though agricultural language was predominant (e.g., crop yield effects or soil cover responses), economic mediators were more prevalent (e.g., access to credit, cost of machinery) than agricultural mediators (e.g., increased burden from pests or weeds).

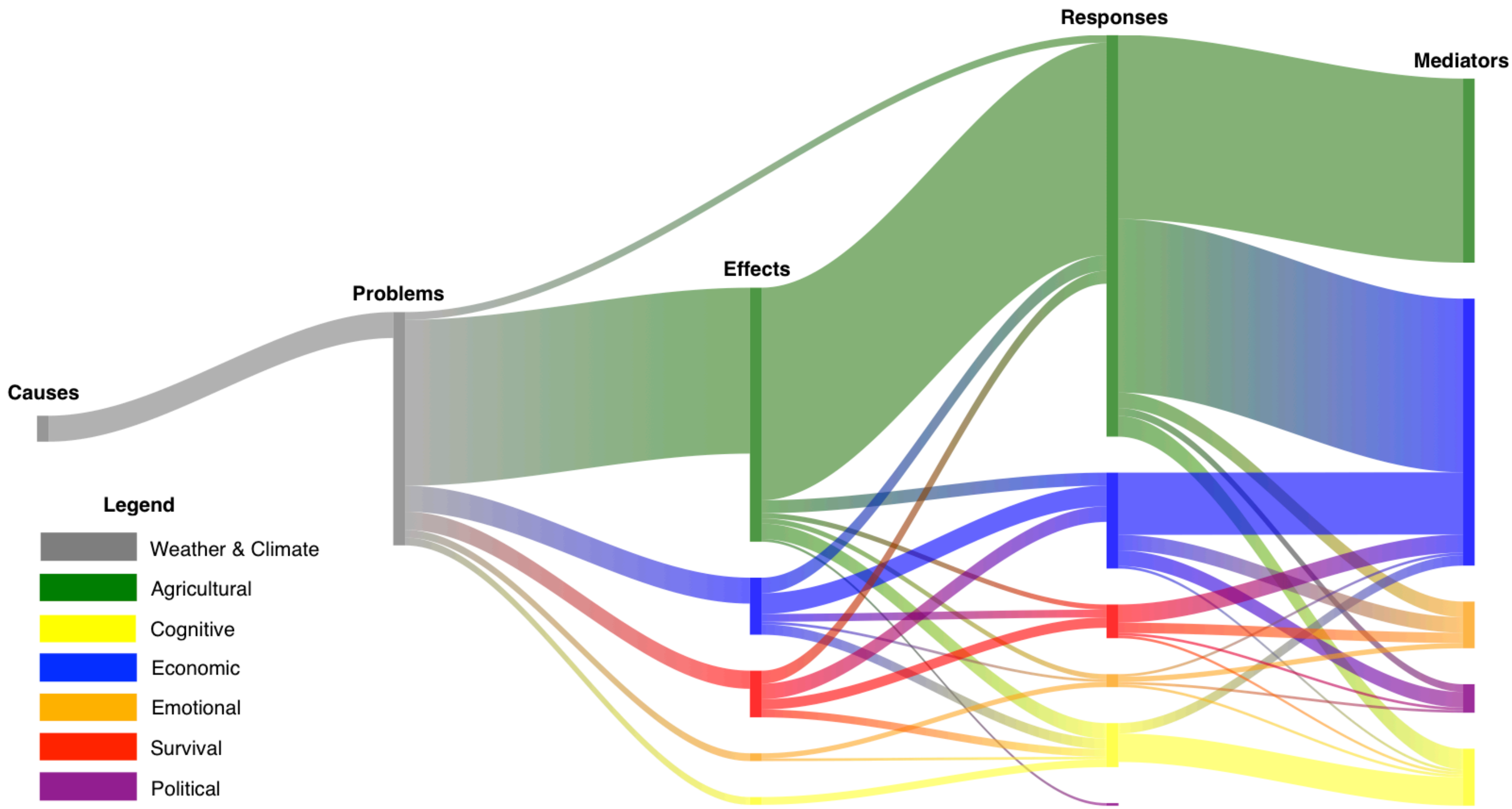


Figure 3.5: Flows of language through farmers' causal mental models of weather risk for those with moderate CA scores (*n* = 10). The figure shows the aggregate number of edges (causal relationships) of each language that connect different mental model sections (i.e., problems, effects, responses, mediators of response), as well as transitions between these languages in the logical sequences of cause and effect. The width of each connection is proportionate to the number of connections it represents. This shows the interconnectedness of each language as evidenced by the number of nodes (concepts) that it influences. For example, though agricultural language was predominant (e.g., crop yield effects or soil cover responses), economic mediators were more prevalent (e.g., access to credit, cost of machinery) than agricultural mediators (e.g., increased burden from pests or weeds).

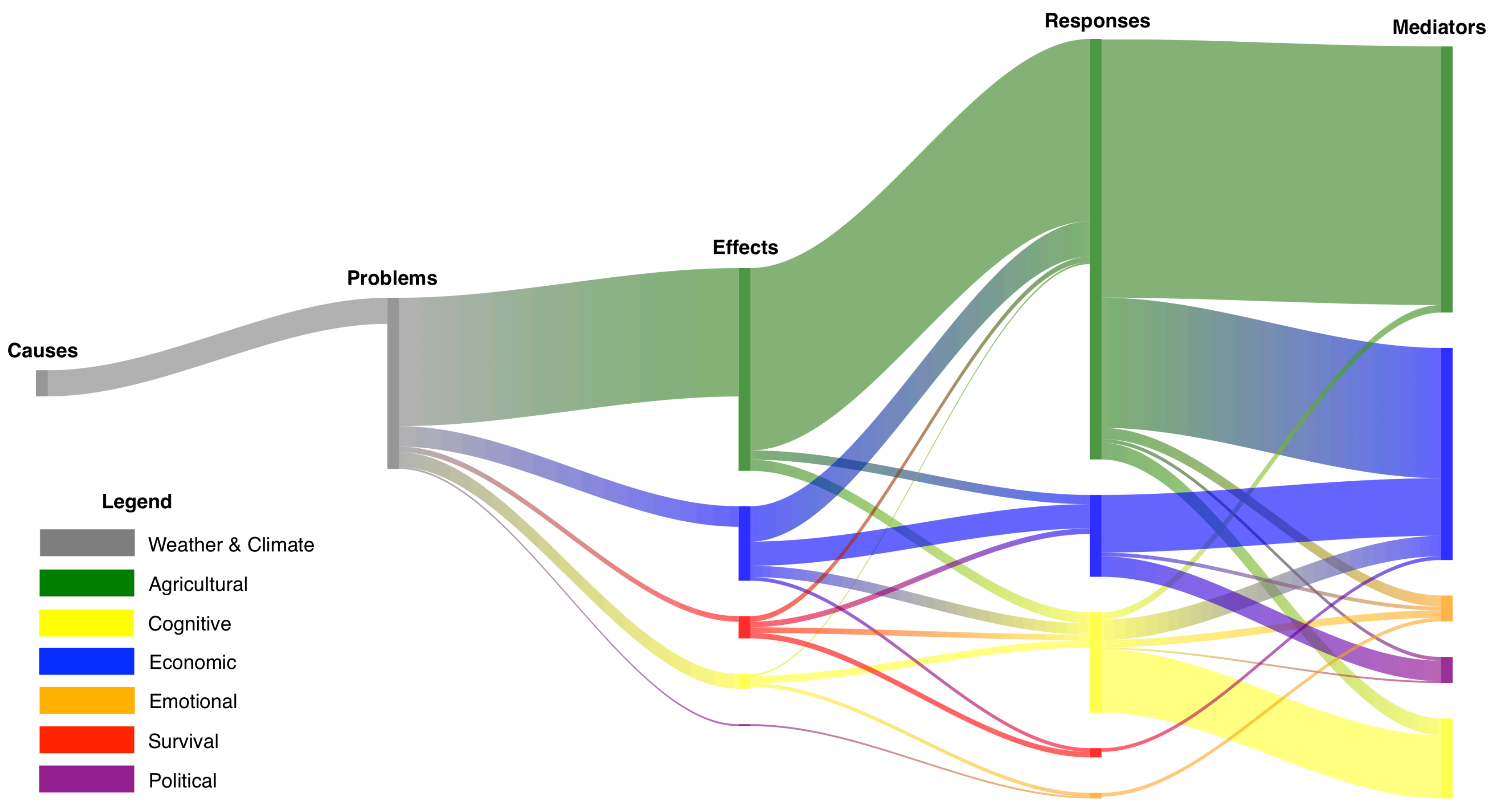


Figure 3.6: Flows of language through farmers' causal mental models of weather risk for those with high CA scores (*n* = 10). The figure shows the aggregate number of edges (causal relationships) of each language that connect different mental model sections (i.e., problems, effects, responses, mediators of response), as well as transitions between these languages in the logical sequences of cause and effect. The width of each connection is proportionate to the number of connections it represents. This shows the interconnectedness of each language as evidenced by the number of nodes (concepts) that it influences. For example, though agricultural language was predominant (e.g., crop yield effects or soil cover responses), economic mediators were more prevalent (e.g., access to credit, cost of machinery) than agricultural mediators (e.g., increased burden from pests or weeds).

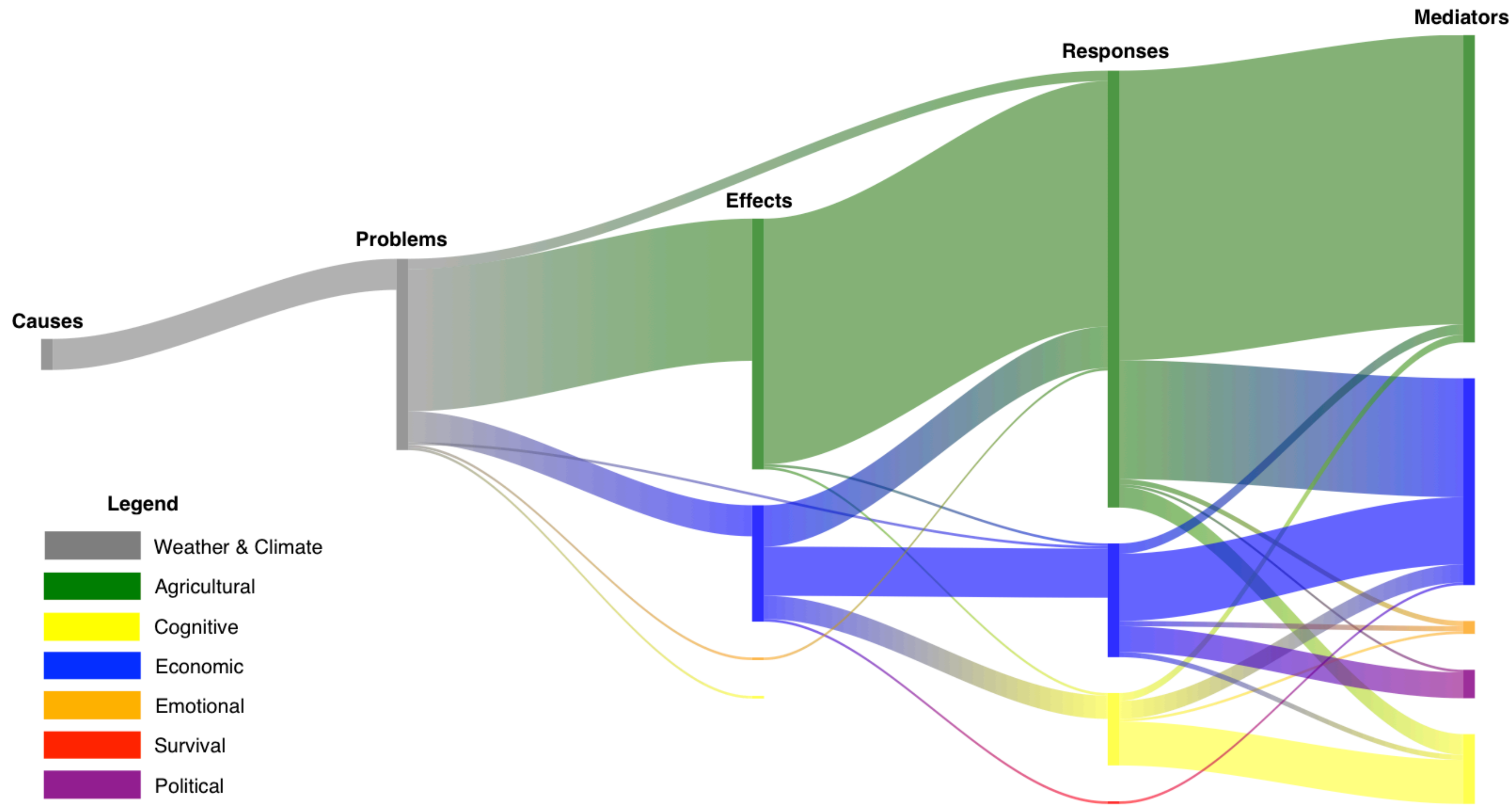
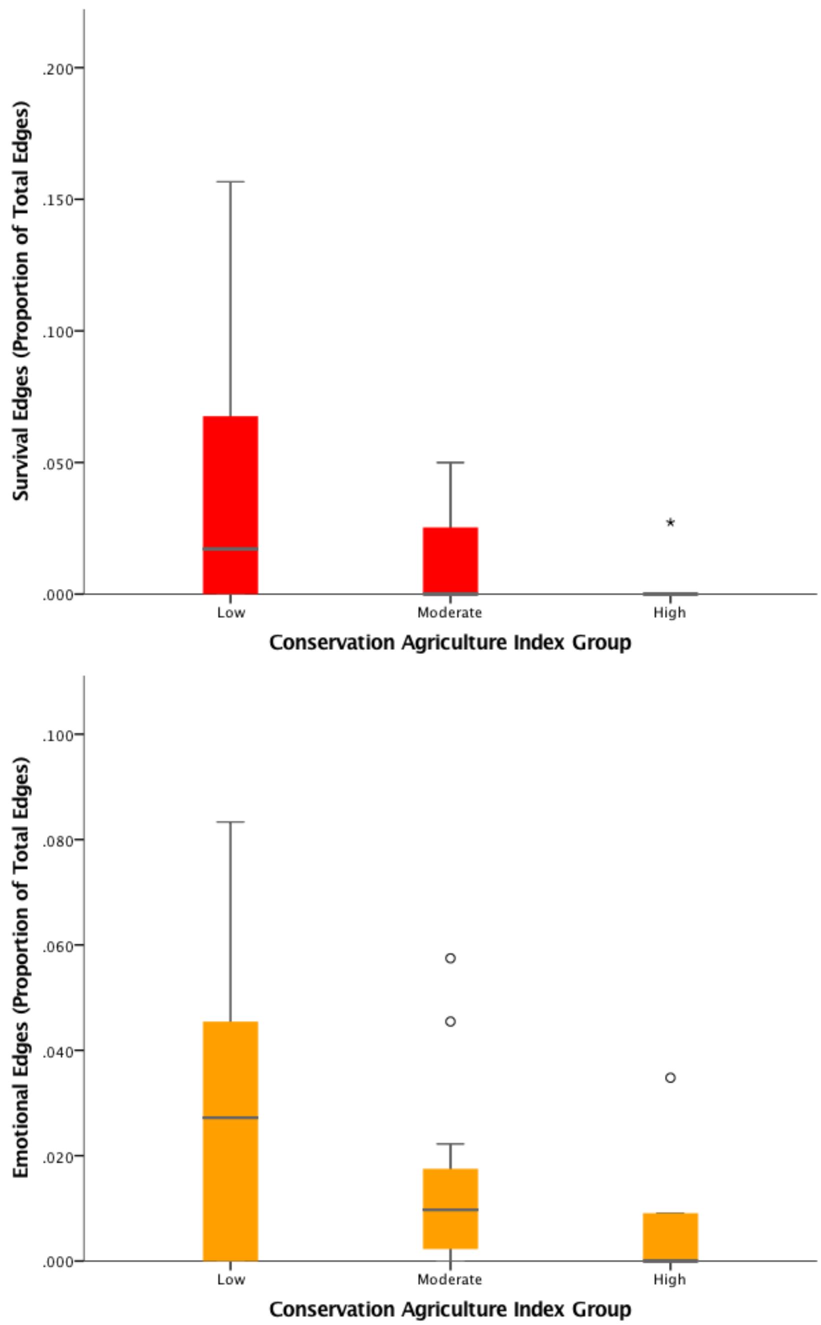


Figure 3.7: Boxplots of survival and emotional edges for each CA index group (n = 30). These are indicated as a proportion of the total number of edges within each participant's mental model.



3.5 Discussion and conclusions

We have contributed to the improved understanding of climate-adaptive behaviours by analyzing farmers' mental models of weather and climate variability in situ, finding evidence of the role of alternate cognitive frames on behavioural outcomes. Participants' linguistic framing of weather risks was predictive of CA adoption – as a measure of climate-resilient farming practice – implying the use of different cognitive frames in decision-making. Farmers used six languages to describe the effects, responses and mediators of response stemming from problems of weather and climate: agricultural, cognitive, economic, emotional, political and survival. The frequencies of these languages in farmers' mental models of weather risks, as indicative of the underlying contexts and processes of decision-making, predicted the extent to which they had adopted CA. Though the vast majority of grain farmers in the Western Cape are committed to improving their CA practices, uptake has occurred differentially, both within and between study regions. This is not a direct consequence of broad differences in aversion to weather and climate change risks, but of divergent sensitivity to particular consequences of such risks.

CA competes with other responses that mitigate weather and non-weather risks. Livestock, widely used for agricultural risk management throughout the world, compete for crop residues as feed and contribute to soil compaction that must be alleviated through soil disturbance. The weather risk-mitigating benefits of CA are also a by-product of strategies that are undertaken primarily to manage rising input costs and labour challenges. Minimum-till reduces labour risks, along with seed and fuel costs, while advanced crop rotations reduce fertilizer and spraying costs. Permanent soil cover is often forgone precisely because it does not directly address any of these proximate concerns. However, most farmers intend to improve soil cover as a weather risk management strategy, because they recognize CA's weather and climate benefits. Those for whom the maintenance of soil cover incurs fewer trade-offs have improved it by managing other objectives by other means – whether foregoing livestock or seeking alternative sources of feed – so that they can direct financial and land resources towards the comprehensive implementation of CA.

The use of different cognitive frames implies the use of different logics that result in different decisions, and therefore different behaviours. CA is an agronomic response, and in this analytical framework its component practices were coded as agricultural language, yet the extent to which farmers had adopted CA was predicted not predominantly by the use of agricultural language, which was pervasive, but by the use of the languages of emotion and survival. High-scoring CA adopters used "rational" agricultural, economic and cognitive languages when characterizing weather problems, effects, responses and mediators of response. Low-scoring CA adopters additionally described weather stimuli using "irrational" survival and emotional languages, while moderate adopters were fittingly positioned in the middle. All groups had similarly low levels of political language. These patterns suggest that anxiety about the survival of the farm is an overriding factor that may render large investments in improved practice moot, regardless of their perceived benefits. Concern for long-term climate change risks, concurrent with the recognition of CA benefits, may not be enough to overcome this barrier and may instead result in a stronger reliance on livestock to mitigate climate change risks.

Farmer behaviours are not always economically rational; such a singular economic focus would underestimate the crucial role of survival risks. Farmers who appear to be financially secure may be unexpectedly averse to survival risks because of their own past experiences or those of other farmers that they trust. Farmers who characterize weather and climate variability in survival and emotional terms are far less likely to have undertaken CA. This suggests that anxiety about the survival of the farm is an overriding factor that inhibits the large investments in equipment and land necessary to achieve adequate economies of scale. Short- to medium-term anxiety about the survival of the farm can therefore impede adaptation to weather risks and changes in climate that may threaten that very survival in the long term. To promote CA adoption, policy-makers might encourage measures that reduce the heavy upfront investment in equipment and land necessary to achieve economies of scale, such as equipment sharing and the use of external contractors for planting and harvesting.

While these farmers are capable of proactive climate change adaptation, their decisions are strongly shaped by the personal, environmental and socioeconomic contexts in which they operate. We can better predict how they will respond to climate change, as just one of many risks, by understanding their use of alternate cognitive frames in perceiving and responding to weather and climate change risks. In the study area, CA is widely understood to be an appropriate method by which to mitigate risks stemming from weather, climate variability and climate change. It is recognized as protecting against these risks both by those who practice it and by those who do not. While its autonomous adoption is driven largely by non-weather risks (e.g., rising input costs, labour challenges), it suggests that farmers are willing and able to adapt proactively to other uncertain long-term risks. Climate change adaptation will not be a straightforward translation of environmental stimuli into agricultural responses, but rather the result of many incremental changes towards more efficient and effective agricultural practices in response to varied stimuli across competing domains of risk.

Chapter 4: Conservation Agriculture adoption: Underestimating the extension challenge and overestimating its results

4.1 Synopsis

Conservation Agriculture (CA) has been widely promoted as a framework to guide productive and climate-resilient grain farming. For example, it has been strongly emphasized by the Food and Agriculture Organization (FAO) of the United Nations in their Climate-Smart Agriculture (CSA) and Sustainable Intensification (SI) foci, and has been affirmed by the Intergovernmental Panel on Climate Change (IPCC) as simultaneously contributing to food security and climate resilience. Meta-analyses of CA's benefits have suggested that comprehensive CA adoption produces crop yield gains in dry climates, but that these are curtailed or even reversed when its principles are applied piecemeal. This implies that the extent of CA's complete – and therefore beneficial – adoption has been broadly overestimated, because researchers typically use narrow proxies (e.g., the use of minimum-till machinery) to monitor its spread, rather than by assessing the implementation of its three principles. A possible case in point is the ongoing and differential adoption of CA and its attendant practices by South African commercial grain farmers, who have the demonstrated incentive, capacity and willingness to mitigate long-term risks through changes in farming practice. To evaluate the utility of the CA concept in promoting and monitoring the adoption of sustainable agricultural practices in this group, we use data from a national survey to investigate their patterns of CA adoption, and to compare their shared definition of "conservation" farming to experts' definition of CA. We find that farmers are not adopting CA as a comprehensive package; instead they decide whether and how to adopt its three principles using different rationales, while demonstrating some difficulty in estimating CA outcomes directly. Farmers' definition of "conservation" farming is strongly influenced by older concepts; though related, these are mismatched with the terms used by experts in promoting CA adoption. The results suggest that beneficial CA adoption is best promoted, monitored and evaluated using specific bundles of locally tailored practices that contribute to each of its overarching principles. Otherwise, the mismatched definitions of experts and farmers and the piecemeal adoption of CA principles will likely lead both to the underestimation of the agricultural extension challenge and to the overestimation of its results.

4.2 Introduction

The Food and Agriculture Organization (FAO) of the United Nations, among others, has marketed Conservation Agriculture (CA) as a coherent set of principles to guide the global adoption of climate-resilient grain-farming practices (Jat et al., 2014). Climate change is projected to increase climate variability in most areas, and to reduce mean rainfall in some (IPCC, 2013). When adopted as a package of complementary practices, CA is expected to reduce the negative effects of these environmental changes on average crop yields, and in some cases to increase yields. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) affirms with "high confidence" that CA has the potential to simultaneously increase food production and reduce climate change risks in Africa (Niang et al., 2014). More broadly, CA is a foundational element of the FAO's Climate-Smart Agriculture (CSA) and Sustainable Intensification (SI) foci. CSA is an overarching framework to guide optimal agricultural responses to climate change towards both mitigation and adaptation, and includes a variety of practical recommendations for various agricultural sectors (FAO 2013a). Concurrently, the SI framework seeks to encourage crop yield growth for improved food security, through the application of less environmentally detrimental forms of industrialized commercial agriculture (FAO, 2013b). For commercial grain farming, the focus of this work, CA is the major feature of both the CSA and SI frameworks.

Adherence to CA involves the application of multiple underlying practices that contribute to its three principles: (1) the maintenance of permanent soil cover to conserve soil moisture and to reduce soil surface temperature extremes; (2) the minimization of soil disturbance to improve soil structure, infiltration and water-holding capacity; and (3) the careful design of advanced crop rotations for natural fertilization and to control pests, weeds and diseases (Hobbs et al., 2008; Kassam et al., 2011). When adopted comprehensively, CA may improve average crop yields, reduce costs, and curb the risk of farm failure (Derpsch et al., 2014). However, there is mounting evidence that CA is often incompletely applied, leading to lower yields and higher costs than expected (Giller et al., 2015). In dry climates like that of South Africa, meta-analyses have shown improvements in average yield when the three pillars are adopted simultaneously, but yield losses when they are implemented separately (Pittelkow et al., 2015; Rusinamhodzi et al., 2011; Van den Putte, 2010). In particular, Pittelkow et al. (2015) find that minimum-till or no-till techniques tend to reduce average yields when implemented alone. For example, without advanced crop rotations and new chemical inputs, minimum-till is likely lead to lower crop yields, because mechanical tillage had previously helped to control weeds, pests and diseases. Furthermore, each of the three CA principles enables the implementation of the others. For instance, permanent soil cover cannot be properly maintained without minimum-till, because tillage incorporates crop residues into the soil. Similarly, advanced crop rotations allow farmers to actively improve soil health by growing cover crops, like nitrogen-fixing legumes for natural fertilization, instead of having to fallow their fields (i.e., leaving them tilled and unseeded) to passively restore soil fertility and to control plant diseases. Livestock husbandry, another common weather risk management strategy, can also impede complete CA adoption. Even when farmers intend to adopt CA comprehensively, competition for crop residues in mixed grain/livestock farming systems curtails CA's benefits (Chapter 2; Pittelkow et al., 2015).

The widespread monitoring of CA adoption has proven unreliable, in part because its manifestation is not universal and in part because the mechanisms of its adoption are not well understood (Giller et al., 2015). In monitoring and evaluation programs, CA uptake is often narrowly defined using a single binary proxy variable for which data is readily available. The most common CA proxy is the use of minimum tillage machinery (also historically known as conservation tillage), though some studies have alternatively tracked the implementation of soil erosion control measures more broadly, the intensity of chemical inputs, the use of cover crops, or the application of compost or mulch (Knowler & Bradshaw, 2007). Our recent qualitative study of CA adoption by South Africa's Western Cape wheat farmers suggests that they are not adopting CA wholesale, but are rather piecing together various related practices for largely non-weather reasons (Chapter 3). The above meta-analyses of CA's benefits imply that if it is not being adopted as a package, monitoring and evaluation programs that use single proxies will seriously overestimate the extent of beneficial CA adoption.

To better understand CA as an enabling concept in the spread of sustainable and climate-resilient practices in South African grain farming, we quantitatively investigate how farmers are adopting CA and how they define "conservation" farming. We first examine the assumption most crucial to its benefits for both farm-level financial security and societal food security, and therefore to its promotion, monitoring and evaluation: that CA is adopted as a package, with a consistent logic underlying its implementation. We then further investigate an important requisite assumption: that farmers' definition of "conservation" farming is aligned with experts' definition of CA.

4.3 Case and methodology

To investigate patterns of CA adoption, we conducted a national survey of South Africa's commercial grain farmers. The survey data were first used in binary and ordinal regression models to identify significant drivers of CA adoption and to evaluate the extent to which it was being adopted as a package. A further binary regression was used to contrast respondents who self-identified as "conservation" farmers with those who self-identified as "conventional" farmers. This revealed an implicit definition of conservation farming, which we then compared with the CA guidelines used by the FAO, IPCC and local experts. The survey was designed and piloted in consultation with Grain SA, the national commodity organization representing commercial grain farmers in South Africa. Grain SA disseminated the final online survey link to their membership by email.

Our sample frame was comprised of South African grain farmers who were dues-paying members of Grain SA. This frame captured more than half of the country's commercial grain farmers, both by internal (Grain SA) estimates and those provided during expert interviews in advance of the survey design. These members were thought to be broadly representative of the larger population, but with fewer very large and very small farms. Grain SA's marketing department forwarded the survey link to their member contact list. The survey was open for eleven weeks, from March 13th to May 31st 2015, during which time three reminders were sent by email. Of the 4757 entries on the contact list, 441 farmers (9%) completed the survey. Twelve additional duplicates were excluded from the analysis, on the basis that they were likely to have been the same farm or farmer judging from identical geographic, demographic and farm-level information. On the advice of local experts with experience surveying commercial farmers, few questions were made mandatory. The sample size therefore varied from 244 to 388 depending on the variables included in the analysis, and is indicated below for each of the results. The survey was offered in both English and Afrikaans, with the vast majority of respondents (92%) selecting the Afrikaans version.

South Africa's commercial grain farmers operate in a highly variable and semi-arid Mediterranean climate (RSA, 2011). As many are white and therefore historical beneficiaries of South Africa's apartheid system, they are also generally well educated, with relatively large farms and good access to financial, informational and institutional resources (Bernstein, 2012; Wilk et al., 2013). Their production methods are broadly similar to those of commercial grain farmers in higher-income countries – input intensive and highly mechanized, using the same types of implements and farming practices – but with few public subsidies. They are therefore closely representative of the autonomous private actor foundational to the climate change adaptation literature. Within South Africa, two major rainfall regions correspond to the cultivation of different crops. Wheat is the most valuable cash crop in the western winter rainfall region, while maize (corn) is most valuable in the eastern summer rainfall region and in the country as a whole (RSA, 2013a). Anthropogenic climate change is expected to exacerbate climate variability in South Africa, and to reduce mean rainfall in the winter rainfall region (RSA, 2011). During preliminary interviews, local experts described the adoption of CA as the most important current trend in the sector, because of its potential benefits for farm-level sustainability and regional food security, and because they perceived that farmers were undertaking this progressive transformation of their own initiative. However, these early interviews also suggested that farmers' definitions of "conservation farming" were imperfectly aligned with experts' definitions of "Conservation Agriculture", leading to some degree of confusion and miscommunication in its promotion, monitoring and evaluation.

CA adoption as a package: To assess the extent to which farmers were adopting CA as a package, we compared and contrasted the drivers of CA adoption. First, respondents were asked to report on outcomes aligned with each of CA's three principles (i.e., amount of soil cover, amount of soil disturbance, and number of crops in rotation). Second, to corroborate these measures of performance, they were asked about their use of a variety of specific farming practices, including two components that are integral to CA implementation (the use of low-tillage implements and the avoidance of crop residue burning). A low-tillage score was constructed based on their reported use of mechanical soil disturbance across four questions (i.e., for primary tillage, secondary tillage, weed control and seeding/planting). The frequency of crop residue burning was converted from a five-point scale to a binary variable (i.e., never burn / sometimes or always burn). Lastly, to assess overall CA adoption as a package, the three CA outcomes were combined into a composite CA Index – the sum of the normalized scores for each outcome. These six measures (the three CA outcomes, the two additional practices, and the CA Index) were used as dependent variables in separate regressions with an identical set of farm and farmer characteristics as independent variables. Depending on their nature, the dependent variables were analyzed using binary logistic regression or ordinal (cumulative logit) regression through the generalized linear modeling interface in SPSS. The signs and significance of these independent variables were compared and contrasted among the six dependents.

Farmers' definition of "conservation" farming: To reveal whether a common definition of conservation farming existed in the population, respondents to the survey were asked to select their overarching system of grain farming from six typical options (conventional, conservation, precision, progressive, biological, and organic).[13] "Conservation" and "conventional" farmers were coded as "1" and "0", respectively, and contrasted using binary logistic regression to determine the significant demographics, farm characteristics and farming practices that led respondents to self-identify as "conservation" farmers. These significant predictors revealed an implicit definition of conservation farming in this group of farmers. This was then compared and contrasted with the common expert definition of CA and historical concepts of conservation farming. An alternative multinomial regression analysis, using all six farming identities, yielded similar results but failed to satisfy important regression assumptions because of the higher number of categories and low number of respondents in some of them.

While most of the independent variables (e.g., demographics and farming practices) stem directly from individual survey questions, the categorical "crop cluster" variable requires further explanation. It was derived from a cluster analysis of the different types of crops grown by each farmer, whether irrigated or non-irrigated. For instance, dry wheat farmers primarily grew rainfed wheat in rotation with other rainfed crops (e.g., barley, canola, oats, lucerne). The

[13] These were determined from earlier interviews documented in Chapters 2, 3 and 5.

clusters used here broadly match known grain-farming patterns in South Africa with one exception: the "mixed" cluster captures farmers whose major crops did not clearly fall into one of the three larger clusters (irrigation, dry wheat and dry maize). Farmers in the "no grain" cluster, who reported not growing any grain in the past year, were excluded from this analysis. Because we were primarily interested in the variety of significant drivers across different dependent variables, we have not included nested regression models for each dependent variable in the results below.

4.4 Results and discussion

Finding 1: CA is not adopted as a package; its three principles are each adopted according to a different logic.

The regression analyses of farming practices suggest that, in South Africa, the three CA principles are not adopted systematically and simultaneously. If CA were adopted as a package, its components would be well correlated with each other, and farmers' performance on these measures would be broadly driven by the same significant factors. In reality, the three variables representing CA outcomes were not significantly correlated with each other (Table 4.1), and they were driven by different significant independent variables (Table 4.2). These differences were masked when CA adoption was assessed as a package (i.e., the composite CA Index). These farmers are therefore adopting CA principles piecemeal, contrary to the simultaneous and systematic mode of adoption promoted by the FAO and implicitly assumed in the most common methods of monitoring and evaluation. This validates a similar qualitative finding from our previous study of South African wheat farmers (Chapter 3).

These findings suggest that the extent of beneficial CA adoption will be seriously overestimated if it is monitored using a single proxy associated with minimum soil disturbance, because of the complementary nature of CA practices as described by Pittelkow et al. (2015). Though the use of low-tillage implements was significantly correlated with all three CA outcomes – and minimum soil disturbance most strongly – correlations among the CA outcomes and associated practices were much lower than expected (Table 4.1). Further, though the avoidance of crop residue burning is a prerequisite for the maintenance of permanent soil cover, the two were not correlated with each other. Moreover, our previous findings (Chapter 3) suggest that farmers have difficulty estimating soil cover and soil disturbance, because these are not intuitive measures relevant to their daily farming practice. In the regression analyses, soil cover and soil disturbance were more weakly predicted than other dependent variables, and were significantly driven by farmer demographics (i.e., age, education and political identity). In contrast, more easily specified responses relating to crop rotation, tillage implements and residue burning were strongly predicted by farm characteristics, including crop cluster, farm size and climate. CA adoption may thus not easily be measured by surveying farmers about their direct performance towards its principles.

Table 4.1: Non-parametric correlation matrix for Conservation Agriculture (CA) outcomes and related practices. Using Spearman's rho, the table shows the strength of relationships among the six dependent variables used in the regression analyses, representing outcomes and practices associated with CA adoption.

Correlation Matrix of Dependent Variables (Spearman's rho)

	CA Index	Soil Cover	Min. soil disturbance	Rotation crops	Low-tillage implements
CA Index	1.000				
Soil cover	.601 ***	1.000			
Min. soil disturbance	.604 ***	.090 †	1.000		
Rotation crops	.425 ***	.096	-.047	1.000	
Low-tillage implements	.467 ***	.276 ***	.353 ***	.168 **	1.000
Less burning	-.011	-.021	.150 **	-.168 **	-.118 *

† p < .10, * p < .05, ** p < .01, *** p < .001 (two-tailed)
Note: *N* varies from 368 to 388, pairwise

Correlation	Significance
$r_s < 0$	p < .01
$r_s > 0$	p < .01

While the composite CA Index was significantly predicted by education, political identity, crop cluster, farm size and the proportion of farm profits derived from grain, its three component indicators were each significantly driven by a different subset of these variables. This implies that each CA principle has different constraints on its adoption. Older farmers with more education tended to report less soil cover, but middle-aged farmers with more education tended to report more soil cover. This suggests that farmers' understanding of soil cover as a farming practice may differ generationally – i.e., it has become more common knowledge than it used to be. Self-identified Liberals showed no effect of education on CA-related outcomes or practices, but Conservatives and Moderates with more education tended to report less soil disturbance. Moderates with more education also tended to report the use of fewer tillage implements. This requires further study to disentangle the effects that political worldview and farmers' values may have on their adoption of progressive farming practices. For example, the results in Chapter 3 suggest that farmers who speak of their relationship to their land in terms of "stewardship" may be more likely to adopt progressive farming practices.

Dry wheat farmers tended to report more soil cover, more rotation crops, the use of fewer tillage implements, and more crop residue burning than dry maize farmers. Strong correlations between province and crop cluster made it impossible to disentangle the effect that differences in governance between provinces may have had on CA implementation. However, prior expert interviews suggested that more effective government extension services in the Western Cape – and their specific focus on CA – may have facilitated the higher adoption rates reported by wheat farmers, who are primarily limited to that province (Chapter 3). Irrigation farmers similarly reported more rotation crops, the use of fewer tillage implements, and more crop residue burning than maize farmers, though with the exception of residue burning, the effect sizes were much smaller than for wheat farmers. Farmers in districts with higher rainfall variability tended to report the use of more tillage implements, but this effect was neutralized for dry wheat farmers and requires further study to understand its cause. Farmers with small farms tended to report fewer rotation crops and the use of more tillage implements. The results in Chapter 3 suggest that farmers with smaller farms must use a larger proportion of their limited land for cash crops in order to be economically viable, and tend to have less capital to invest in new low-tillage implements. Farmers who reported earning a greater proportion of their income from grain farming tended to report more soil cover. This may be because their focus on grain production encourages them to make long-term improvements in grain farming practices. Corroborating our previous finding that CA is being adopted for largely non-climatic reasons (Chapter 3), no statistically significant relationships were found between CA adoption and belief in climate change or concern for its likely future impacts.[14]

[14] Respondents' climate change risk perceptions, and their implications, are further explored in Chapter 6.

Table 4.2: Odds ratio estimates for binary and ordinal regression analyses of CA adoption. Descriptions of each independent variable may be found below.

Conservation Agriculture Practices: Odds Ratios (from GZLM)

	CA Index	Soil Cover	Minimum Soil Disturbance	Crop Rotation	Low-Tillage Implements	No Residue Burning
Independent variable	*Exp(B)*	*Exp(B)*	*Exp(B)*	*Exp(B)*	*Exp(B)*	*Exp(B)*
Age [a]						
Younger	1.339	.864	.805	1.478	.987	.951
Middle-aged	.718	.666	.791	.897	.930	1.303
Older	Ref	Ref	Ref	Ref	Ref	Ref
Education [b]	.291 *	.362 *	.465	.914	.829	.845
Age x Education						
Younger x Education	1.408	1.289	.887	2.028	.480	.405
Middle-aged x Education	1.400	2.476 *	.447 †	2.728 †	.525	.406
Older x Education	Ref	Ref	Ref	Ref	Ref	Ref
Political identity [c]						
Conservative	.769	.703	.874	1.550	.934	.818
Moderate	.878	1.351	.730	1.157	.906	.562
Liberal	Ref	Ref	Ref	Ref	Ref	Ref
Political identity x Education						
Conservative x Education	3.735 **	1.993	4.831 **	.779	2.050	1.278
Moderate x Education	2.852 *	1.331	5.419 ***	.632	2.934 *	3.347
Liberal x Education	Ref	Ref	Ref	Ref	Ref	Ref
Crop cluster [d]						
Mixed	3.388 †	3.496 †	.757	9.271 *	.636	.158 *
Irrigation	2.713 *	2.129 †	.851	6.003 ***	2.549 *	.084 ***
Dry wheat	7.089 ***	3.520 **	.609	32.938 ***	12.752 ***	.112 ***
Dry maize	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability [e]	.991	1.049	1.090	.786	.395 **	.504
Crop cluster x Rainfall variability						
Mixed x Rainfall var.	2.533	1.968	.773	9.601 *	.391	.230
Irrigation x Rainfall var.	2.029	1.421	1.116	2.652 †	2.232	1.033
Dry wheat x Rainfall var.	.647	.896	.999	.595	3.134 **	1.284
Dry maize x Rainfall var.	Ref	Ref	Ref	Ref	Ref	Ref
Farm size [f]						
Annual crops < 500 ha	.524 *	.774	.792	.212 ***	.567 *	1.168
Annual crops > 500 ha	Ref	Ref	Ref	Ref	Ref	Ref
Percentage of profit from grain [g]	1.628 ***	1.481 **	1.282 †	1.217	1.211	.764
Model Summaries						
Regression type	Ordinal	Ordinal	Ordinal	Binary	Ordinal	Binary
-2 log-likelihood (-2LL)	300.252	309.652	310.649	161.236	271.047	112.804
Likelihood ratio chi-square	64.436	42.408	33.878	90.756	90.951	85.485
Degrees of freedom	18	18	18	18	18	18
Model significance (p)	**0.000**	**0.001**	**0.013**	**0.000**	**0.000**	**0.000**
Sample size (N)	305	308	307	306	297	309

† p < .10, * p < .05, ** p < .01, *** p < .001
Note. The coefficients (B) are not directly comparable between nested logistic models (Karlson et al., 2012).

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Independent Variables

[a] Age is an ordinal variable with three levels (recoded from six). Because its relationship with the dependent variables was non-linear, it was entered as a categorical variable, with "Older" as the reference category.

[b] Education is an ordinal variable with three levels (recoded from five), with values of -1 (no post-secondary), 0 (short post-secondary) and +1 (long post-secondary). It was entered as a continuous variable.

[c] Political identity is an ordinal variable with three levels (recoded from five), with values of -1 (conservative), 0 (moderate) and +1 (liberal). Because its relationship with the dependent variables was non-linear, it was entered as a categorical variable, with "Liberal" as the reference category.

[d] Crop cluster is a categorical variable with four categories, derived from a cluster analysis of major crops grown with and without irrigation. "Dry maize farming" is the reference category.

[e] Rainfall variability (coefficient of variation (CV)) is a continuous, standardized variable.

[f] Farm size is a binary variable, indicating that arable land area is less than 500 hectares. "Annual crops > 500 ha" is the reference category.

[g] Percentage of farm profit from grain is a continuous variable, ranging from 0 to 100%. It was standardized and entered as a continuous variable.

Finding 2: Farmers' definition of "conservation" farming is misaligned with experts' definition of CA.

To reveal farmers' implicit definition of conservation farming and to compare it to experts' definition of CA, we conducted a binary logistic regression that contrasted self-defined "conventional" and "conservation" farmers, coded as "0" and "1", respectively. "Conservation" identity was correlated with some but not all CA-related measures, and was not strongly delineated by performance towards the three CA principles (Table 4.3). Self-identification by respondents as conservation farmers was driven primarily by the tillage implements that they used, and to a lesser extent by the diversity of their crop rotations and by their aversion to the burning of crop residues. The use of fewer tillage implements was by far the strongest predictor of "conservation" identity, while reported soil disturbance had no significant effect − this despite the fact that the two predictors were significantly correlated with each other (as shown in Table 4.1), and are strongly related in practice. Reported soil cover was not a significant predictor of "conservation" identity; however, a specific behaviour necessary to maintain such soil cover (i.e., the avoidance of crop residue burning) *was* significant. Together, these findings suggests that farmers are relying on older and narrower definitions of "conservation" farming as no-tillage or minimum-tillage − behaviours that have been promoted as methods of soil erosion control since the 1930s "dust bowl" in the United States (Hobbs et al., 2008). These rules of thumb for "conservation" practice are related to CA, but are not sufficient to ensure its benefits. For instance, by avoiding crop residue burning, farmers enable the maintenance of permanent soil cover, but the soil cover will be insufficient unless they also plan for their rotation crops to produce enough residues, avoid incorporating the residues through tillage, and forego the baling of residues, the grazing of livestock and the fallowing of their fields.

Intriguingly, small farm size remained a significant predictor of farming identity even after controlling for farming practice (Table 4.3). All practices being equal, those respondents with less than 500 hectares of arable land were less likely to self-identify as conservation farmers – an effect that was second in size only to the use of tillage implements. Previous interviews suggest that this effect may stem in part from farmers' self-perception of their capacity to adopt further CA practices, rather than from a dispassionate assessment of their current practice. In Chapter 3, farmers with less than 500 hectares of arable land felt constrained in their flexibility to include non-cash crops in rotation (which contribute to natural fertilization and weed control, but reduce cash flow), to set land aside for experimentation and incremental changes in farming practice (the most common method of adoption), and to forego the risk-mitigating benefits of livestock husbandry in favour of continuous cropping with permanent soil cover. Economies of scale also allowed larger farmers to invest more readily in the costly equipment necessary for minimum tillage. Because of these perceived limits to further adoption, farmers in that study who had smaller farms were more likely to underestimate their present level of CA adoption.

Preliminary expert interviews suggested that farmers producing different crops, generally grown in different regions, might have different definitions of conservation farming as it applied to their own practices. Different crops imply distinct practical challenges in water and temperature sensitivity, agricultural inputs, planting, emergence, weed control, etc., which may lead to understandable differences in established best practices. However, our results show that after controlling for farming practices, the crop cluster variable (i.e., mixed, irrigation, dry wheat, dry maize) did not significantly predict "conservation" identity. All else being equal, respondents in all crop clusters were therefore similarly likely to identify themselves as conservation farmers. This suggests that that there is a single implicit definition of conservation farming shared by all South African commercial grain farmers.

Table 4.3: Odds ratio estimates for drivers of "conservation" farming identity in binary logistic regression. To reveal the implicit definition of conservation farming in contrast with conventional farming, respondents to the survey were asked to select their overarching system of grain farming from six typical options (conventional, conservation, precision, progressive, biological, and organic). Those who broadly identified their farming practices as "conservation" were coded as "1", and those who identified themselves as "conventional" farmers were coded as "0". Odds ratios above 1 indicate a greater likelihood of identifying as a "conservation" farmer, while odds ratios below 1 indicate a greater likelihood of identifying as a "conventional" farmer.

Conservation vs. Conventional Farmers: Odds Ratios (from GZLM)

Independent variable	*Exp(B)*
Age [a]	
Younger	1.882
Middle-aged	1.258
Older	Ref
Education [b]	1.150
Political identity [c]	.761
Crop cluster [d]	
Mixed	1.490
Irrigation	2.190
Dry wheat	1.432
Dry maize	Ref
Farm size [f]	
Annual crops < 500 ha	.230 **
Annual crops > 500 ha	Ref
More soil cover [h]	1.438
Less soil disturbance [i]	1.477
More crops in rotation [j]	2.630 **
Low-tillage implements [k]	9.202 ***
Crop residue burning [l]	
Never burn	5.074 **
Sometimes or always burn	Ref
Model Summaries	
Regression type	Binary
-2 log-likelihood (-2LL)	87.907
Likelihood ratio chi-square	132.016
Degrees of freedom	13
Model significance (p)	**0.000**
Sample size (N)	244

** p < .01, *** p < .001

Odds Ratio	Significance
Exp(B) < 1	p < .01
Exp(B) > 1	p < .01

Independent Variables
Note: Descriptions for variables "a" through "f" accompany Table 4.2.
[h] More soil cover is an ordinal variable with three levels (recoded from four). It was entered as a continuous variable.
[i] Less soil disturbance is an ordinal variable with three levels. It was entered as a continuous variable.
[j] Number of crops in rotation is an ordinal variable with three levels (recoded from four). It was entered as a continuous variable.
[k] Low-tillage score is an ordinal variable with three levels (recoded from five). It was entered as a continuous variable.
[l] Never burn crop residues is a binary variable. "Sometimes or always burn crop residues" is the reference category.

Overall, farmers' implicit definition of conservation farming broadly captures CA-related practices, but not the outcomes aligned with two key CA principles (i.e., soil cover and minimum soil disturbance). It is instead heavily weighted towards the use of fewer tillage implements and the avoidance of crop residue burning, both associated with older concepts of "conservation" farming. The limiting effect of small farm size on "conservation" identity, after controlling for farming practices, suggests that self-perceived constraints on farmers' capacity to adopt more progressive practices in the future leads them to underestimate their own progressiveness in the present. Combined with our previous qualitative findings, these results suggest that the commonly held definition of conservation farming substantially differs from the expert definition of CA. This may lead to confusion and miscommunication if CA's proponents fail to recognize and adjust for this disagreement.

Finding 3: The mismatched definitions of experts and farmers and the piecemeal adoption of CA principles will lead to both an underestimation of the communication challenge and an overestimation of its results.

CA is a combination of practices that provides maximum benefits only when adopted comprehensively, yet the survey data suggest that it is not generally adopted this way. Evaluating CA as a coherent package masks important differences in the factors that influence adherence to each of its principles, and unique challenges in their implementation. Its principles are commonly pursued piecemeal, each driven by a distinct rationale. Furthermore, farmers' self-perception of "conservation" farming practice is strongly rooted in concepts that predate CA. The misunderstanding created by the confluence of "conservation farming", "conservation tillage" and "Conservation Agriculture" presents persistent barriers to the communication of the crucial need for comprehensive CA adoption. The self-reporting of "conservation" and CA outcomes is therefore inconsistent; soil cover, in particular, is challenging to measure and does not significantly contribute to "conservation" identity.

4.5 Conclusion

The results here strongly imply that farmers are not attending to CA as a coherent package. They are also much better at monitoring and reporting specific elements tailored to existing norms and common metrics than they are at reporting broader outcomes that are more directly aligned with CA's three principles. This corroborates other findings within and beyond South Africa: reports of fractured adoption, hints of inaccurate adoption estimates, and varied definitions of CA. Since the drivers of adoption are different for each CA principle, they are taken up differentially; farmers' performances on the three principles were far less correlated than expected. Any single proxy will therefore necessarily misconstrue the extent of comprehensive – and thus beneficial – CA adoption. This overestimation may be compounded by the misalignment of farmer and expert definitions of "conservation" practice, which may lead farmers to believe that they have adopted CA, as recommended by local experts, when they have only implemented minimum (or conservation) tillage. CA adoption may therefore be a mirage, both for those who promote it and for those who attempt to practice it: apparent at a glance, but fading under scrutiny.

In South Africa, despite farmers' explicit sensitivity to climate change risks, CA's relationship to CSA has little current relevance since farmers are adopting CA principles for largely non-climatic reasons. Highlighting climate change risks is likely to be a poor way for experts to motivate adoption. More accurate, more contextually meaningful and therefore more useful estimates of CA adoption may be obtained by measuring CA performance using a basket of simple, locally-tailored everyday factors or practices that are necessary to achieve each principle. The most appropriate measures by which to promote and monitor its adoption in South Africa require further investigation, but may include crop rotation diversity (enabling the use of selective herbicides and including legumes), the use of tillage implements (including rippers), livestock grazing density, and crop residue burning and baling. This will in turn enable better understanding of the processes of adoption, the agricultural extension challenge, and ultimately the assurance of CA's climate-resilience and food security benefits.

Chapter 5: Integration anxiety: The cognitive isolation of climate change risk

5.1 Synopsis

The harmonization of climate-adaptive behaviours with pre-existing decision-making processes will be vital to the realization of climate-resilient futures. Prevailing wisdom holds that decision-makers should 'mainstream' their management of climate change risks by integrating them with weather and other risks (e.g., economic, ecological) when planning risk-mitigating responses in vulnerable sectors. Yet the mechanisms by which individuals might do so are poorly understood. To better appreciate the mainstreaming task, this paper applies mental modeling techniques to evaluate the integration of climate change with the management of weather and other 'normal' risks among commercial grain farmers in South Africa. We argue that this group closely resembles the autonomous private actor from the climate change adaptation literature; they are well educated, with good access to informational, financial and institutional resources. They practice large-scale, mechanized, rainfed farming in a highly variable climate, and broadly recognize that climate change is an important threat. They thus appear to have the incentive, capacity and willingness to adapt. As a group, they should be early adopters of climate-adaptive behaviours, and have indeed been shifting towards Conservation Agriculture – a set of farming practices widely understood to be climate-resilient by farmers and experts alike. We evaluate the extent to which these farmers have integrated climate change risks into the mental models that they use to manage weather risks and to make decisions around farming practices. We find that participants' causal mental models of climate change risks are distinct from their mental models of weather and other 'normal' risks – that is, their stated and implied logic of climate change risk management is linguistically and structurally isolated from that of weather. They frame climate change in different terms, and their proposed responses to climate change are largely novel. Their climate change logic contains more intuitive leaps, where they suggest adaptive responses without describing the intermediate problems and/or effects that these responses are intended to mitigate. We argue that this linguistic and structural isolation is indicative of farmers' use of mismatched cognitive frames in understanding and responding to climate change and weather risks. In turn, such a mismatch will make it more difficult for these farmers to mainstream their climate-adaptive behaviours.

5.2 Introduction

The concept of climate change adaptation as a conscious and planned adjustment implies that climate-adaptive decision-making occurs as a distinct process independent of other risks (Bassett & Fogelman, 2013). Researchers have, however, widely recognized that climate change is only one of many stressors that shape multi- and cross-scalar decisions towards varied and competing objectives (Bassett & Fogelman, 2013; Chapter 2; Eakin et al., 2016). The integration of climate change adaptation into pre-existing decision-making processes across policy domains and scales has thus become an important pre-occupation of the adaptation literature (Dovers & Hezri, 2010; Howden et al., 2007). In developing countries, in particular, development goals may compete with adaptation for scarce resources, necessitating the integration of climate and development planning (Huq et al., 2004; Klein et al., 2007). However, such 'mainstreaming' of climate-adaptive behaviours by individuals is understudied and under-theorized (Clayton et al., 2015; Grothmann & Patt, 2005). The processes of judgment and decision-making involved in harmonizing the management of weather, climate variability and climate change risks are therefore poorly understood, and the literature is fraught with untested or disproven assumptions.

The mainstreaming of climate change adaptation in *institutional* decision-making is widely perceived to be challenging, because the nature of climate change impacts is mismatched with that of other risks (Kunreuther et al., 2013). In this vein, there are two important hurdles to mainstreaming. First, predictions of some climatic variables at the local scale are uncertain in both sign and magnitude; this makes 'perceive-predict-act' approaches hard to design and harder to implement. Second, climate change risks are often mismatched temporally and spatially with concurrent objectives (Hallegatte, 2009). Allied literatures have consequently taken various approaches to the integration of climate change with other priorities, from the explicit integration of climate change risks through structured and robust decision-making protocols (e.g., Kunreuther et al., 2013) to their more implicit integration through broader resilience, transformation and development agendas (e.g., O'Brien, 2012).

Despite this broad recognition that climate change presents unique challenges, the climate-adaptive behaviours of *individuals* have received little empirical treatment in 'real world' situations (Dilling et al., 2015; Grothmann & Patt, 2005). This has led to a general failure to understand whether and how individuals will mainstream, and so adapt to, climate change risks. One fruitful area of work has been in the study of cognitive frames and risk perceptions (Spence & Pidgeon, 2010) – such frames comprise the specific perceptions, preferences, memories and mental models that individuals use to understand and respond to specific problems. For objectively similar tasks, the use of different cognitive frames can result in different decision-making strategies (Thaler, 1999). These 'framing effects' stem in part from the application of decision-making heuristics, or rules of thumb, that people use to rapidly evaluate the information provided and choices available (Shah & Oppenheimer, 2008; Tversky & Kahneman, 1981).[15] The precise nature of individuals' cognitive frames is in turn shaped by their psychological and demographic profiles (Levin et al., 2002). In the case of climate change, the hope is that such research will help us to understand how climate-sensitive decisions are made in practice, with an appreciation for the characteristics of both the individual and their context.

In theory, such framing effects should be less evident in commercial farmers' decisions around weather and climate change risks. In particular, commercial farmers epitomize the individual private actor foundational to the adaptation literature, and are typified as autonomous and largely rational decision-makers who are sensitive to both weather and climate change in similar ways. They have deep technical and experiential knowledge and are thus each expert in their micro-environment. In Chapter 2, we showed that their decisions about weather risks are deeply enmeshed with decisions around other 'normal' risks (e.g., economic, agricultural). They are therefore expected to perceive and mainstream climate change risks more readily than other groups of decision-makers (Grothmann & Patt, 2005; Eakin et al., 2016). Rainfed crop production, in particular, is among the sectors anticipated to be most vulnerable to climate change impacts (Lobell et al., 2008). Given their large personal and financial investments in climate, we might expect such farmers to have sought to understand the implications of climate change at the farm level, to hold consistent and stable beliefs about climate change risks, and therefore to readily integrate climate change risks into their mental models of weather and other 'normal' risks, as an analogous risk on a longer timeframe. Yet, few studies have examined this

[15] Many scholars posit that such heuristics are cognitive short-cuts that lead to suboptimal choices (Tversky and Kahneman, 1981; Shah and Oppenheimer, 2008), though some have suggested that they may actually lead to better choices in circumstances characterized by high uncertainty (Goldstein and Gigerenzer, 2002).

kind of climate-sensitive decision-making in situ – that is, within the multi-faceted and uncertain environments in which farmers actually make decisions towards risk management.

The commercial grain farmers of South Africa's Western Cape province are, ostensibly, a case in point. They practice large-scale, mechanized, rainfed grain production (RSA, 2013a) in a semi-arid environment with highly variable rainfall (RSA, 2011). They are relatively well educated, with good access to financial, informational and institutional resources (Wilk et al., 2013). However, as many are white beneficiaries of South Africa's apartheid legacy, they generally receive little explicit support from government (e.g., few of the subsidies enjoyed by commercial farmers in higher-income countries) (Bernstein, 2012). They have, however, been targeted for more than a decade by risk communication experts from the local and international agricultural and climate science communities (Findlater, 2013). A singular focus of these communications has been the promise of grain-farming practices known as Conservation Agriculture (CA) (RSA, 2013c) – a set of climate-resilient techniques that may contribute to both mitigation and adaptation if implemented comprehensively (Derpsch et al., 2014).

However, climate change is locally recognized as a novel challenge, with unique characteristics that may impede adaptive responses. In our preliminary interviews, local experts conveyed widely held skepticism that commercial grain farmers, who routinely deal with weather variation, were thinking about climate change or were prepared to respond to it. The concern is that while these farmers recognize CA's climate-resilience, they are adopting it primarily to manage other, more immediate, risks (Chapter 2). Consequently, they may fall well short of the comprehensive adoption necessary to ensure its climate-adaptive benefits (Giller et al., 2015). They are thus understood to perceive and respond to climate change in different ways than they do to 'normal' weather and climate variability.

In this study, we therefore make a distinction between weather-sensitive and climate-sensitive decision-making: these farmers are widely understood to react readily to perceived weather risks (i.e., they are weather-sensitive), but not to perceived climate change risks (i.e., they are not climate-sensitive). This is consistent with Eakin et al. (2016), who contend that there are inherent barriers to climate change adaptation that are outsized relative to their role in weather risk management, and are thus underestimated in the adaptation literature. These barriers may include (1) psychological "buffering", i.e., that the salience of long-term climate change risks has been muted by institutional or farm-level measures (e.g., irrigation) that mitigate short- to medium-term risks from weather and climate variability; (2) education and experience, i.e., that farmers have deep experiential knowledge of weather risks, but little or none of climate change risks; (3) access to finance, knowledge and technology; and critically, (4) self-perceived agency, i.e., that farmers perceive themselves as less capable of understanding and responding to climate change risks.

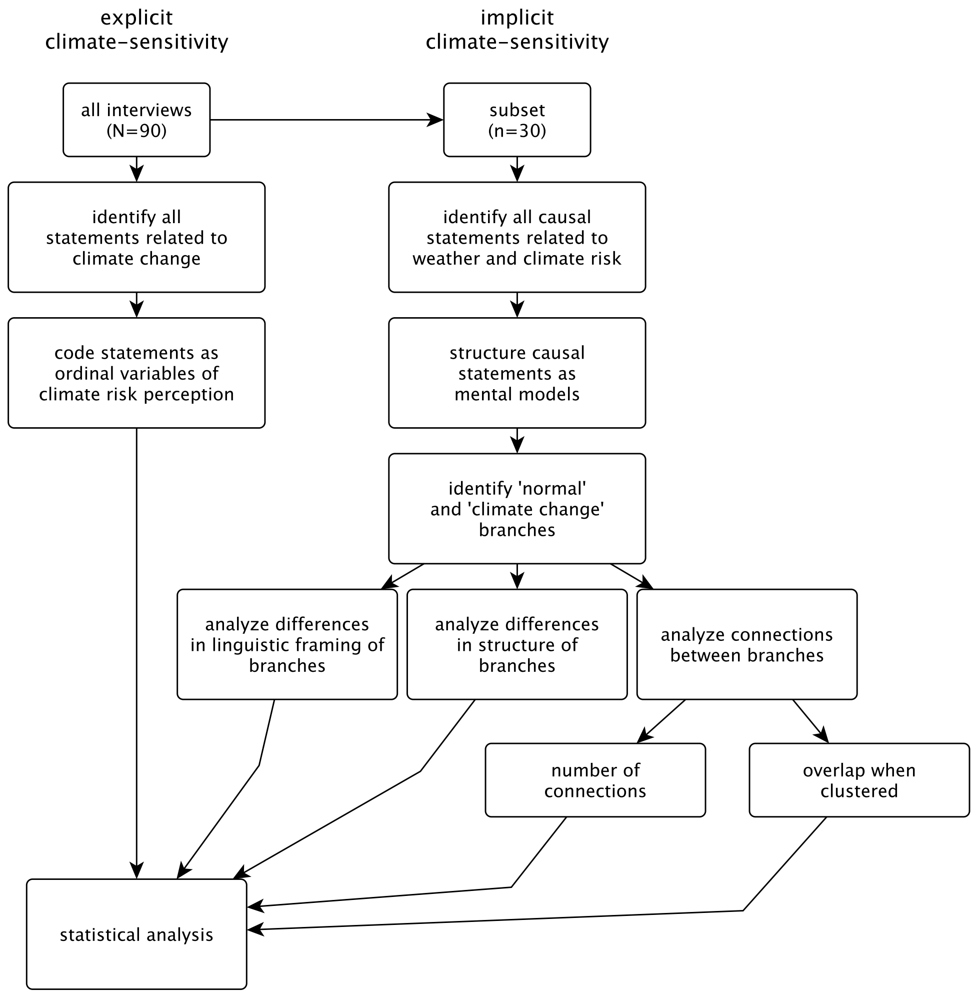
Using a mental models protocol, this paper attempts to disentangle this apparent contradiction for a group of commercial grain farmers in South Africa's Western Cape province ($N = 90$): Why do farmers who are sensitive to weather risks, and who are progressively adopting more climate-resilient practices partly as a result of this sensitivity, seem to be unprepared to adapt to climate change? For this weather-sensitive, climate-exposed, resourceful and adaptive group, we therefore seek to understand whether and how they are sensitive to climate change risks, among the myriad other 'normal' risks that present day-to-day challenges in commercial farming. To do so, we test a hypothesis that follows from local experts' skepticism of farmers' readiness to adapt: that climate change risks are not mainstreamed in farmers' decision-making processes towards the management of weather and other 'normal' risks (i.e., they are not climate-sensitive). As a prerequisite, we first ask whether these farmers are *explicitly* sensitive to climate change, as they are to weather: Do they express concern about climate change risks, along with the willingness to respond to them? We then ask whether their decision-making processes are *implicitly* sensitive to climate change risks: Are their mental models of climate change well-integrated with those of weather and other 'normal' risks, and thereby actionable?

5.3 Methods

To evaluate farmers' explicit sensitivity to climate change risks, and to evaluate their integration of climate change with weather and other 'normal' risks, we interviewed grain farmers ($N = 90$) in South Africa's Western Cape province. In doing so, we used a mental models protocol (Section 5.3.1) to elicit their climate change risk perceptions, alongside the cognitive logic that they use to perceive, predict and manage weather and climate change risks among myriad others at the farm level. As elaborated below, we first tested whether and to what extent all participants (N = 90) were explicitly sensitive to climate change risks, using a coding scheme to quantify and then analyze the risk perceptions that they each expressed during their interviews (Section 5.3.2). For a subset of participants (n = 30), we then analyzed their mental models to determine whether and how their climate change risk perceptions and climate-adaptive behaviours were integrated (i.e., mainstreamed) with those of weather and other 'normal' risks (Section 5.3.3). Figure 5.1 shows a flow chart of the analytical steps taken in this paper, as a guide to understanding the methods elaborated below. The study protocols were designed, piloted and implemented in consultation with partners at the University of Cape Town, Stellenbosch University and the Western Cape Department of Agriculture.

The data collection comprised 90 structured interviews conducted during two months prior to the grain harvest in late 2013. This corresponded to the end of a three-year period of above-average rainfall, with record wheat yields (RSA, 2013a), so farmers were likely less sensitive to weather and climate change problems than might otherwise have been the case. Willing participants were recruited by phone and email through geographically stratified random sampling. Recruitment was facilitated by representatives from the four major co-operatives and agribusinesses that market and distribute grain produced in the region. All interviews were conducted in English. Approximately 20% of those contacted declined to participate, most frequently citing time constraints, but with some suggesting a discomfort with English. None were given any material incentive to participate.

Figure 5.1: Flow chart of the analytical steps taken in Chapter 5. This figure illustrates the parallel evaluation of participants' explicit and implicit climate-sensitivity.



These farmers generally practiced mixed grain and livestock farming centred on rainfed wheat production. Their ongoing adoption of CA is among the most important changes in practice currently underway in South African commercial agriculture (RSA, 2013c) – nearly all have adopted at least some aspect of CA practice. As part of our previous analysis, participants were scored on their adherence to CA best practices as a measure of climate-resilient adaptation (Chapter 3). These scores were incorporated as an independent variable in the statistical analyses described below. In keeping with demographic trends in the local farming population, all of the participants were male, ranging in age from 25 to 62 years (*M* = 43.9, *SD* = 9.3). Their available arable farmland ranged from 250 to 4500 hectares (*M* = 1443, *SD* = 880). All participants had finished high school, with the majority (76%) having a university or college degree. A plurality (39%) of participants had completed one- or two-year technical degrees, while one-third (33%) held Bachelor's degrees and a small fraction (3%) held Master's degrees. Though most spoke Afrikaans as their first language, all were conversant in English.

5.3.1 Mental models protocol

To elicit the internal representations of reality that participants accessed in managing weather and climate change risks, the interview script was designed in accordance with established mental modelling methods (Jones et al., 2011; Morgan et al., 2002), and followed a 'broad-to-narrow' structure. The mental model elicitation method was indirect rather than direct – in the indirect method participants are unaware that the interviewer seeks their mental models of weather and climate change risks, whereas in the direct method, participants are explicitly tasked with the elaboration of causal relationships stemming from a given problem. Thus, the procedure elicited perceived causal relationships between weather/climate change stressors and farming practices for each participant, with as little introduction of any leading content by the interviewer as possible. Whereas the direct elicitation method may encourage participants to identify and resolve inconsistencies and competing logics in their mental models, the indirect method preserved these patterns of in situ thinking.

The elicitation of causal relationships was performed in two stages within each interview. First, participants were tasked with listing and elaborating important risks that they faced in their farming businesses. These were documented by the interviewer on sticky notes pasted to an erasable white board. The boundaries of the risk landscape were therefore participant-defined, with the interviewer providing only standard prompts related to broad categories (e.g., on the farm, beyond the farm, short term, long term, the economy, the environment). The interviewer then used vague questions (i.e., "What comes to mind when you hear the term…") and standardized follow-ups (e.g., "What is the effect of….") to prompt participants to elaborate on causal relationships relevant to specific domains of interest – particularly weather and climate change risks, and agricultural practices.

The script culminated in a final section introducing climate change, if the participant had not already done so, and exploring its on-farm implications in depth. Climate change-related language was purposefully excluded from the rest of the interview script, in an attempt to avoid triggering the most overt forms of motivated cognition found in other studies of climate change perceptions (e.g., stereotype threat (Lewandowsky et al., 2015)) or cultural cognition (Kahan, 2015)). The interview script therefore explicitly explored risks in farming, while implicitly examining how weather and climate change are enmeshed in broader processes of farm-level risk management. Using this interview data, we conducted two complementary analyses: (1) we assessed participants' *explicit* climate-sensitivity across all interviews (N = 90) as indicated by their expressed climate change risk perceptions; and (2) we assessed their *implicit* climate-sensitivity by measuring the integration of participants' mental models of weather and climate change risks (n = 30) (Section 5.3.3), using both linguistic (Section 5.3.3.1) and structural (Section 5.3.3.2) analyses.

5.3.2 Analysis of explicit climate change risk perceptions

To assess participants' explicit sensitivity to climate change risks, each of the 90 interviews was comprehensively searched for references to climate change. First, to measure the extent to which participants had to be prompted to speak of climate change, each participant was assigned a score corresponding to the section of the interview script in which they first raised the topic (from 9 for those who raised it prior to the first question about risks, to 0 for those who did not speak of it until the interviewer introduced it in the final section of the script). Their statements about climate change were then coded to create a set of ordinal variables representing different measures of risk perception: (1) belief that climate change is occurring or will occur (i.e., none, partial, full); (2) observed climatic changes, past or ongoing, attributable to climate change (i.e., no, maybe, yes); (3) the sign of its likely overall effect on their farm (i.e., negative, neutral, positive); (4) expressed levels of concern for these impacts (i.e., none, low, medium, high); and (5) the perceived manageability of the impacts (i.e., unmanageable, partially manageable, fully manageable). For each participant, their statements about belief in climate change and concern for its impacts were then analyzed for changes in tone over the course of the interview (i.e., no observable change, expressed weaker/stronger belief, became less/more concerned). Finally, each participant's proposed adaptations to climate change were compiled and compared.

These variables were quantitatively analyzed to elucidate possible relationships and inconsistencies among the expressed climate change risk perceptions, demographic variables, farm characteristics and farming practices. For example, we hypothesized that the different measures of climate change risk perception (i.e., belief, observed change, overall effect, concern and manageability) would be well-correlated with each other, and that participants who raised climate change earlier and unprompted would be more likely to believe in climate change and to be concerned about its likely impacts. We also hypothesized that participants who believed in climate change would be more likely to have adopted CA practices, given their climate-resilient benefits, but that these participants would also be less concerned about climate change's likely impacts than those who had not adopted CA practices. Non-parametric, rank-based Spearman's rho was chosen as the primary statistical measure of correlation in this paper, since most variables were ordinal with few levels (two to five). SPSS automatically adjusted the results for tied ranks. Kendall's tau-b was considered as an alternative, but the results appeared broadly similar to those of Spearman's rho for the findings reported in this paper. Participants' explicit climate-sensitivity, as measured here, was then compared and contrasted with their implicit climate-sensitivity, as evaluated below.

5.3.3 Analysis of participants' mental models

To derive their mental models of weather and climate change risks, the interview transcripts of a subset of participants (n = 30) were comprehensively coded for causal statements related to weather and climate change. Only 30 interviews were selected for modeling, because of the time-consuming nature of the process and the diminishing utility of additional mental models; generally, 30 are considered sufficient to capture the breadth of thinking in a homogeneous group (Morgan et al., 2002). The candidates for modeling were selected on the basis of their farming practices (to capture their breadth), their language proficiency, and the extent to which they had elaborated on simple answers (whether unprompted or prompted) as a measure of interview quality. The language criterion may have led to some bias in the modelled subset, since the English language proficiency of Afrikaans-speaking farmers likely depends in part on their social integration; however, the inference of causal relationships during analysis was expected to be more precise where participants were comfortable expressing nuance in English.

The coded causal relationships were then visualized as influence diagrams consisting of nodes (concepts) connected by directional edges (causal relationships between concepts). For instance, SA050 said, *"When you really go the minimum [tillage] way, you get more pests like snails that live underneath that material."* Therefore, his mental model showed that minimum tillage causes an increased risk of pests (and specifically snails). The influence diagrams were structured left-to-right, stemming from problems of weather, climate variability and climate change, producing negative effects that evoked specific responses mediated by non-climatic factors. Figure 2.1 shows the simplified concept of the causal mental model, while Figure C.1 in Appendix C shows a full-scale example of one participant's mental model. For instance, the participant may have stated (whether sequentially or at various points in the interview) that climate cycles cause interannual rainfall variability (a problem), leading to low soil moisture (an effect), which can be mitigated by increasing soil cover using crop residues – a response which is mediated (or in this case inhibited) by the competing need to use crop residues as livestock feed.

Each node (or concept) was classified as either 'normal' or 'climate change' depending on the cause that the participant stated or implied within the context of the interview (i.e., weather/climate variability versus climate change).[16] Within each participant's mental model, there were therefore two major branches stemming from 'normal' and 'climate change' causes, respectively. The 'normal branch' comprised causal relationships originating from problems of weather and climate variability attributed to climatic processes consistent with historical conditions. In contrast, the 'climate change branch' consisted of causal relationships originating from weather and climate problems attributed to present or future global climate change, whether or not such change was explicitly referred to as anthropogenic. Where specific concepts (i.e., problems, effects, responses and mediators) were referenced under both conditions, they were categorized as 'normal' nodes, and created connections between the 'normal' and 'climate change' branches. The two branches were therefore more interconnected for participants who spoke of weather and climate change in similar terms.

[16] The 'normal' weather and climate variability sections of participants' mental models has been treated in more depth in Chapters 2 and 3.

Having derived 30 participants' mental models of weather and climate change risks, we used two approaches (described below) to assess the extent to which these two branches were integrated (i.e., how well climate change risks and climate-adaptive behaviours were mainstreamed): (1) the language that participants used to frame weather and climate change risks; and (2) the structure and interconnectedness of the weather and climate change branches of each participant's mental model.

5.3.3.1 Analysis of linguistic framing

The analysis of linguistic framing followed from that conceived in Chapter 3. As we found in that study, participants described weather and climate change risks using six exhaustive and mutually exclusive 'languages' indicative of different cognitive framings (Table 3.2). Following the identification of these categories, each node in each participant's mental model was coded into one of the six languages (see Figure 5.2 for a partial mental model coded for language). Participants' linguistic framings of the 'normal' and climate change branches, as indicative of their underlying decision-making processes, were then quantitatively compared and contrasted. Specifically, using paired-samples t-tests, we analyzed the difference between branches in the number of nodes coded into each language, as a proportion of the total number of nodes in each branch.

5.3.3.2 Analysis of structure and interconnectedness

To evaluate the causal relationships between weather and climate change in participants' mental models, we analyzed the structure of each branch and their interconnectedness. We initially compared and contrasted the overall structure and size of each branch, including the frequency of intuitive leaps (e.g., where participants neglected to identify the specific problems or effects that they were targeting with proposed risk-mitigating responses). For instance, in Figure 5.2, there are three 'normal' responses (fallow land, increase soil cover and minimum soil disturbance) stemming directly from the 'climate change' cause with no identification of the intervening problems or effects. The interconnectedness of the 'normal' and climate change branches was then assessed using two simple measures: (1) the number of connections between the two branches; and (2) the amount of overlap between the two branches when each mental model was algorithmically clustered to illuminate natural "communities" of nodes (concepts). We finally analyzed the variation in these two measures of interconnectedness with respect to participants' explicit climate change risk perceptions and CA practices, as previously assessed.

For the first measure of interconnectedness, we simply counted the number of edges (causal relationships) connecting 'normal' and climate change nodes within each participant's mental model. For example, Figure 5.2 shows a mental model with ten connections between the two branches, which was towards the upper end of the range, while Figure 5.3 shows a climate change branch with no connections to the 'normal' branch. This provided a rough measure of the extent to which the two branches were integrated. For the second measure of interconnectedness, we corroborated the first finding using a simple form of network analysis to compare the importance of connections within each branch to those between them. The Girvan-Newman edge betweenness clustering algorithm (Girvan & Newman, 2002),[17] as implemented in the yEd network graphing software, was used to identify natural "communities" of nodes (Figure C.2 in Appendix C shows an example of such a clustered mental model). We counted the number of climate change nodes appearing in clusters other than that containing the 'climate change' cause, as well as the number of 'normal' nodes appearing in the climate change cluster. The extent of this combined overlap between the 'normal' and climate change branches thus provided an independent measure of their integration – that is, it revealed the extent to which participants' climate change branches were distinct and cohesive clusters, separate from the 'normal' branches.

[17] The Girvan-Newman algorithm defined communities of structural groups by iteratively removing edges from the original network. The 'betweenness' of a particular edge was the number of unique pairs of nodes between which that edge was the shortest distance. Betweenness was first calculated for every edge in the graph. The edge with the highest value was then removed, and the process was repeated until the maximum proportion of edges ("modularity") occurred within defined communities or groups. Though more efficient clustering methods have been developed for computationally intensive networks, the Girvan-Newman method is easily implemented for small networks and provides a general understanding of community structure (Lancichinetti & Fortunato, 2009).

Figure 5.2: Partial mental model showing close integration of the climate change and 'normal' branches. This farmer had the second highest number of inter-branch connections of any participant. The full climate change branch is shown, along with each point of initial connection to the 'normal' branch. For clarity, the remainder of the 'normal' branch is omitted from the figure. The colour of each node indicates its language classification (i.e., green for agricultural, yellow for cognitive, and blue for economic).

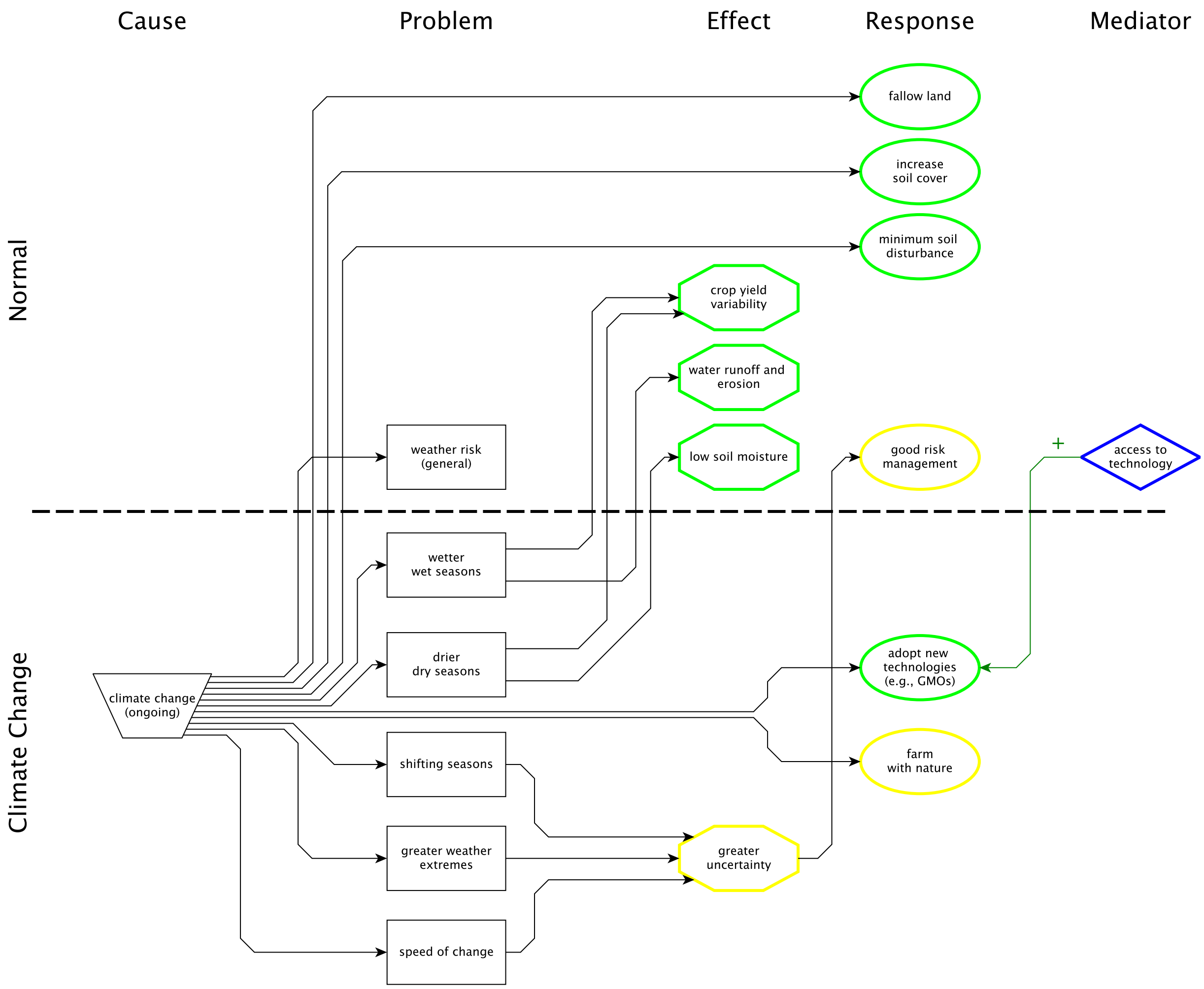
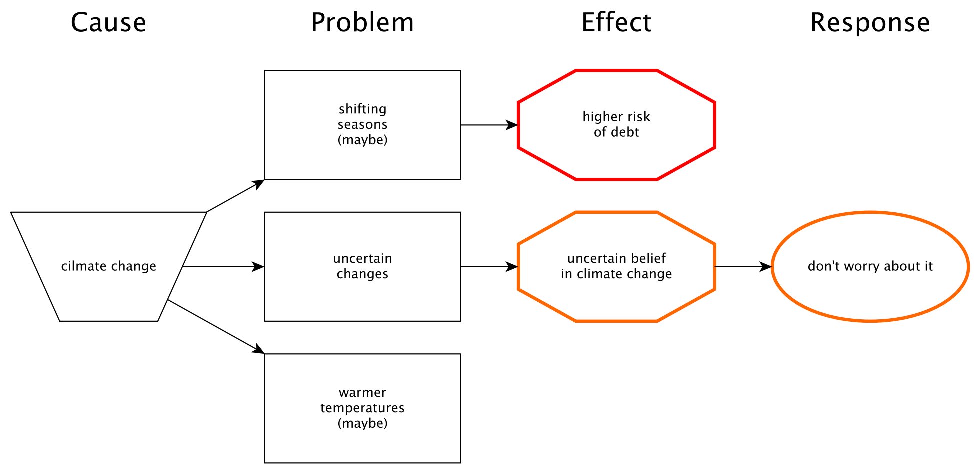


Figure 5.3: Partial mental model with no integration between the 'normal' and climate change branches. This farmer was one of four participants with no inter-branch connections. Only the climate change branch is shown. The colour of each node indicates its language classification (i.e., orange for emotional, and red for survival).



5.4 Results

To assess participants' explicit sensitivity to climate change risks, we first analyzed their expressed climate change risk perceptions and proposed climate-adaptive responses ($N = 90$) (Section 5.4.1). We then investigated the extent to which they were implicitly climate-sensitive by evaluating the integration (i.e., mainstreaming) of climate change into their mental models of weather and other 'normal' risks ($n = 30$) (Section 5.4.2).

5.4.1 Expressed perceptions of climate change ($N = 90$)

To assess participants' explicit sensitivity to climate change risks, we analyzed every statement referencing climate change across all 90 interviews. Many participants raised the topic of climate change with little prompting. During the initial risk elicitation exercise, 17% of participants spoke of climate change when asked broadly about "risks or concerns that you face as a farmer." A further 49% of participants referred to climate change in response to standard prompts about risks related to "weather" or "environment". Overall, two-thirds (66%) of participants raised the topic before it was formally introduced at the end of the interview script. As described in the methods and as applied below, "promptedness" is thus a quantitative measure of the extent to which participants had to be prompted by the interviewer before they spoke of climate change – i.e., the higher the "promptedness" value, the later in the interview the participant mentioned the topic. In making unprompted references to climate change, participants used terms like "changing weather patterns", "global warming", "global heating", "climate control", and most often "climate change" itself.

5.4.1.1 Measures of climate change risk perception

Most participants believed in present or future climate change, expressed concern for its likely impacts, and reported having already observed changes in climate. Specifically, the vast majority of participants (84%) expressed at least partial belief in present or future climate change. When asked directly, nearly two thirds (62%) expressed strong belief and a further quarter (22%) expressed partial belief. Only a small minority (16%) of participants expressed explicit disbelief. An even greater share (91%) expressed some concern for climate change's potential impacts, with a minority (20%) highly concerned. Many participants reported ongoing changes to their local climate, commonly including increasingly intense rainfall events, more variable rainfall, hotter summers, colder winters, and shifts in the seasonality of rainfall (i.e., starting and ending later). Nearly two thirds (60%) reported having observed environmental changes that they explicitly attributed to climate change. A further 14% reported changes that they thought might be attributable to climate change, but with a high level of uncertainty. Only one quarter (26%) of participants reported having observed no environmental changes that they might attribute to climate change.

As an example of an explicit statement about climate change, SA087 was firm in expressing his belief: "*It's already busy changing, definitely…. Adapt or die.*" In contrast, SA114 adamantly disbelieved in the idea: *"That's bullshit man, totally. That's a buzz word."* Such expressions of belief, concern and observed climatic changes were not necessarily consistent with each other. For example, SA113 initially scoffed at the idea of climate change: "*Climate? Change? Hah. Many people talk about it, but I don't think it's so."* However, when asked whether or not he was concerned about its potential effects, he said, *"I think so, yes. We will get less rain, they said, we will get less rain. And when you get less rain, you must change your farming."*

There were statistically significant relationships among these measures of climate change risk perception (Table 5.1). Strong correlations were found between belief in present or future climate change, concern for its likely future impacts, and observed climatic changes. Earlier and unprompted references to climate change were also strongly correlated with those three measures, suggesting a relationship between the extent to which climate change risks were top-of-mind and their perceived severity. No significant correlations were found between these expressed climate change risk perceptions and region, education, age or farm size. Overall, we found that by all measures, most participants were explicitly sensitive to climate change risks. Even those who disbelieved in climate change nonetheless usually expressed some concern for its impacts.

Table 5.1: Non-parametric correlation matrix for climate change risk perceptions. Using Spearman's rho, the table shows the strength of relationships among the various measures of climate change (CC) risk perception (N = 90). These ordinal variables were derived from the systematic coding of participants' statements about climate change throughout their interviews. Promptedness is an indication of how much prompting, by the interviewer, was needed before the participant raised the topic of climate change.

Correlation Matrix (Spearman's rho)

	Promptedness	CC Belief	CC Concern	CC Observed	CC Overall Effect
Promptedness	1.000				
CC Belief	-.385 ***	1.000			
CC Concern	-.400 ***	.590 ***	1.000		
CC Observed	-.250 *	.520 ***	.425 ***	1.000	
CC Overall Effect	-.022	-.153	-.349 **	-.025	1.000
CC Manageability	-.022	.126	-.091	.112	.201 †

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed)
N = 90

Correlation	Significance
$r_s < 0$	$p < .05$
$r_s > 0$	$p < .05$

5.4.1.2 The malleability of climate change risk perceptions

The climate change risk perceptions of many participants appeared to be malleable; qualitative changes in the tone of their expressed perceptions were evident in 41% of interviews. More than a third of participants (38%) appeared to become more concerned or to express more belief the longer they spoke of climate change, while a small minority (3%) became less concerned and expressed less belief. For the remainder of participants (59%), there were no such qualitative changes in the level of their concern or belief, though their expressed perceptions predictably became more nuanced with time. As an example of such malleability, SA109 was somewhat skeptical of climate change at the beginning of the interview (unprompted), but expressed belief in both ongoing and future climate change at the end of the interview (prompted):

> Unprompted: *"[People] talk a lot about global warming, but if you say that to the old people, they say, 'No, that year, 1922, it was also dry and rained like that.' So I don't really know."* – SA109

> Prompted: *"I think it [the climate] will change…. It is storming more. I remember, when I was a little boy it rained softly, not these storms we have now. Before, it would rain 12 or 15 millimetres [at a time]. Now it's about 50 or 60 millimetres, then a long dry period and then a lot of rain. It is changing…. I think about it a lot."* – SA109

Earlier unprompted references to climate change provided better opportunities to observe such malleability. Of those who raised the topic of climate change unprompted (66%), more than half (54%) exhibited qualitative changes over the remainder of the interview. There was correspondingly a strong and significant correlation between the point at which the concept of climate change was first raised (either unprompted or prompted) and the malleability of expressed perceptions ($r_s(28) = .334$, $p = .001$). Such malleability was evident prior to the climate change section of the interview script, but became more pronounced when participants were questioned directly about climate change. For instance, when asked at the end of the interview to predict how climate change would interact with other existing risks, SA128 spoke in apocalyptic terms: *"I think it will affect all of us, if the climate changes. It will be the end. Nobody will survive in this land, in the whole world. I can't see how anybody will survive. Maybe it won't be in our time, but in our children's time, in the future."*

For the subset of participants who spoke of climate change only when prompted (34% of all participants), no qualitative malleability was observed for the vast majority (84%). This lack of malleability may have been a result of the short time left in the interview; participants were not prompted about climate change until the final section of the script. No significant difference in malleability was found between believers and disbelievers – both were prone to changes in their expressed perceptions. No significant correlations were found between malleability and other measures of climate change risk perception.

5.4.1.3 The explicit manageability of climate change risks

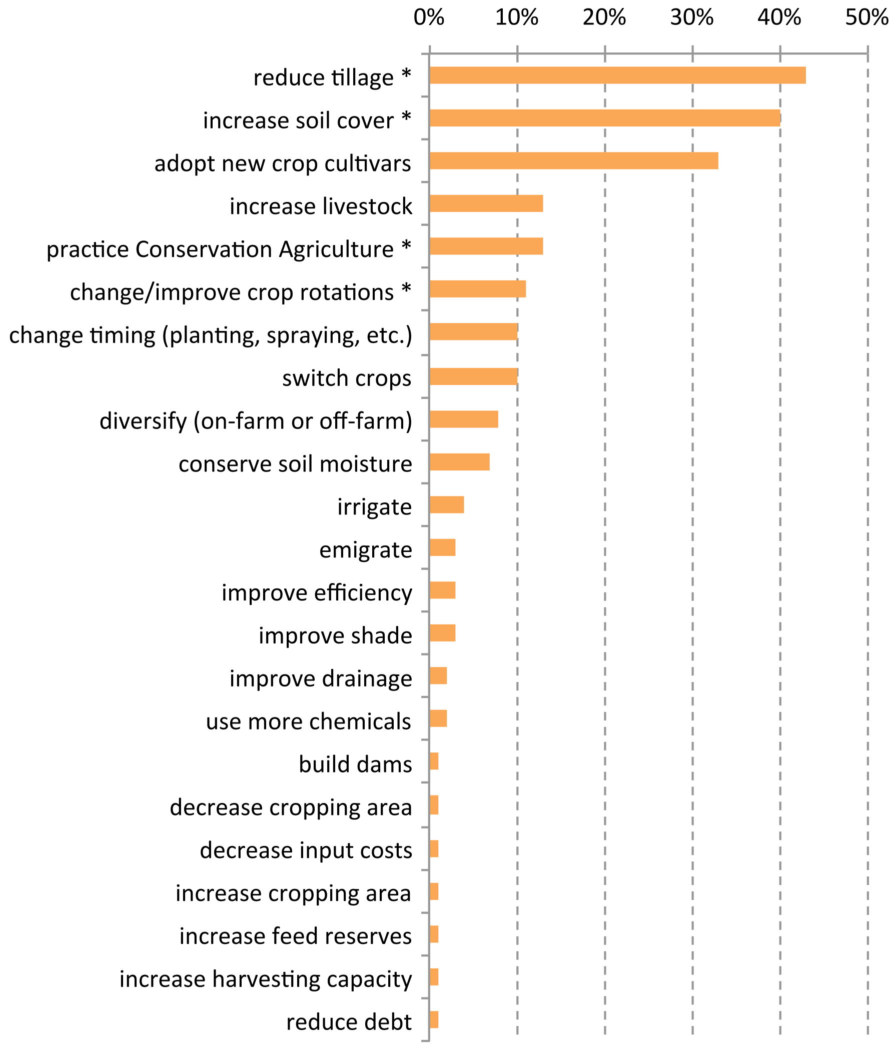
Participants generally predicted that the overall effect of climate change on their farm would be negative – i.e., that it would make farming more difficult, for example, by increasing water stress or reducing average crop yields. However, most thought that they could sufficiently manage its impacts through changes in agricultural practice and better planning. Specifically, more than two thirds of participants (71%) perceived that climate change would have broadly negative impacts at the farm level, while one quarter (23%) thought that the impacts would be neutral or mixed, and a small minority (6%) believed that climate change would have broadly positive effects (e.g., that it would increase mean rainfall and thus improve crop yields). However, more than two-thirds of participants (71%) thought that they could manage climate change impacts at the farm level through adaptation, and a further 20% thought that the impacts would be somewhat manageable. A small minority (9%) predicted that negative climate change impacts would be unmanageable. There was a significant correlation between the predicted overall effect of climate change and concern for its likely impacts ($r_s(88) = -.349$, $p = .001$), but the predicted overall effect was not significantly correlated with belief or observed climatic change.

In keeping with its widely perceived manageability, most participants readily listed possible ways of adapting to climate change, both unprompted and prompted. Many indicated that the ongoing adoption of CA, or its component practices, was climate-adaptive. This recognition of CA as an adaptation was positively correlated with agriculture-specific education ($r_s(88) = .270$, $p = .010$). The perceived manageability of climate change risks was then understandably correlated with participants' CA practices. Specifically, perceived manageability was significantly correlated with the uptake of advanced crop rotations ($r_s(88) = .216$, $p = .040$) and permanent soil cover ($r_s(88) = .213$, $p = .044$), though not with minimum soil disturbance ($r_s(88) = -.002$, $p = .988$). There were no significant correlations between the perceived manageability of climate change impacts and other measures of climate change risk perception, age, education or farm size.

Each participant proposed between zero and six specific adaptations ($M = 2.2$, $SD = 1.3$), though most such adaptations were offered by only a small number of participants (Figure 5.4). Apart from CA and its components, which were explored at length within the interview script, the only adaptations that were proposed by more than 10% of participants were the adoption of new crop cultivars (33%) and the increased reliance on livestock for income stability (13%). The number of specific adaptations proposed by each participant was positively correlated with education ($r_s(88) = .355$, $p = .001$), the perceived manageability of climate change risks ($r_s(88) = .242$, $p = .022$) and earlier unprompted references to climate change ($r_s(88) = .243$, $p = .021$). The number of adaptations was negatively correlated with small farm size (less than 500 hectares) ($r_s(88) = -.218$, $p = .039$). No significant correlations were found between the number of proposed adaptations and region, age, or other measures of climate change risk perception.

All of the proposed adaptations were also collectively described as effective responses to the risks created by weather and climate variability, though often by participants other than those who had characterized them as adaptations to climate change. For instance, SA128 described two such adaptations, which other participants had mentioned as possible responses to weather and climate variability, but which he had not: *"[If] our summers get hotter, I can put up more shade for my animals. And if our summers get drier, I can build more dams so that they have enough water during the dry periods."* Overall, participants readily proposed adaptations to climate change that were similar to responses to 'normal' weather and climate variability risks.

Figure 5.4: Frequencies with which participants (N = 90) proposed each climate change adaptation.
* Components of Conservation Agriculture that were specifically prompted by the interviewer, though not in reference to climate change.

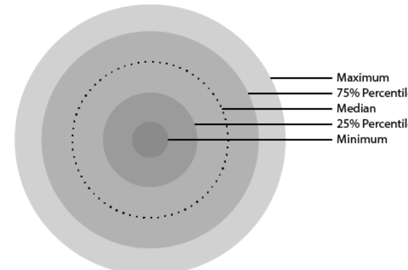


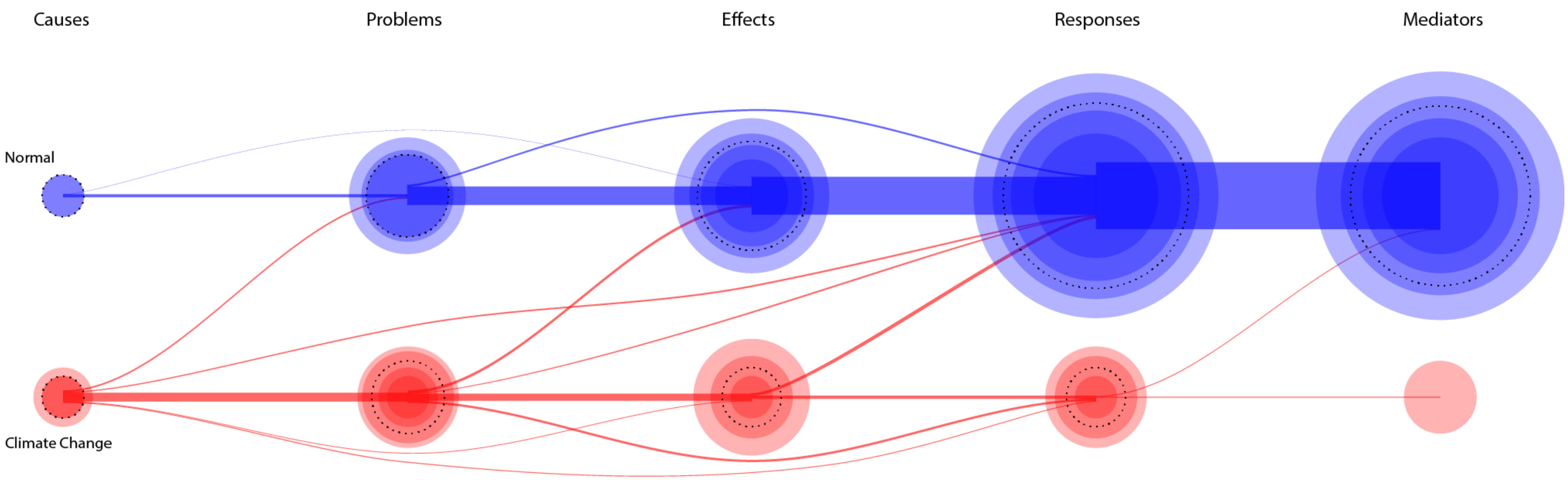
5.4.2 The isolation of climate change from weather (n = 30)

Having established that most participants were explicitly climate-sensitive (i.e., they were concerned about its likely impacts and readily proposed climate-adaptive responses), we assessed their implicit climate-sensitivity by evaluating their mainstreaming of climate change risks into 'normal' decision-making processes. To this end, we analyzed the relationship between weather and climate change risks in their causal mental models, both in terms of the linguistic framing of each branch and in terms of their structures and interconnections. Below, we demonstrate that the climate change branches of participants' mental models were clearly different from the ‘normal’ branches, linguistically and structurally. Participants framed climate change risks in different terms from those of weather and climate variability, and largely proposed responses that were novel to each farmer individually. Participants’ logic stemming from climate change contained far more frequent intuitive leaps than that stemming from ‘normal’ weather and climate variability – e.g., they described risk-mitigating responses without indicating the specific problems or negative effects that these responses were intended to address. There was little structural integration of participants’ mental models of ‘normal’ and climate change risks, both as measured naïvely by the number of connections between these branches, and as measured by the amount of overlap when clustered algorithmically. Figure 5.5 illustrates the broad distinction between the ‘normal’ and climate change branches of participants’ mental models.

Figure 5.5: Participants' aggregate mental models (*n* = 30), showing the 'normal' and climate change branches. This figure demonstrates the relative isolation of climate change logic from that of weather and other 'normal' risks. Within these mental models, nodes (concepts) are connected by edges (causal relationships). Thus, the 'normal' and climate change branches are connected where participants spoke of weather and climate problems, effects, responses and mediators of response in similar terms. Participants' climate change logic exhibits a greater frequency of intuitive leaps – for example, they more often described climate-adaptive responses without specifying the problem or negative effect that they were intended to mitigate.

Note: Aggregate mental models of normal and climate change risks. The area of each circle is proportionate to the average number of nodes in each model section (distribution shown by shading). The width of each flow is proportionate to the mean number of edges connecting the paired model sections. The size of the circles is not proportionate to the width of the flows.





5.4.2.1 Linguistic isolation

To assess the extent to which climate change risks were framed similarly to weather and climate variability, we extended the analysis of linguistic framing performed in Chapter 3. In that study, we found that participants spoke of weather and climate change risks using six "languages" indicative of distinct cognitive framings: agricultural, cognitive, economic, emotional, political and survival.[18] In the present analysis, we found clear differences in the linguistic framing of the 'normal' and climate change branches of participants' mental models.[19] Overall, participants spoke of climate change in different terms than they did weather and climate variability, with important differences in the prevalence of cognitive language (i.e., describing challenges in cognition, decision-making, uncertainty and access to information). The proportions of each language within participants' climate change branches were far more variable than those of their 'normal' branches (Figure 5.5), in part because the climate change branches tended to contain far fewer nodes (concepts). Nonetheless, the statistical analyses revealed significant and meaningful patterns.

Participants' logics related to climate change contained more cognitive language and less agricultural and economic language than those related to weather (Figure 5.6). These differences were confirmed through paired-samples t-tests for each language, which compared the number of nodes coded into that language as a proportion of the total within each farmer's 'normal' and climate change branches, respectively.[20] For instance, we found that there were significantly higher proportions of cognitive nodes (concepts) in the climate change branches of farmers' mental models ($M = .21$, $SD = .28$) than in their 'normal' branches ($M = .08$, $SD = .06$) ($t(28) = -2.405$, $p = .023$). In contrast, there were lower proportions of economic nodes for climate change ($M = .07$, $SD = .14$) than 'normal' ($M = .16$, $SD = .08$) ($t(28) = 2.900$, $p = .007$). There were also lower proportions of agricultural nodes in the climate change branches ($M = .58$, $SD = .33$) than

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[18] Definitions for each of these languages may be found in Table 3.2.

[19] As detailed in the methods section, the 'normal' branches in each mental model consisted of causal relationships stemming from weather and climate variability attributed to climatic processes consistent with historical conditions. The 'climate change' branches comprised causal relationships stemming from problems attributed to present or future changes in climate that were attributed to climate change, whether or not it was characterized as anthropogenic.

[20] We excluded mediators of response from this analysis because of their very infrequent occurrence in the climate change branches – only three participants described any such mediators.

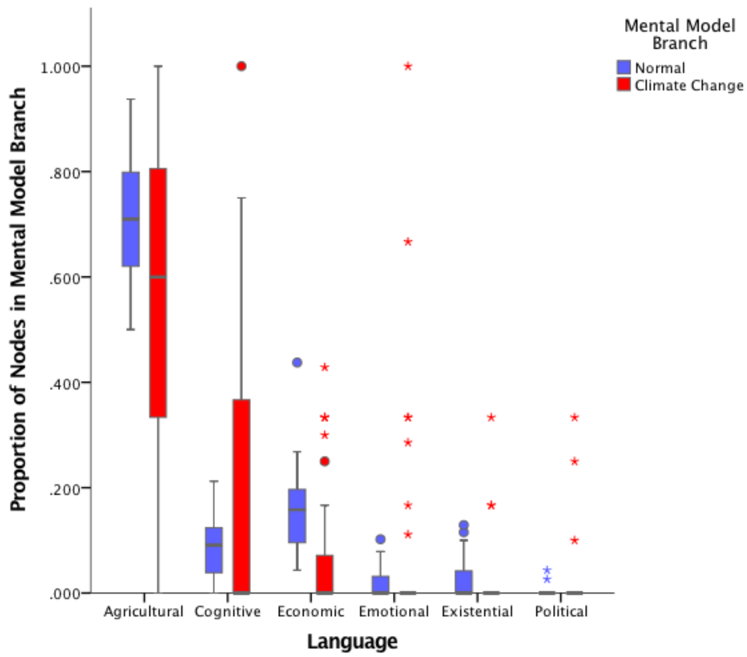
‘normal’ (*M* = .71, *SD* = .11), though the test statistic was not quite significant ($t(28) = 2.040$, p = .050).

Such differences in language were also evident within the narrower “effects” and “responses” sections of participants’ mental models.[21] Agricultural language was more often used to describe ‘normal’ effects ($t(25) = 2.070$, $p = .049$) and economic language to describe ‘normal’ responses ($t(27) = 6.691$, $p < .001$), when compared with climate change effects and responses, respectively. Cognitive ($t(27) = -2.077$, $p = .047$) and emotional ($t(27) = -2.063$, $p = .049$) languages were more often used to describe climate change responses than ‘normal’ responses, though most participants had no emotional response nodes in either branch. Within the climate change branch, emotional and survival nodes were well correlated ($r(28) = .401$, $p = .025$).

Participants who expressed stronger belief in climate change tended to use less survival language in their climate change branches ($r_s(28) = -.426$, $p = .017$), while those who thought that the overall effect of climate change would be more positive tended to use more agricultural language ($r_s(28) = .371$, $p = .040$). No other significant correlations were found between linguistic framing and explicit climate change risk perceptions.

[21] The set of relevant boxplots may be found in Appendix F.

Figure 5.6: Boxplot of the number of nodes (concepts) in participants' mental models (n = 30) that were coded into each 'language'. These are shown as a proportion of all nodes in each mental model branch (i.e., 'normal' versus climate change). This figure excludes mediators of response, because of their very low frequency in participants' climate change branches.



Participants who used cognitive language tended to frame climate change as a novel problem, but also as an intensification of existing processes: *"Everything's just going to be more intense, more crucial."* [SA059]. Uncertainty in both the sign and magnitude of predicted changes was perceived to inhibit proactive adaptation. For example, SA123 highlighted the challenge created by predictions of mean rainfall, without having more information about its future variability: *"An average can be a very dangerous thing…. You can't make proper decisions on that [basis]."* On a similar theme, SA050 described the fraught relationship between the process of adaptation envisioned by experts and his usual method of experiential learning and adjustment:

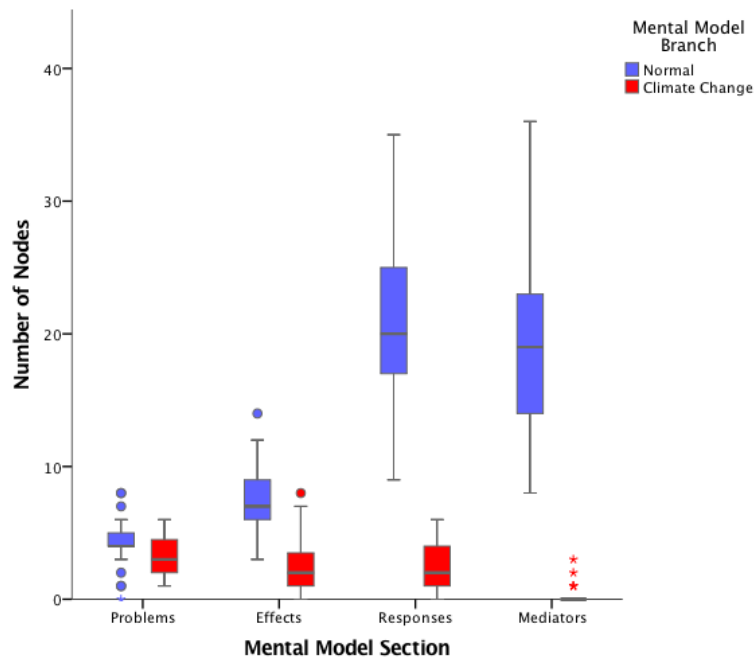
> *"Half the people with degrees tell us that we are going to have… global warming. And the other half say we're going to have an ice age…. It is getting hotter. You can't say it isn't so. It is getting hotter. So what do you now do? Do you listen? Do you go the path you are now going? And 20 years from now you are gone. Or do you change now? And to what do you change? ... So you go [based] on what you see and what you hear. And then you are always five years behind the trend. And what is a trend?"* – SA050

The relative dearth of economic and agricultural language in participants' climate change branches also reflected the perceived scarcity of practical approaches to adaptation. For example, SA073 described his lack of agency in managing the impacts of climate change, despite having specified some possible adaptations: *"In a way, it's manageable [using] cover crops and stuff…. On the other hand, you can do nothing. If it doesn't rain, it doesn't rain. If it gets hotter, you can do nothing about it."* In contrast, SA130 was confident that he would readily adapt: *"I'm not really scared about it [climate change], because if we keep doing what we're doing now – with Conservation Agriculture and adapting the whole time – it can come and go. We'll manage."*

5.4.2.2 Structural isolation

To further evaluate the integration of participants' climate change mental models with those of weather and climate variability, we analyzed their structure and interconnectedness. Overall, we found that the 'normal' and climate change branches were structurally distinct, with few interconnections and little overlap when clustered algorithmically. The 'normal' branches (i.e., weather and climate variability) were large and well developed, with many connections between nodes, overlapping and competing responses, and myriad mediators of response (Figure 5.5). In contrast, the climate change branches were small, with short causal chains, rarely including many responses or any mediators. For instance, there were far more responses and mediators in the 'normal' branches than there were problems and effects, whereas the opposite was true for climate change (Figure 5.7).

Figure 5.7: Boxplot comparing the size of the 'normal' and climate change branches for each section of participants' causal mental models (*n* = 30).



The climate change branches contained more intuitive leaps, where participants described responses to climate change without describing the intermediate problems and/or effects. Figure 5.5 illustrates the prominence of intuitive leaps in the climate change branches, with many effects and responses stemming directly from the climate change cause. The proportion of such intuitive leaps, relative to the size of the branch, was much higher in the climate change branches (17% of edges, excluding mediators) than in the 'normal' branches (3% of edges, excluding mediators). Many participants thus described adaptations to climate change without providing a clear rationale for their choice (i.e., the negative impact that the specific adaptation would lessen). For instance, SA123 suggested that he could mitigate the risk of climate change by "farming with nature," without specifying any of the problems that would be caused by climate change and would therefore be attenuated by this response.

The distinction that participants made between weather and climate change was reflected in the small number of connections between the climate change and 'normal' branches of their mental models. Figure 5.5 shows that there were few connections between the two branches compared with the number of connections within each branch. Figure 5.2 and Figure 5.3, in the methods section, show specific examples of well connected and disconnected climate change branches, respectively. The two branches were connected where participants described similar problems, effects, responses or mediators of response stemming from the two causes. For instance, both climate change and weather might cause droughts leading to low soil moisture. Climate change might also cause heavy rainfall and subsequent soil erosion, which could be mitigated by improving soil cover – a response that also mitigates the negative impact of high soil surface temperatures in 'normal' summers. The number of interconnections between the two models ranged from zero to thirteen ($M = 3.7$, $SD = 3.1$), with 16% of participants describing no such connections at all. The distribution was right-skewed – that is, most participants drew few connections, with only 13% describing more than six. The number of connections was positively correlated with earlier and unprompted introductions of the topic of climate change by the participant ($r_s(28) = .472$, $p = .007$), and with participants' expressed level of belief in present or future climate change ($r_s(28) = .502$, $p = .004$) and their concern for its likely impacts ($r_s(28) = .455$, $p = .010$). It was not significantly correlated with the other measures of explicit climate change risk perception.

The scarcity of connections between the branches showed that there was little expressed overlap in the problematic effects and proposed responses stemming from 'normal' and climate change risks within each participant's mental model. The small number of climate change-specific responses was only slightly augmented by connections from negative climate change effects to 'normal' responses. On average, each climate change effect was connected to less than half as many 'normal' responses ($M = 0.31$, $SD = .52$) ($t(62.2) = 3.375$, $p < .001$) as climate change-specific responses ($M = 0.88$, $SD = .97$). This suggests that most proposed responses to climate change were novel within each farmer's mental model. Moreover, responses to climate change effects were scarce overall compared with those to the 'normal' effects of weather and climate variability. On average, participants described nearly twice as many possible responses to each 'normal' effect ($M = 2.01$, $SD = 1.55$) as to each climate change effect ($M = 1.19$, $SD = .97$) ($t(85.591) = 4.509$, $p < .001$). Many connections from climate change effects to 'normal' responses were related to the three CA practices – CA nodes were present in every mental model because of their prominence in the interview script and were commonly recognized as being climate-adaptive. However, there were no significant correlations between the number of connections and participants' CA practices.

For participants who had no connections between the two branches, there was a clear lack of integration, but for those whose branches were somewhat connected, algorithmic clustering further illuminated the extent of their integration. Since problems, effects and responses stemming from climate change were often poorly connected to the 'normal' branch, the algorithm naturally grouped climate change nodes separately from 'normal' nodes. The extent to which the 'climate change' cluster included 'normal' nodes (and vice versa) thus provided another simple measure of integration. By this measure, one third (33%) of participants exhibited no integration between the two models. Predictably, models with fewer interconnections tended to have less overlap ($r_s(28) = .710$, $p = .000$). No significant relationship was found between the size of the climate change model and the amount of overlap, though the two participants with complete overlap had the smallest climate change models (four nodes each). The amount of overlap was positively correlated with the participants' earlier and unprompted introductions of the climate change topic ($r_s(28) = .406$, $p = .023$), but not with any other measures of explicit climate change risk perception.

5.5 Discussion

In preliminary interviews, local experts were skeptical that this group of farmers were thinking about climate change and were prepared to respond to its effects. Why then do farmers who appear to be weather-sensitive and are progressively adopting more climate-resilient practices not seem to be prepared to adapt to climate change? We have attempted to answer this conundrum in this work. In so doing, we make a distinction between weather-sensitive and climate-sensitive decision-making: these farmers are widely understood to react readily to perceived weather risks (i.e., they are weather-sensitive), but not to perceived climate change risks (i.e., they are not climate-sensitive). As a prerequisite, we confirmed that these farmers are indeed explicitly sensitive to climate change risks. We then evaluated their implicit climate-sensitivity by analyzing the integration (i.e., mainstreaming) of climate change risks in their mental models of weather and other 'normal' risks. We first found that most believe in present or future climate change, and many that say they do not are nonetheless somewhat concerned about its possible effects.

Though broadly concerned with the potential impacts of climate change, they are generally confident in their ability to adapt to it and readily describe possible adaptations.

However, climate change's physical uncertainty is mirrored by farmers' perceptual uncertainty. Farmers' climate change risk perceptions are malleable and internally inconsistent. Their expressed perceptions shift, both in tone and nuance. Their responses to direct questions about climate change are often different from those offered unprompted. However, such direct questions also produce deeper and more nuanced answers, with farmers recognizing the potential for climate change to produce cascading effects at both local and global scales. The unique cognitive challenges created by climate change are also reflected in the higher proportions of cognitive language and the lower proportions of agricultural and economic language in farmers' climate change mental models. It may be that they access different mental models depending on the context and method of elicitation (as suggested by Brügger et al. (2015)), or that they actively construct their preferences, and therefore their mental models of climate change, during elicitation (as implied by Lichtenstein and Slovic (2006)).

Climate change is therefore isolated from farmers' mental models of everyday risks, both rhetorically and structurally, despite the recognition that many relatively 'normal' agricultural responses would likely help to lessen the impacts of climate change. The causal relationships that farmers perceive as stemming from climate change are rarely developed well enough to include many responses or any mediators of response. Most farmers speak of climate change in largely abstract terms, recognizing systemic impacts, but drawing few connections to existing farm-level processes. Only where climate change's effects are explicitly recognized as similar or identical to existing weather and climate variability risks do farmers conceive of these linkages. Farmers' climate change logics are thus largely disconnected from those of 'normal' stressors and risk-mitigating responses. Though largely rational, they are isolated from other behaviours; climate change risks are managed in parallel, rather than in concert, with weather and climate variability.

Having little experiential knowledge of climate change, farmers seek novel responses to a novel problem. Though many proposed adaptations are unique to climate change within individuals' mental models, even those that may seem most extreme (e.g., crop-switching, emigration) are offered by other farmers as responses to weather and climate variability, either directly or in combination with other stressors. Therefore, despite the cognitive isolation of climate change, farmers' proposed adaptations are implicitly reasonable responses to 'normal' environmental, economic, social and political risks. It seems that the 'normal' and climate change branches are not disconnected because climate change is a severe threat that requires radical solutions, but rather because its perceived novelty prompts farmers to seek responses that are new within their own range of experience.

The cognitive frames that farmers use to perceive, interpret and respond to climate change risks are thus mismatched with those that they use for weather and climate variability. In managing other risks, farmers depend on social and experiential learning combined with incremental experimentation to arrive at appropriate responses (Chapter 2). Our present findings suggest that climate change creates cognitive challenges by disrupting this learning model. Farmers have no previous experience with climate change. Their understanding of it is therefore strongly influenced by agricultural and climate risk communication from experts, which is incongruent with the learning processes that normally shape farmer decision-making. Having to rely so much on imparted expert knowledge, which is incorporated uneasily and abstractly into their mental models of environmental risks, creates a mismatch between the cognitive frames that they use for 'normal' risk management and those that they use to think about climate change. As found in Chapter 2, farmers tend to distrust expert knowledge that is not well-situated within the specific context of their farms. Despite their frequent recognition of changes similar to those that experts predict, they remain uncertain and skeptical; outreach that emphasizes the consensus among experts, as opposed to farmers' lived experiences, may thus unintentionally drive these frames further apart (as implied by Moser (2010)).

In general, farmers' mental models of climate change do not appear to be actionable. Those who isolate climate change from their 'normal' multi-faceted, multi-causal decision-making processes seem less likely to respond to it. They may recognize that climate change requires proactive adaptation; most even recognize that their ongoing adoption of CA is a climate-resilient adjustment that requires years of advanced planning and action. However, they are unlikely to respond to climate change as rationally as they presently respond to other risks, because their climate-adaptive responses are not connected to processes of 'normal' risk management. Some are already poorly adapted to present climate; farmers do not always choose to mitigate weather risks when given the opportunity, because environmental risk management competes with other risks and other objectives. For climate change, foregone adaptive opportunities are likely to become more frequent. Rather than framing the mainstreaming of climate change adaptation as the integration of novel *climate change* risks into existing processes of risk management for weather and other 'normal' risks, it might be more effective to catalyze farmers' sensitivity to *weather* risks as a means of sharpening their focus on all of the environmental risks that they experience directly, including climate change.

5.6 Conclusions

South African commercial farmers have long been targeted by specific campaigns stressing the importance of climate change impacts and adaptation within the country's highly variable and semi-arid climate. However, their mainstreaming of climate change adaptation will be difficult if they think about climate change risks in isolation of weather and climate variability. They need not be convinced that climate is dynamic; they do not conceive of 'normal' weather and climate variability as stable and predictable. They experience and respond to daily fluctuations in weather, and multiple overlapping climate cycles on various timescales, some of which may only recur once or twice during their working lives. They therefore generally perceive themselves as capable of adapting to climate change. They also perceive themselves as highly adaptive to myriad other uncertain long-term risks related to agronomics, economics and politics, and they largely understand the climate-resilient benefits and shortcomings of their current practices. They are self-critical and pragmatic in dealing with varied farming risks. The perceived manageability of climate change is determined in part by actual farming practice; however, their level of expressed concern for climate change's likely impacts is not. The divergence of perceived manageability and expressed concern reflects a disconnection between rhetoric and reality. Their risk perceptions are often malleable and internally inconsistent. Climate change's physical uncertainty is thus mirrored by farmers' perceptual uncertainty.

Overall, these farmers appear explicitly climate-sensitive in their expressed risk perceptions, but they are implicitly insensitive to climate change risks in the isolation of climate change from their mental models of weather and other 'normal' risks. Farm-level risk management is not a singular decision-making process. It is rather comprised of many overlapping and intersecting processes towards diverse objectives. In this messy web of linked stressors, responses and mediators, climate change is unique. The cognitive frames that farmers use to perceive, interpret and respond to climate change are thus mismatched with those they use for weather and climate variability. Having little experiential knowledge of climate change, they seek novel solutions to a novel problem. They rely heavily on imparted expert knowledge of climate change in place of the social and experiential learning that drives 'normal' risk management. Their mental models of climate change therefore appear poorly developed and less actionable. The mainstreaming of climate change will be difficult if it is perpetually framed as distinct from 'normal' climate. These farmers need help in understanding the ways in which climate change is similar to and compatible with the myriad risks that they otherwise routinely manage. If they are unable to integrate climate change with their pre-existing risk management frameworks, they are unlikely to respond to climate change risks proactively, even when they recognize this strategy as preferable. The climate risk communication challenge is thus much larger for this group of commercial farmers than broadly recognized in the climate change adaptation literature.

Chapter 6: The unquestioned assumption of equivalence in farmer perceptions of weather and climate change risks

6.1 Synopsis

The climate change literature increasingly emphasizes that adaptation planning should be mainstreamed into existing decision-making processes as a matter of risk management best practice. However, commercial farmers are often assumed to have already done so, intuitively treating climate change risks as an equivalent, long-term extension of risks stemming from weather and climate variability. In fact, there is only tangential evidence that farmers perceive and respond to the two categories of risk similarly. A small but growing number of in-depth case studies suggest that they do not – that this assumption of equivalence masks important differences in their perceptions of weather and climate change. This paper seeks to quantitatively test the proposition that farmers treat the two risks as equivalent. Using a risk ranking exercise in a national survey of South African commercial grain farmers – a group with the demonstrated incentive, capacity and willingness to adapt to climate change – we found that weather and climate change risks were not perceived similarly. Individual farmers tended to prioritize one over the other, but the risk that they prioritized varied; nearly identical proportions of farmers selected each risk as a high priority and not the other. Further, farmers who selected one were no more or less likely to select the other. In ordinal regression, the ranks of the two risks were driven by different demographic variables, farm characteristics and farming practices. Further, all of the independent variables that were significantly associated with both weather and climate change ranks had effects on the two that were of opposite sign to each other. These differences persisted and were often amplified when we analyzed the distance between the weather and climate change ranks using multivariate linear regression. The findings suggest that the assumption of equivalence between climate change and weather risks is inaccurate, at best; these farmers do not generally think about climate change risks in the same way that they do weather risks. This suggests a major, unrecognized risk communication challenge for climate scientists and policymakers. Farmers will have difficulty mainstreaming climate change adaptation under risk communication regimes that presently assume the integration of weather and climate change in their decision-making. They are therefore less likely than previously thought to respond to climate change risks rationally and proactively.

6.2 Introduction

The climate change literature has increasingly emphasized the need to mainstream adaptation into existing decision-making processes to facilitate integrated, proactive and planned adaptations (Porter et al., 2015). The pervasive view of agriculture holds that farmers do so intuitively, because they perceive climate change risks as equivalent, long-term extensions of weather risks (Smit & Skinner 2002). Farmers manage myriad risks across a variety of domains and towards complementary and competing objectives (Chapter 2). They recognize that they must integrate climate change risks into their existing risk management processes to ensure that they undertake efficient and effective adaptations that are in keeping with their existing objectives. Farmers are thus generally expected to adapt autonomously to climate change as they anticipate (proactively) or experience (reactively) its impacts through changes in weather and climate variability (e.g., Thomas et al., 2007). Within this paradigm, perceptions of and responses to weather, climate variability and climate change risks should therefore be more or less aligned, and should even be proxies for each other in some cases (Reidsma et al., 2010). The foremost difference between these stressors is timeframe: weather is uncertain in the short term, climate variability in the medium term, and climate change in the long term. Consequently, commercial farmers represent an important archetype in the adaptation literature as a highly adaptable, autonomous private actor.

The literature thus holds both that farmers *ought* to integrate weather and climate change risks (i.e., mainstreaming adaptation) (e.g., Howden et al., 2007), and that they are *likely to do so* intuitively and autonomously (e.g., Mertz et al., 2009). However, there has been little empirical investigation of the novel challenges that farmers may face in perceiving, interpreting and integrating responses to weather and climate change stimuli (Clayton et al., 2015). This paper seeks to quantitatively test the claim that farmers treat weather and climate change risks as equivalent. We use a national survey of South African commercial grain farmers, which includes a risk ranking exercise, to establish whether they perceive climate change and weather risks as being similar, and whether these risk perceptions are driven by similar factors.

In what follows, we summarize the existing literature on the mainstreaming of adaptation by institutions, publics and individual actors (Section 6.3). We then detail the small but growing number of in-depth, qualitative case studies that appear to weaken the assumption of equivalence in farmer perceptions of weather and climate change risks. This review is then used to specify the objectives and hypothesis motivating this study: that farmers do not prioritize weather and climate change risks similarly. The case and survey methodology (a national survey of South Africa's commercial grain farmers) are presented in Section 6.4, whereas Section 6.5 explains our significant challenge to the assumption of equivalence between climate change and weather risks, as evident in differences in the farm and farmer characteristics that significantly drive the risk rankings. We conclude in Section 6.6, with the implications of this study for communication challenges in the mainstreaming of climate change risks in agriculture.

6.3 Mainstreaming climate change risks into farming

In contrast with the intuitive mainstreaming assumed of farmers, there is plenty of evidence that *institutional* decision-makers have difficulty integrating climate change risks into existing decision-making and risk management processes (Kunreuther et al., 2013). Scholars have widely recognized that uncertain, incremental and long-term climate changes create new and potentially intractable challenges for policy-makers (Dittrich et al., 2016). Numerous studies have identified and categorized potential systemic barriers to adaptation, including social limits, which might create unforeseen problems beyond those posed by weather and climate variability (Adger et al., 2009). The Fifth Assessment Report (AR5) from the Intergovernmental Panel on Climate Change (IPCC), for example, highlights four main categories of barriers: institutional, technological, informational and economic (Porter et al., 2015). The authors emphasize the need for new climate risk management frameworks to guide policy-making in such a way that it distinguishes between 'normal' and climate change risks while coordinating their management. The novel systemic challenges of climate change adaptation are thus relatively well documented, and are reflected in recent policy prescriptions.

In parallel, climate risk perceptions surveys among experts and broader publics have intimated important differences in how individuals understand and prioritize risks stemming from climate change and weather. Generally based on large-scale surveys, these results provide strong evidence of the roles of politics, culture, identity and psychological distance in perceptions of climate change risks that do not exist to the same extent for weather (Clayton et al., 2015;

Hornsey et al., 2016; Wolf & Moser, 2013). Dilling et al. (2015) argue that such differences in the perception of climate change and weather risks can lead to maladaptive choices if the two are either conflated or managed in isolation from each other. Because climate change presents unique challenges, they conclude that pursuing "no regret" adaptation strategies that target climate variability instead of climate change will therefore be insufficient. Specifically, the authors suggest that, in some cases, adapting to climate variability alone can even increase vulnerability to climate change, because of the potential for unanticipated systemic effects that may increase exposure and sensitivity to climate change risks, or decrease future adaptive capacity. For example, flood control measures can stimulate development in floodplains (i.e., the 'levee effect'), leading to greater exposure during low-frequency extreme flooding events (Kates et al., 2006). Similarly, Eakin et al. (2016) argue that irrigation farmers experience psychological "buffering" with respect to climate change risks, because their use of irrigation infrastructure to reduce weather risks decreases the salience of all water-related risks. Hence, the two must be addressed in concert but clearly distinguished.

However, the literature on individual climate-adaptive behaviours remains highly conceptual, despite periodic calls for better empirical evidence. Grothmann and Patt (2005) argue that climate change risk perceptions and self-perceived adaptive capacity are the strongest determinants of individual adaptation. However, few authors have since attempted to identify the similarities and differences among the weather, climate variability and climate change risk perceptions of individual actors. The literature on social (or psycho-social) limits to adaptation (Evans et al., 2016), though tangentially related, falls short. In a review of the psychology of climate change, Clayton et al. (2015, p. 643) offer an fittingly scant summary of our understanding of climate-adaptive responses: "Compared with the focus on mitigation, psychological researchers have given relatively little attention to climate change adaptation responses. The possibilities for positive adaptations, and ways to encourage them, should be further explored."

What we do know conceptually, at least, is that early adaptation studies showed little consensus about whether or not policy responses were needed to support adaptation by commercial farmers. Some scholars anticipated that farmers' adaptation strategies would be largely autonomous; adaptation studies were thus judged unnecessary as farmers were assumed to be fundamentally adaptable, both in self-perception (Bryant et al., 2000) and in objective assessment (Mendelsohn & Dinar, 1999). Farmers, it was argued, would continue to adapt to changing external conditions – in markets, weather or politics – as had always been the case. Other studies, however, began to identify barriers to agricultural adaptation that were analogous to those theorized more broadly (Smit & Skinner, 2002). The AR5 summarizes nine types of barriers to adaptation in food systems: "inadequate information; inadequate extension; institutional inertia; cultural acceptability; financial constraints; insufficient fertile land; infrastructure; lack of functioning markets; and insurance systems" (Porter et al., 2015, p. 518). The authors emphasize that agricultural adaptation by local actors should therefore be supported by nuanced, contextualized, and multi-dimensional policy responses.

The empirical literature on adaptation mainstreaming by farmers is thus poorly developed. In reviewing the state of the literature, the AR5's brief treatment of individual actors – concluding that farm-level risk management is multi-faceted – is symptomatic of the wider gap in knowledge. In the absence of a clear alternative, most adaptation studies implicitly assume that farmers will adapt to climate change risks by direct extension of the decision-making and risk management strategies that they might use, equally, for weather (e.g., Ash et al., 2012; Jain et al., 2014; Meinke et al., 2009; Reidsma et al., 2009; Truelove et al., 2014; Wreford & Adger, 2011). In the analysis of farmer risk perceptions, in particular, researchers often make the assumption of equivalence between weather and climate change when anticipating future responses (e.g., van Duinen et al., 2015) – even in some studies that explicitly distinguish between perceptions of weather and climate change risks (e.g., Hamilton-Webb et al., 2016). Other authors simply sidestep the intricacies of decision-making altogether (e.g., Iglesias et al., 2011).

More recently, a small but growing number of case studies suggest that there are important differences in the ways that individual farmers presently perceive and manage weather and climate change risks. Specifically, these cases provide qualitative empirical evidence that farmers are sensitive to both weather and climate change as distinct risks, that they respond separately to each, and that these responses are often isolated from one another (Chapter 5; Eakin et al., 2016; Kenny, 2011). For instance, our recent analysis found that farmers may access different mental models in addressing climate change risks versus weather and climate variability (Chapter 5). Even where the effects and responses stemming from the two stressors were qualitatively similar (e.g., low soil moisture, either from normal rainfall variability or as an anticipated climate change impact), farmers' mental models of climate change tended to be disconnected from those of "normal" risk management. Because they treated climate change risks separately, we argue that these farmers were less likely to adapt proactively even when they thought that this would be beneficial. Across the full sample of 90 farmers in Chapter 5, all of their proposed responses to climate change risks, in aggregate, were also reported as existing responses to weather risks. Crucially though, those climate-adaptive responses were usually new within each farmer's own experience – novel responses for a novel risk. Consistent with this result, Eakin et al. (2016) find that farmers who otherwise perceive themselves as highly adaptable to a wide variety of risks may nonetheless express a lack of agency in responding to climate change risks. Some commercial farmers doubt their ability to adapt to future climate change because they perceive it to require greater flexibility, and better access to information, finance and technology. Thus, while the consensus holds that farmers *ought* to treat weather and climate change equivalently in mainstreaming climate change adaptation, these cases have begun to suggest that they presently *do not*.

The findings in Chapter 5 suggest that farmers perceive and respond to climate change using expert-driven cognitive frames that are distinct from and mismatched with their normal processes of risk management. However, the qualitative analysis used in that study was necessarily limited to a narrow group and small sample ($N = 30$). This work complements those qualitative findings, but focuses instead on quantitatively testing the assumption of equivalence between climate change and weather. The results are derived from a national survey of South Africa's commercial grain farmers. Specifically, we examine whether the distinction made between short-term variations in weather and long-term climate change holds true among a broader population of farmers. Our approach is similar to the recent study of drought risk perceptions among farmers in the Netherlands by van Duinen et al. (2015), which examined the drivers of perceived weather risk; however, the analysis here emphasizes the differences between weather and climate change. We test a hypothesis about risk perceptions stemming from the qualitative findings and opposing the assumption that farmers think about and respond to messages about weather, climate variability and climate change equivalently: that farmers do not prioritize climate change and weather risks similarly. In doing so, we explore the demographic, farm-level and behavioural (i.e., farming practice) variables that might help explain the observed differences in weather and climate change risk perceptions.

6.4 The case and methods

To evaluate the relationship between farmers' weather and climate change risk perceptions, we conducted a national survey of South Africa's commercial grain farmers. We first compared the proportions of respondents who identified weather and climate change as high-priority risks, and their explicit belief in climate change and concern for its impacts. We then used ordinal regression to identify the demographic, farm-level and behavioural (i.e., farming practice) variables that explain variations in the ranks given to weather and climate change risks, separately. Finally, we used multivariate linear regression to explain the observed distance between each respondent's weather and climate change ranks. The survey was designed and piloted in consultation with Grain SA, the national commodity organization representing South African grain farmers. Grain SA disseminated the final survey link to its members by email.

South Africa's commercial grain farmers are uniquely positioned to adapt proactively to uncertain, long-term risks. They operate in a Mediterranean climate vulnerable to climate change (RSA, 2011), and are immersed in a culture that reveres multi-generational farming heritage (Devarenne, 2009). They are relatively well educated, with good access to informational, financial and institutional resources (Wilk et al., 2013). However, as many are historically privileged, white beneficiaries of South Africa's apartheid legacy, they generally receive little explicit support from government (e.g., few of the subsidies enjoyed by commercial farmers in higher-income countries) (Bernstein, 2012). They are therefore closely representative of the archetype of the autonomous private actor in the climate change adaptation literature. The ongoing, but uneven, adoption of Conservation Agriculture (CA) is among the most important trends in the sector (RSA, 2013c). CA is a set of three climate-resilient principles (advanced crop rotations, minimum soil disturbance, and permanent soil cover) advocated by the Food and Agriculture Organization of the United Nations as part of their Climate-Smart Agriculture and Sustainable Intensification foci (Giller et al., 2015; McCarthy et al., 2011). With a long implementation period and established benefits across an array of climate and non-climate risks (Niang et al., 2014), CA's adoption suggests that these farmers are willing and able to undertake substantial changes in practice to mitigate uncertain long-term risks (Chapter 3).

To characterize the landscape of risk in commercial grain farming, broad categories of risk were first identified through in-depth risk elicitation in a prior study (Chapter 2). These categories were used in the present survey as a risk ranking exercise. Given thirteen options, survey respondents were asked to select the five highest-priority risks, and to rank those five from highest to lowest priority. The resulting ranks were reordered so that higher numbers were associated with greater priority (5 being highest ranked; 1 being lowest). The unselected risk categories (those not in the top five) were assigned a rank of zero. All complete cases were included in the analysis.

Weather and climate change risk ranks were analyzed separately and then together, with a common set of farmer demographics, farm characteristics and farmer behaviours (i.e., farming practices) as predictors. The weather ranks and climate change ranks were first each analyzed as dependent variables using ordinal logistic regression (i.e., a generalized linear model with a cumulative logit link). To analyze the drivers of differences in weather and climate change risk perceptions, a dissimilarity measure was defined as the distance between the weather and climate change ranks assigned by each respondent. This was calculated by subtracting the weather rank (0 to 5) from the climate change rank (0 to 5). The resulting dependent variable ranged from +5 (when climate change was ranked highest and weather was not selected) to -5 (when weather was ranked highest and climate change was not selected). This variable, constructed to reflect differences in climate change and weather risk perceptions, was used as the dependent variable in a multivariate linear regression model (i.e., a generalized linear model with an identity link) with independent variables identical to those in the above ordinal regressions.

Our sample frame was comprised of South African grain farmers who were dues-paying members of the national commodity organization, Grain SA. This frame captured more than half of the country's commercial grain farmers, both by internal (Grain SA) estimates and those provided during expert interviews in advance of the survey design. Grain SA members were thought to be broadly representative of the larger population of commercial grain farmers, though with fewer very large and very small farms. Grain SA's public relations department forwarded an introductory email containing the survey link to their membership list. The survey was open for eleven weeks, from March 13th to May 31st 2015, during which time three reminders were sent by email. From a contact list containing 4757 entries, 441 farmers (9%) responded to the survey; this response rate matches that reported by van Duinen et al. (2015) in the Netherlands. Twelve additional responses were found to be duplicates (i.e., likely to be the same farmer responding twice, based on geographic, demographic and farm-level information) and are excluded from this total. For each pair of duplicates, the most complete case was retained, or the first case if equally complete. Of the remainder, 246 farmers entered complete information for all questions relevant to the regression analyses. For other analyses, the sample size is noted in the results. On the advice of local experts who had previously surveyed commercial farmers in South Africa, only a small number of survey questions were made mandatory, resulting in a higher frequency of missing data. The survey was offered in both English and Afrikaans, though the vast majority of respondents (92%) chose to answer the Afrikaans version.

6.5 Results

Overall, we found that the assumption of equivalency between climate change and weather is not consistent with the evidence gathered in this study. Specifically, respondents to the survey ranked weather and climate change risks differently, and the rankings of the two risks were driven by different independent variables. Section 6.5.1 first demonstrates clear differences in the patterns of selection of weather and climate change as high priority risks. In Section 6.5.2, we then use ordinal logistic regression on the weather and climate change ranks, separately, to show that the significant drivers of rank were different for the two categories of risk. In Section 6.5.3, we further investigate the reasons for these differences in ranks by applying a multivariate linear regression model to predict the distance between the weather and climate change ranks assigned by each farmer. We show that weather and climate change ranks were significantly related to different demographic variables, farm characteristics and farming practices, which often had effects on the two risks that were of opposite sign to each other (i.e., a positive effect on one risk's rank, and a negative effect on the other's).

6.5.1 Selection of weather and climate change as high-priority risks

To assess the level of priority that farmers give to weather and climate change, respondents were asked to select five factors that posed the "greatest threats to the future success" of their farming businesses from thirteen options (Figure 6.1). Weather and climate change were among the six categories of risk that were selected by at least half of respondents. Similar proportions of farmers selected weather (63%) and climate change (60%); however, only a plurality of respondents (37%) selected both (Table 6.1). Roughly equal proportions selected only weather (26%) or only climate change (23%), and a small minority (14%) selected neither weather nor climate change. Half of respondents (49%) therefore selected one of the two risks – weather or climate change – as a high-priority threat, while excluding the other. Thus, simply based on their initial selection of five high-priority risks, half of individual farmers prioritized weather and climate change differently.

No significant statistical relationships were found between the selection of weather and the selection of climate change, nor between the ranks assigned by each farmer to the two risks. A chi-square test showed no relationship between the selection of weather and the selection of climate change, X^2 (1, N = 378) = .320, p = .572). Therefore, farmers who selected one were no more or less likely to select the other. Similarly, Spearman's rho showed no correlation between the ranks assigned to weather and to climate change (r_s(376) = .011, p = .830). While weather and climate change were selected as high-priority risks at about the same rate, a Wilcoxon signed-ranks test showed that individual farmers tended to rank weather (M = 1.88, SD = 1.837) slightly higher than climate change (M = 1.58, SD = 1.58) (Z = -2.333, p = .020).

To determine their overall belief in anthropogenic climate change and broad concern for its impacts, respondents were asked to indicate their level of agreement (on a Likert scale) with five statements about climate change. The lowest rate of agreement was 59% with the statement that human action is the primary cause of climate change. All other statements received more than 70% agreement (Figure 6.2), suggesting that most farmers were explicitly sensitive to the threat of climate change even when they were uncertain of its cause. Three quarters (75%) of respondents agreed or strongly agreed that they would need to consider the effects of climate change on their farms in planning for the next five or ten years. As would be expected, the prior selection of climate change as a high-priority risk was well correlated with agreement with the climate change statements. For instance, the respondents' level of agreement with the final statement (consider climate change in planning) was well correlated with their selection of climate change as a high priority risk ($r_s(376) = .390$, $p < .001$), as well as the rank that they assigned to it ($r_s(374) = .370$, $p < .001$). Overall, these Likert-scale questions confirmed that the risk ranking data were broadly consistent with other expressions of concern for climate change risks.

Figure 6.1: Percentage of survey respondents who selected each category of risk as one of the five "greatest threats to the future success" of their farming businesses.

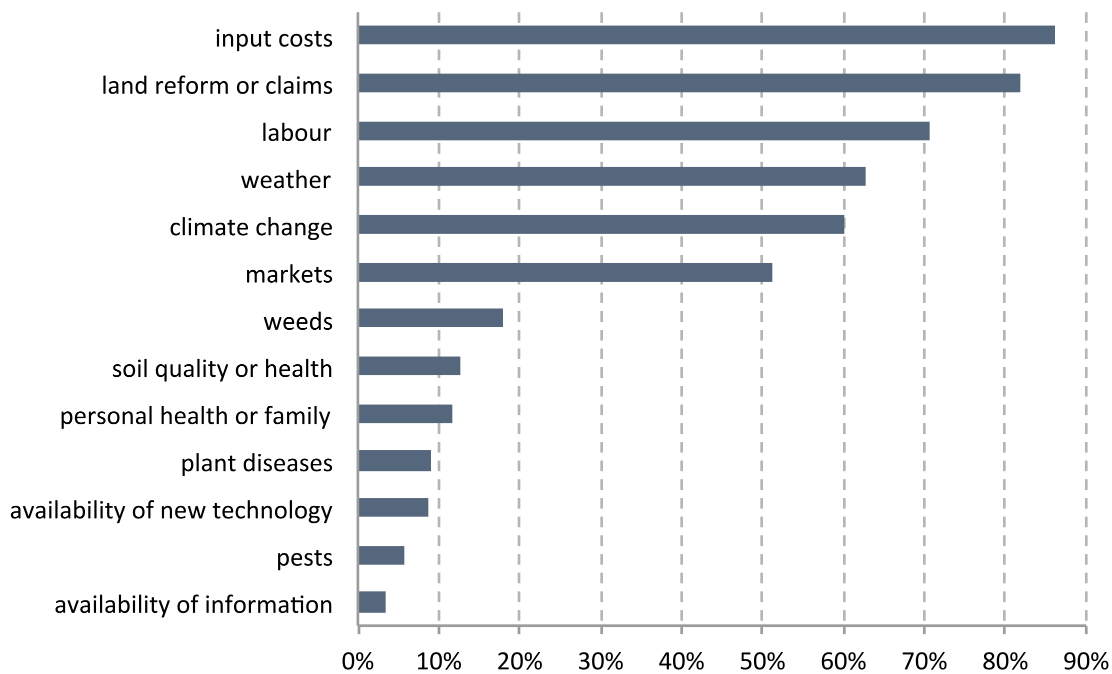
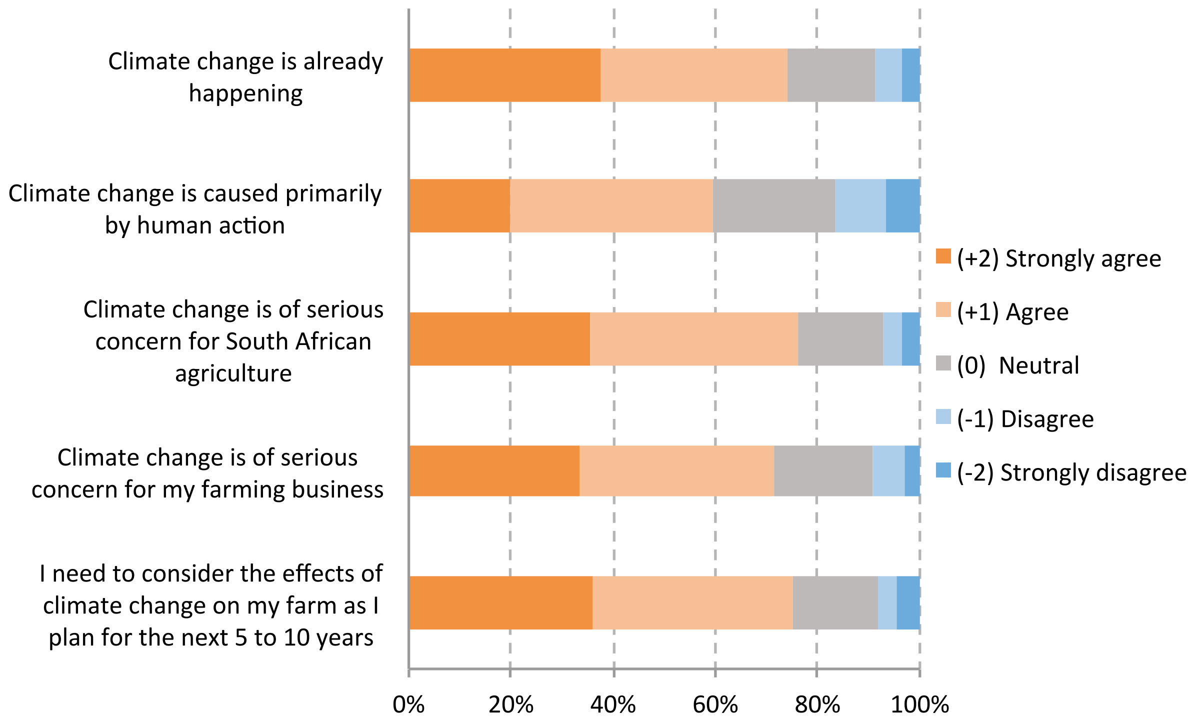


Table 6.1: Participants' selection of weather and climate change as high-priority risks. Percentage of survey respondents who selected weather and/or climate change as among the five "greatest threats to the future success" of their farming businesses.

		Weather	
		Selected	Not Selected
Climate Change	Selected	37%	23%
	Not Selected	26%	14%

Figure 6.2: Likert-scale climate change risk perceptions. Survey responses to direct questions about respondents' belief in climate change and concern for its impacts.



6.5.2 Drivers of weather and climate change ranks, separately

To determine the drivers of weather and climate change risk perceptions, the weather and climate change ranks were each analyzed as dependent variables in ordinal logistic regression using the same set of independent drivers. The results below show that the weather and climate change ranks were generally driven by different independent variables (i.e., the farm and farmer characteristics that were significantly associated with weather were generally different from those significantly associated with climate change) (Figure 6.3).[22] Furthermore, all variables that were significantly associated with both risks had effects on the two that were of opposite sign to each other. No independent variables had significant effects of the same sign on both dependents.

[22] Since we are primarily interested in demonstrating that there are important differences between weather and climate change risk perceptions, we do not herein show the nested regression models (e.g., including only crop cluster or only farming practices as independent variables). These may be found in Appendix G. Further, we do not intend that the odds ratios be compared among independent variables – only that their signs and significance be compared between the two dependents.

Both ordinal regressions provided significant results overall, as indicated by the likelihood ratio test (for weather rank, $X^2(19) = 44.101$, $p < .001$; for climate change rank, $X^2(19) = 53.622$, $p < .001$). With respect to specific drivers, the weather ranks were significantly associated with main or interaction effects of age, education, crop cluster[23], rainfall variability and crop residue burning. Most conspicuously, farmers who primarily grew irrigated crops were far less likely to prioritize weather (Figure 6.4). Maize farmers were more likely to prioritize weather in municipalities with more variable rainfall. Wheat farmers displayed the opposite tendency, but they only appeared in the upper two quartiles of rainfall variability and the effect was small. More educated farmers were more likely to prioritize weather, but there was a significant interaction between age and education (Figure 6.5):[24] middle-aged farmers were equally likely to prioritize weather regardless of education. Farmers who reported never burning their crop residues were much less likely to prioritize weather.

In contrast, the ranks assigned to climate change risk were significantly related to political identity, education and crop residue burning (Figure 6.3). Respondents who self-identified as politically liberal were more likely to prioritize climate change, overall, but this pattern was complicated by the interaction of political identity with education (Figure 6.6). Education did not have a significant main effect, but its interaction with political identity was significant: among conservative farmers, those who were more educated were significantly more likely to prioritize climate change, whereas the opposite was true for liberal farmers. Farmers who reported never burning their crop residues were far more likely to prioritize climate change. Farmers in the "mixed" crop cluster were significantly more likely to prioritize climate change, but the number of farmers in this category was too small to produce a significant effect for the crop cluster variable overall.

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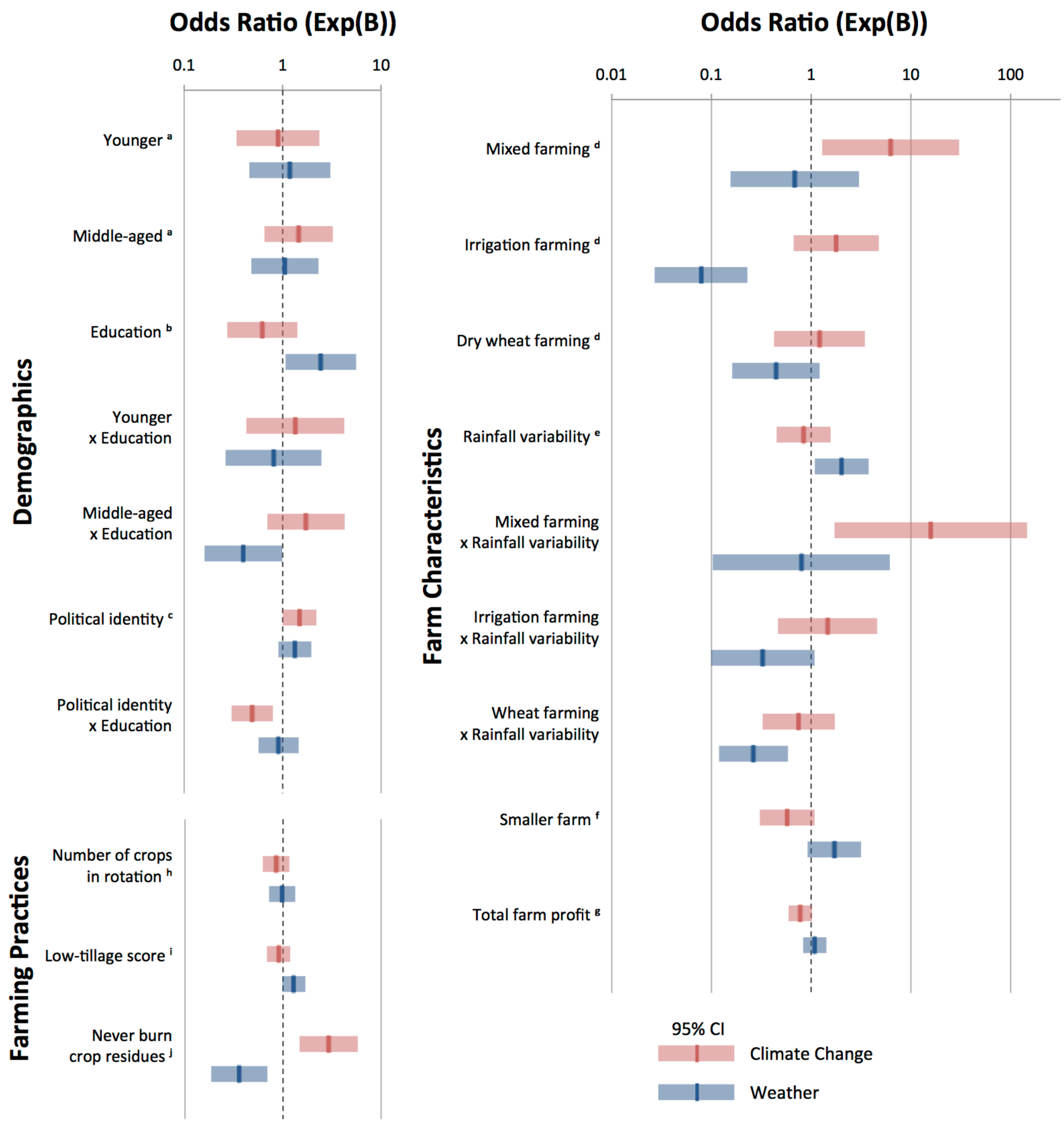
[23] While most of the independent variables stem directly from individual survey questions, the categorical "crop cluster" variable requires further explanation. It was derived from a cluster analysis of the different types of crops grown by each farmer, whether irrigated or non-irrigated. For instance, dry wheat farmers primarily grew rainfed wheat in rotation with other rainfed crops (e.g., barley, canola, oats, lucerne). These clusters broadly match known grain-farming patterns in South Africa, though the "mixed" cluster captures farmers whose major crops did not clearly fall into one of the three larger clusters (irrigation, dry wheat and dry maize). Farmers in the "no grain" cluster, who reported not growing any grain in the past year, were excluded from this analysis.

[24] For comparative purposes, figures showing other interaction effects may be found in Appendix G.

Figure 6.3: Odds ratio estimates for independent predictors of climate change rank (red) and weather rank (blue). These were obtained using ordinal regression (i.e., a generalized linear model with cumulative logit link) (n = 246). The dark lines show the mean estimates, while the shaded bars show the 95% confidence intervals. When the shaded bar does not cross the dashed line (Exp(B) = 1), the associated effect is statistically significant (p < .05). Interaction terms are indicated by an "x".



Independent Variables

[a] Age is an ordinal variable with three levels (recoded from six). Because its relationship with the dependent variables was non-linear, it was entered as a categorical variable, with "Older" as the reference category.

[b] Education is an ordinal variable with three levels (recoded from five), with values of -1 (no post-secondary), 0 (short post-secondary) and +1 (long post-secondary). It was entered as a continuous variable.

[c] Political identity is an ordinal variable with three levels (recoded from five), with values of -1 (conservative), 0 (moderate) and +1 (liberal). It was entered as a continuous variable.

[d] Crop cluster is a categorical variable with four categories, derived from a cluster analysis of major crops grown with and without irrigation. "Dry maize farming" is the reference category.

[e] Rainfall variability (coefficient of variation (CV)) is a continuous, standardized variable.

[f] Smaller farm is a binary variable, indicating that arable land area is less than 500 hectares. "Larger farm" is the reference category.

[g] Total farm profit is an ordinal variable with eight levels. It was standardized and entered as a continuous variable.

[h] Number of crops in rotation is an ordinal variable with four levels. It was standardized and entered as a continuous variable.

[i] Low-tillage score is an ordinal variable with five levels. It was standardized and entered as a continuous variable.

[j] Never burn crop residues is a binary variable. "Sometimes or always burn crop residues" is the reference category.

Figure 6.4: The effect of crop cluster on the rank assigned to weather. Error bars indicate 95% confidence intervals.

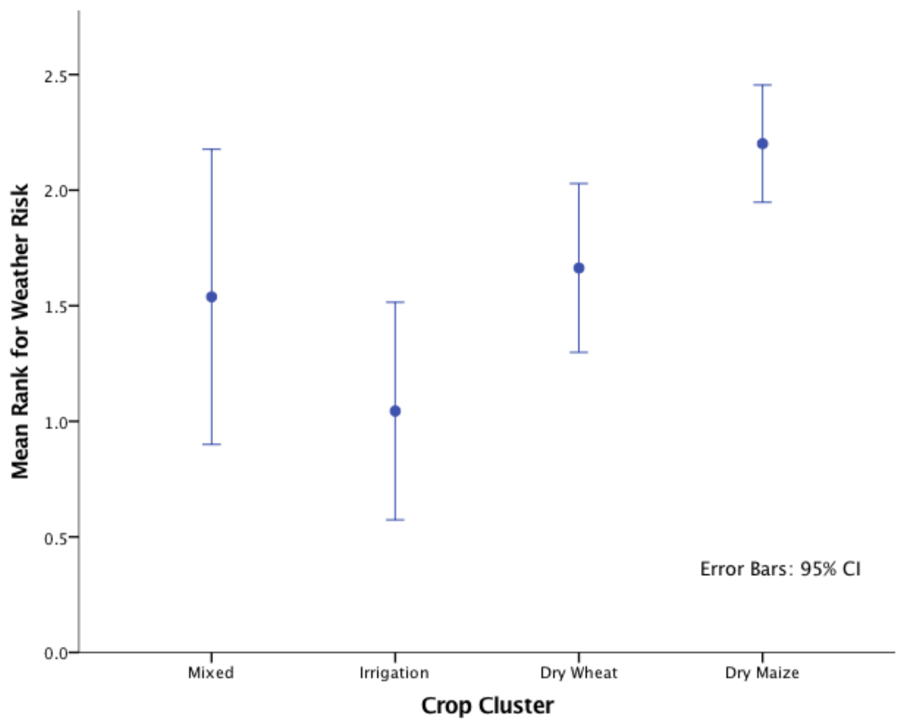


Figure 6.5: The interaction effect of age and education on the rank assigned to weather.

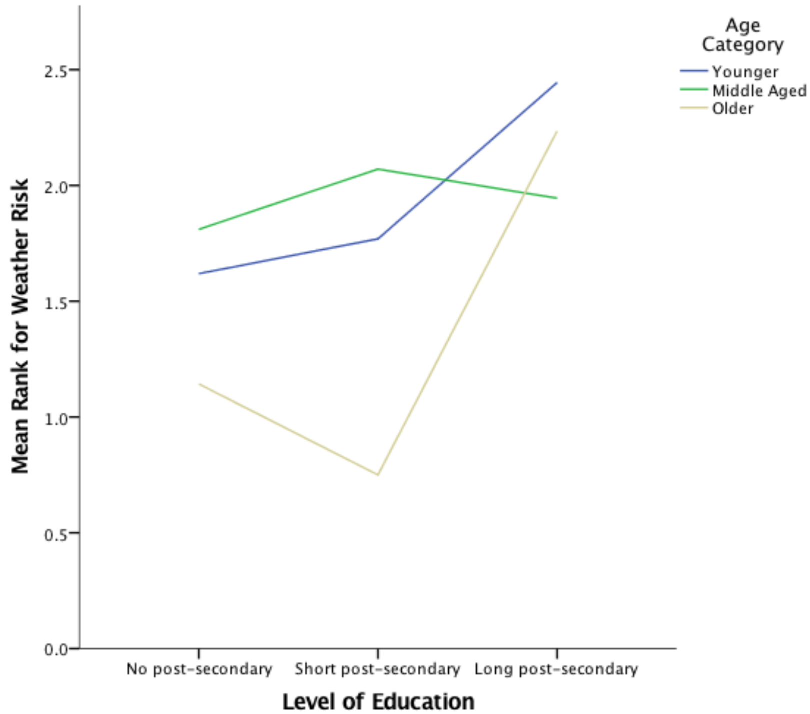
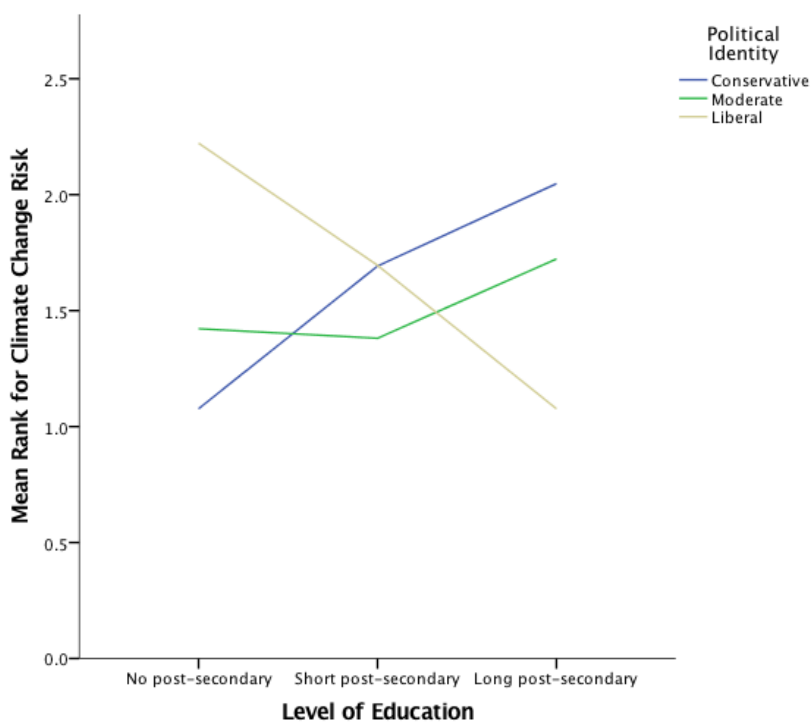


Figure 6.6: The interaction effect of political identity and education on the rank assigned to climate change.



6.5.3 Drivers of the distance between weather and climate change ranks

To explore possible reasons for the observed differences in the prioritization of weather and climate change, the distance between their ranks was modeled using multivariate linear regression. The regression model was significant overall, as indicated by the likelihood ratio test ($X^2(19) = 43.110$, $p = .001$). Most of the independent variables that were significant in predicting the ranks assigned to weather and climate change, separately, were also significant in predicting the distance between their ranks (Figure 6.7). For instance, irrigation farmers were more likely to rank climate change risks as having a higher priority than weather risks. Higher education was again significantly associated with a higher rank for weather risks over climate change risks among younger and older farmers, and not among middle-aged farmers (Figure 6.8). However, political identity was not significant in predicting the distance between ranks, despite being significant in the separate analysis of climate change. Similarly, rainfall variability and its interaction with crop cluster were not significant in predicting the distance between weather and climate change ranks, though they were significant in the separate analysis of weather.

Overall, differences that were observed in the drivers of weather rank and climate change rank, when analyzed separately, persisted and were often amplified when they were analyzed together. The effects of individual predictor variables on climate change rank were often opposite to the effects of the same variables on weather rank – of the 19 main and interaction effects, only five were of the same sign for both dependent variables. For variables whose coefficients had opposite signs, the net effect was greater when predicting the distance between the weather and climate change ranks. For instance, the effect of farm size was not quite significant in the separate regressions ($B = -.56$, $p = .09$ for climate change; $B = .54$, $p = .09$ for weather); however, it had opposite effects on weather and climate change, and it was therefore significant in predicting the distance between their ranks ($B = -.94$, $p = .01$). Farmers with smaller arable land areas (less than 500 ha) were more likely to prioritize weather and less likely to prioritize climate change, whereas the opposite was true for those with larger farms. Similarly, the effect of crop residue burning was amplified in the joint analysis because of its divergent effects in the separate analyses. Farmers who reported never burning their crop residues were far more likely to prioritize climate change over weather than those who sometimes or always burned their residues.

Figure 6.7: Parameter estimates for independent predictors of the distance between the ranks assigned to climate change and weather. These were obtained using multivariate linear regression (i.e., a generalized linear model with identity link) (n = 246). The dark lines show the mean estimates, while the shaded bars show the 95% confidence intervals. When the shaded bar does not cross the dashed line (B = 0), the associated effect is statistically significant (p < .05). See above for notes on the independent variables, indicated by letters in superscript. Interaction terms are indicated by an "x".

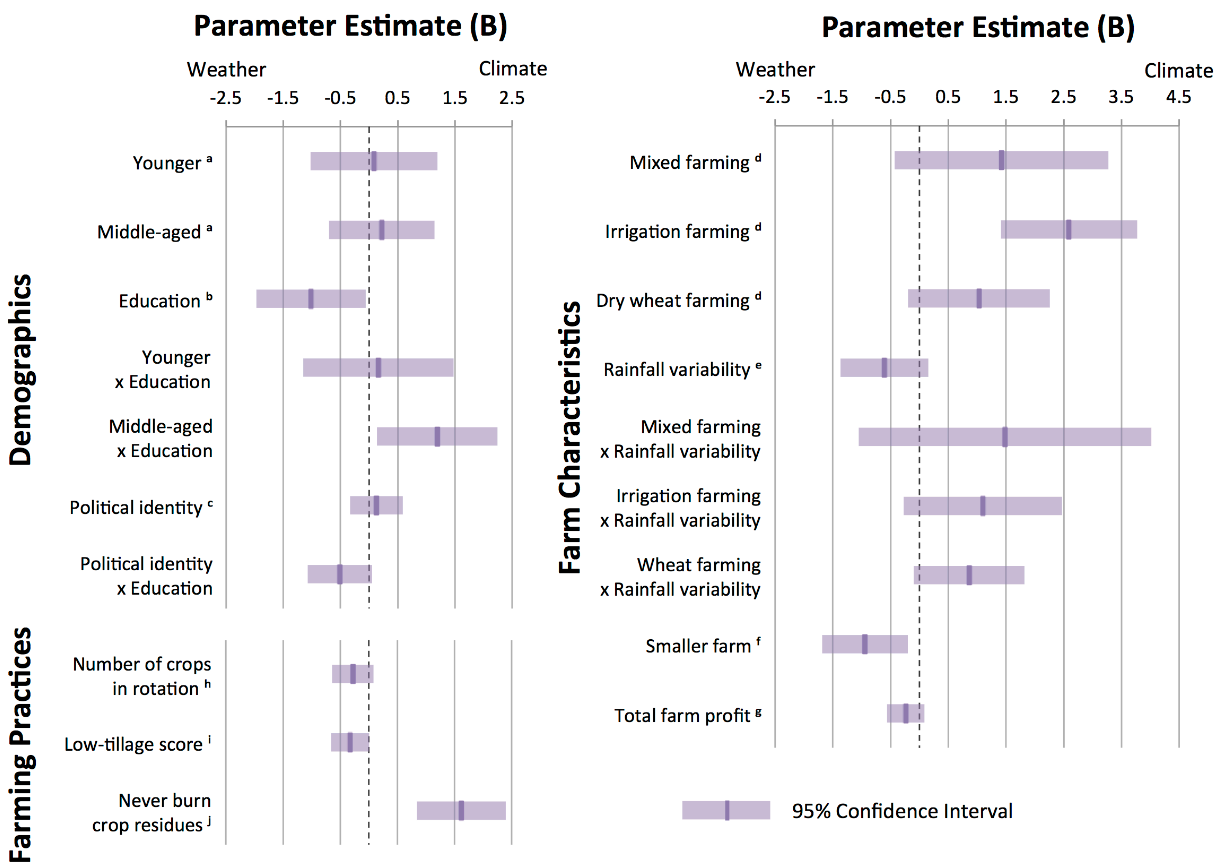
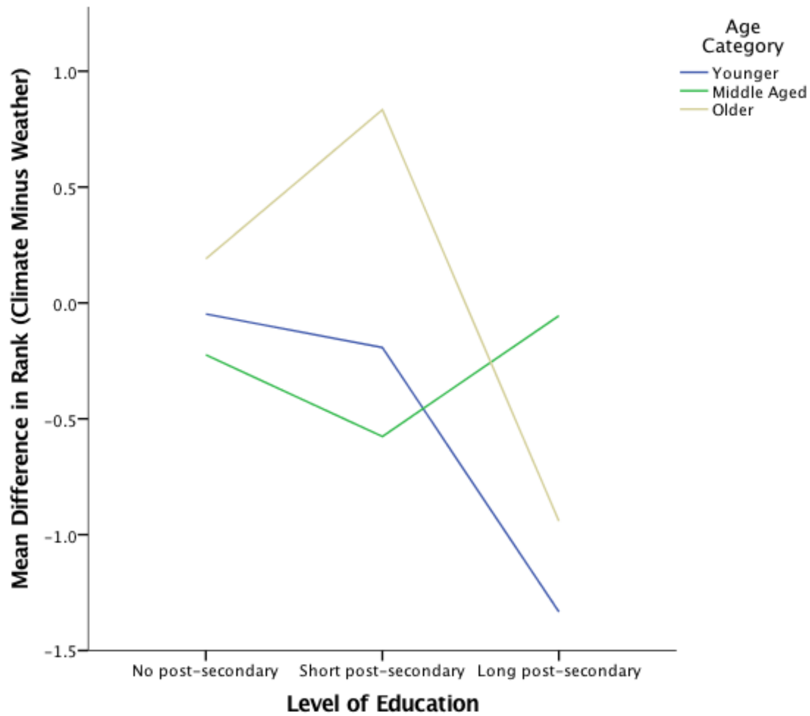


Figure 6.8: The interaction effect of age and education on the distance between the ranks assigned to climate change and weather.



6.6 Discussion and conclusion

Overall, the patterns of selection of weather and climate change as high-priority risks suggest that many individual farmers think about weather and climate change differently. That is, rather than being equivalent and so substitutable, perceptions of weather and climate change risks appear to be distinct, and in some regards, oppositional. Climate change and weather are not similarly prioritized, their risk perceptions are driven by different factors, and all of the variables that are significantly associated with both risk ranks have effects on the two that are of opposite sign to each other. These apparent differences persist and are often magnified in the linear regression model predicting the distance between their assigned ranks. Hence, farmers do not simply perceive climate change adaptation to be an extension of existing weather risk management practices.

The significant effects of the independent variables are broadly aligned with previous qualitative findings:

- Notably, irrigation farmers are insulated from weather risks because their crop production is not restricted by short-term water shortages. However, they are as equally concerned about climate change as non-irrigation farmers, perhaps because they recognize the potential for long-term water shortages to affect their water rights or physical access to stored water.
- While higher rainfall variability makes farmers more sensitive to weather risks, it does not appear to affect their sensitivity to climate change.
- Farmers with smaller arable land areas are more likely to prioritize weather, while those with larger land areas are more likely to prioritize climate change. Our previous qualitative analysis (Chapter 3) suggests that farmers with smaller farms may prioritize more acute, short-term risks, because they tend to be more focussed on economic survival.
- Farmers who burn their crop residues are less likely to prioritize climate change, while those who do not burn their residues are less likely to prioritize weather. This is consistent with our previous finding (Chapter 4) that farmers who refrain from burning their crop residues perceive themselves as more agriculturally progressive and, by extension, forward thinking.
- Farmers who are more highly educated are more likely to prioritize weather, while those who have less education are more likely to prioritize climate change – except for middle-aged farmers, for whom the effect is negligible. This effect is as yet unexplained and warrants further study. Our previous qualitative analysis suggests the possibility that more highly educated farmers perceive themselves as better able to manage the effects of climate change through changes in practice (Chapter 5).

Overall, these quantitative results reinforce the qualitative findings of our previous study of farmer mental models of environmental risk, in which we found that participants may access different mental models of when discussing either weather or climate change (Chapter 5). Farmers' objective capacities to adapt to climate change are determined by their level of education, their climate-specific knowledge, and the resources at their disposal (i.e., financial, institutional, technological). However, their *likelihood* of adapting is determined by their perception of climate change, and its integration into the existing decision-making processes that they use to manage myriad overlapping risks towards competing objectives. In combination with our previous findings (Chapter 5), the results of this study suggest four important drivers of the differential perceptions of weather and climate change: short- versus long-term risk orientation; self-perceived adaptive capacity; tension between experiential and expert knowledge; and individual worldview. Policy-makers should treat smaller commercial farms differently – these farmers appear less likely to respond to climate change risks. Education matters, but not quite as expected, requiring further investigation to examine the interplay of social learning with expert and experiential knowledge.

Across diverse adaptation studies – by economists, geographers, sociologists and climate scientists – there is an implicit assumption that climate change adaptation will occur as an equivalent, long-term extension of the processes by which farmers perceive and respond to weather and climate variability. The assumption of equivalency is applied both by those who argue that farmers need no help adapting and by those who argue that farmers need strong public support: given enough education, technology, resources and time, farmers will adapt to climate change as they have always adapted to weather. Though there is a strong literature on similarities and differences in the psychology of weather and climate change among broader publics, few adaptation studies have explicitly recognized that the psychology of weather and climate change may differ for individual actors. As shown here climate change and weather are not similarly prioritized, and their risk perceptions are driven by different factors. Overall, the findings provide confirmatory evidence that farmers perceive and process climate change risks differently than they do those stemming from weather and climate variability. They are therefore likely to respond to them differently.

As implied in Chapter 5 and corroborated in this paper, there is a crucial and unrecognized risk communication challenge for adaptation researchers and policy-makers. Experts' understandings of climate change risk perceptions are misaligned with those of farmers. This is in part because the nature of climate change knowledge (i.e., expert-driven, long-term, deeply uncertain) triggers the use of mismatched cognitive frames. These alternative frames are evident both in the qualitative ways in which farmers speak of weather and climate change, and in the quantitative ways in which they prioritize one over the other. Researchers and policy-makers should not assume that farmers will treat climate change risks as an equivalent, long-term extension of risks stemming from weather and climate variability, and that they will therefore integrate weather and climate change risk management with ease. The fundamental changes in farming practice that might be needed for climate change adaptation operate on generational timescales, requiring experiential and technical knowledge, advanced planning, incremental experimentation, and access to trusted sources of information, new technologies and capital. Researchers and policy-makers might better facilitate mainstreaming by communicating the everyday similarities of climate change impacts to normal risks, as opposed to emphasizing their novelty. The hope is that by overcoming climate change's cognitive challenges now, farmers will be better able to solve its practical challenges in the long term.

Chapter 7: Conclusion

7.1 Summary of key findings

Each chapter has built on the findings of those previous to provide broader insights into farmers' climate-adaptive behaviours. In the first three empirical chapters, I sought to understand climate-as-usual behaviours: How are farmers sensitive to weather risks? In Chapter 2, this involved a characterization of the risk-based decision-making strategies by which farmers manage weather and climate variability in concert with other 'normal' risks. These messy and sometimes contradictory processes are the engine driving all of the risk perceptions and risk-mitigating responses described in subsequent chapters. I proposed that farmers are using two important heuristics to make trade-offs within and between domains of risk – hazy hedging and bounded trade-offs – and argued that these rough trade-offs are used to coordinate among the different cognitive frames that farmers use to perceive and respond to different risks, and to make progress towards concurrent objectives. In Chapter 3, I demonstrated that farmers apply different frames in the management of similar risks, evident in the language they use to describe weather and climate change problems, cascading effects and their own responses. I found that the use of particular frames inhibits longer-term risk management strategies for farmers who are acutely concerned with shorter- to medium-term risks to farm survival. In Chapter 4, I showed that there are important challenges in using CA as a concept by which to frame the promotion, adoption and monitoring of sustainable and climate-resilient farming practices. Farmers are not adopting CA as expected, and their definitions of conservation farming are at odds with experts' definitions of CA.

In the last two empirical chapters, I examined more closely the relationship between weather and climate change in farmers' risk perceptions and risk management: How is farmers' sensitivity to climate change risks different from their sensitivity to weather? In Chapter 5, I demonstrated that the mental models that farmers use to perceive and respond to climate change risks are isolated from those with which they address weather and other 'normal' risks. These mental models are linguistically and structurally distinct, with few interconnections between climate change and 'normal' risk management. I argued that this was indicative of their use of expert-driven cognitive frames for climate change that were misaligned with those driven by social and experiential learning that they apply to weather and other 'normal' risks. Finally in Chapter 6, using another method with a larger sample, I again showed that farmers do not think of climate change and weather in equivalent ways. I argued that climate change risk communication efforts will fail if experts continue to assume such equivalency, and that farmers are unlikely to respond effectively and efficiently if the cognitive frames that they apply to climate change continue to be driven primarily by imparted expert knowledge.

I have thus demonstrated that misaligned frames are creating cognitive and communication challenges in farmers' attempts at climate-adaptive behaviour. These misalignments create reciprocal and multi-faceted miscommunication that explains in part why local experts perceive farmers to be climate-insensitive, despite their explicit weather sensitivity and adoption of CA. In risk communication and agricultural extension, differences in the ways in which farmers and experts think and talk about weather, climate change and agricultural practices have built under-recognized barriers. Climate change experts generally agree that farmers ought to treat climate change risks as an equivalent long-term extension of weather risks, but farmers do not presently perceive them as such. In parallel, experts in agricultural practice agree that farmers ought to adopt CA as a package, but farmers are not generally doing so and use different "conservation"-related concepts that impede CA's promotion, adoption and monitoring. In farmers' mental models of 'normal' risks, the adoption of CA as an economically and ecologically sustainable set of farming practices is limited unexpectedly by farmers' use of cognitive frames steeped in anxiety about the survival of the farm. Further, farmers' climate change knowledge is largely excluded from the mechanisms of social and experiential learning that they use to improve their management of weather and other 'normal' risks. Climate change risk management is thus isolated from the processes of incremental experimentation that ultimately underlie generational shifts in farming practice. In combination, these findings suggest that farmers are less likely than previously thought to perceive and respond to climate change risks, broadly, and climate-adaptive agricultural extension efforts, specifically.

7.2 Strengths, limitations and lines of future inquiry

These analyses powerfully demonstrate the complementary strengths and weaknesses of qualitative and quantitative methods. The indirect mental modelling approach allowed for the analysis of emergent and in situ patterns of risk perception and response that would not have been captured by, let alone evident in, more direct and explicit methods of data collection. However, the method does not allow for the direct observation and rigorous analysis of constrained processes, and it remains under-sensitive to emotional facets of decision-making. Narrower and more quantitatively-oriented exercises will be necessary to further delineate the decision-making heuristics proposed in Chapter 2, to explicate the framing effects described in Chapter 3, and to parse the isolation of climate change logics as observed in Chapter 5. In parallel, affective approaches will be necessary to more deeply understand the role of family and place in shaping risk perceptions and farming practices, evident here in the anxiety about farm survival described in Chapter 3, and in the greater prevalence of emotional language in farmers' mental models of climate change, described in Chapter 5. The survey methods used in Chapters 4 and 6 allowed for more rigorous statistical analyses, but were also necessarily superficial in their treatment of cause, effect and context. The larger sample sizes and quantitative methods enabled by the survey provided better opportunities to parse the findings along specific continua (e.g., the risk rankings), but simultaneously limited the depth of their interpretation. The discussions in the narrower survey-based chapters therefore relied heavily on the broader findings of the interview-based chapters.

Ultimately, my goal was to offer empirical evidence that could describe and make replicable the qualitative and quantitative methodologies applied herein. Researchers inevitably introduce bias in identifying and selecting problems, cases and methods of inquiry, alongside the more discernably subjective nature of the ways in which they frame the data and its implications. I have thus attempted to make these inquiries as transparent as possible to allow for critical interpretations and re-interpretations of my results. Such research, I would argue, is the backbone of evidence-based policy-making. Rigorous and replicable qualitative methods are particularly difficult and time-consuming to apply. The mental models design, implementation, coding, analysis and interpretation took far longer than expected, leading to repeated delays in the completion of this doctoral work. The more widespread application of such methods will absolutely require the development of computer-assisted tools to collect, parse and analyze the internal representations of reality that are so crucial to in situ decision-making processes that are shaped by the detailed, challenging and varied cognitive and social environments in which they occur.

Nuances in the observed climate change risk perceptions derived from contrasting methods – the mental models interviews and the online survey – strongly suggest the need to develop survey methodologies that illuminate the use of different cognitive frames. The malleability of participants' mental model-derived climate change risk perceptions, the contradiction evident among some aspects of belief, concern and observed climatic changes, and the isolation of climate change logics from those of weather suggested that farmers might be accessing different mental models to think about climate change under different circumstances (e.g., unprompted versus prompted). This implies that explicit climate change risk perceptions measured using Likert-scale survey questions will not necessarily be those that climate-sensitive respondents apply in interpreting and reacting to direct stimuli. This is further evidenced in my use of both risk ranking and Likert-scale questions to measure climate change risk perceptions in Chapter 6. The risk ranking exercise had much more analytical utility; the Likert-scale answers were significantly correlated with the ranks assigned to climate change, but this correlation was too weak to observe significant drivers of risk perception (i.e., demographics, farm characteristics and farming practices) akin to those found in the analysis of the climate change ranks. This misalignment of more explicit and less explicit measures suggests that survey methodologies seeking the direct elicitation of climate change risk perceptions through Likert-scale or similar questions will tend to overestimate the relevance of this data to the in situ practice of risk-based decision-making.

These results show that these farmers do not think about climate change and weather in similar ways, and that their perceptions of and responses to environmental stimuli are enmeshed in messy webs of risk management towards concurrent and competing objectives. This large group epitomizes the autonomous private actor and provides key insights into the climate-adaptive behaviours of individuals. The challenges that they face in responding to climate change risks strongly imply that other groups will encounter similar difficulties. For instance, subsistence farmers, who tend to have less education and restricted access to informational, financial and institutional resources, are likely to be even more constrained in their ability to recognize climate change and weather as distinct risks while managing them in concert. Similar cognitive barriers may well exist among decision-makers in institutional settings, but their symptoms are likely masked by the explicitly calculated and structured nature of many institutional processes.

However, individuals are ultimately at the heart of all climate-sensitive decisions. We would do well to recognize that the quirks of human judgment and decision-making will inevitably shape climate-adaptive responses at all scales. We must give more thought to the ways in which real-world adaptation and resilience are impeded and enabled by these cognitive processes.

7.3 Final thoughts on "adaptation"

Just as the linguistic expression of cognitive frames shaped risk-mitigating responses in Chapter 3, so does the conceptual framing of climate change adaptation shape climate-adaptive responses more broadly. The circumscribed concept of climate change adaptation was conceived in dichotomous opposition to climate change mitigation. It laid bare the need to respond to climate threats by revealing their costs (or harms) if mitigation was delayed. Yet responses to climate change impacts are complex and difficult, impeded by social, institutional and cognitive barriers. Even in climate-exposed sectors the climate signal is diffuse, filtered through complex webs of perceived causation. The adaptation concept is prescriptive – it implies rational adjustments to a known risk that is implicitly separate from other stressors (Basset & Fogelman, 2013). It thus promotes a fundamental misunderstanding of the processes underlying human responses to climate change effects, rendering climate change risks oblique and theoretical.

The "need" to adapt is nothing new. When has adaptation not been a central theme in the human enterprise? There is thus a growing understanding that the concept loses much of its meaning beyond its natal dichotomy. In their systematic review of observed adaptations captured by the peer-reviewed and grey literature, Ford et al. (2011) found plenty of evidence of the reorientation of conceptual frames towards "adaptation", but little evidence of "adaptive" actions. Where they exist, they are invisible to superficial analyses that fail to recognize the multi-faceted and multi-causal nature of real-world decision-making processes. Even the IPCC's own documentation has begun to speak more of resilience-building and transformation, rather than adaptation (IPCC, 2014). On the other hand, academic definitions of concepts and terminology have often, if not always, diverged from lay (or "common") definitions. If researchers understand each other and can, in collegial deliberation and through their influence on public policy, improve societal responses to climate change impacts, then in some circumstances it may not matter whether their specific meanings cohere with those held by society more broadly.

However, for climate change risks in particular, it is crucial that expert and lay understandings cohere, since risk-mitigating responses will span the full breadth of the contexts in which humans operate. In most such decisions, experts will have little direct influence.

The tensions among expert and lay framings have been evident throughout the empirical results presented in this dissertation. We now know that farmers do not necessarily think of weather and climate change in similar ways. Climate change has generated a cognitive branch largely disconnected from other processes of risk management, and weather and climate change are explicitly prioritized in different ways. But climate change is likely to manifest primarily through increasingly risky weather and climate variability long before the changes in mean precipitation and temperature are noticeable in practice. We do not yet know how best to help farmers reintegrate climate change risks with those of weather and other 'normal' risks, though my results suggest that climate change learning is better treated like other risks, emphasizing experience and experimentation. As farmers experience specific weather events, we might help them to understand how these stressors may have been exacerbated by climate change, or might be so magnified in the future. Even if we cannot attribute specific phenomena to climate change, we can thereby help farmers to interpret environmental signals through a climatic lens, and enable them to apply their well-honed skills in social and experiential learning to this new but altogether familiar problem.

Narrative Epilogue

My eyes open to the dusky promise of dawn, the hearth at my side still warm with the memory of flame. My new home is comfortable and familiar. I have shaped it, and it has shaped me in turn. I know well its nooks and crannies. I see charm in its Whims and Quirks. Yet something tickles at the nape of my neck, the suggestion of an itch long forgotten. My thoughts trace the paths along which I arrived so fortuitously at this tranquil moment.

A smile dances at my lips as I relive my slip-turned-somersault down the Slopes of Self-Sabotage, my daring climb from of the Sinkhole of Simplistic Solutions, my gritty march through the Dunes of Dreadful Determination, and my bold charge across the Meadow of Misunderstood Metaphors. Never have I felt so alive as when leaping from the Cliffs of Collegial Calamity into the Pool of Principled Pragmatism, ravenous hordes of the Great Scholars' disciples nipping at my heels.

My head turns as Curiosity calls from the open window,
its melody luring me back to the untraveled road.
At first light on dewy Hope, I set out anew.

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Appendices

Appendix A: Writing for a general audience during exploratory fieldwork

These three fieldwork-oriented blog posts and two research backgrounders were written in fulfillment of the requirements of the fieldwork grant that I received from the Centre for International Governance Innovation (CIGI). The blog posts are no longer available online, but the backgrounders may still be found online at the time of this writing (https://www.africaportal.org/dspace/authors/findlater-kieran). They are here reproduced with the explicit permission of CIGI staff, obtained by email on 23 January 2017. As requested by CIGI, the backgrounders are unaltered and are included in their entirety.

A.1 Studying Climate Adaptation in South Africa's Dynamic Policy Landscape (13 July 2012)

CAPE TOWN – South Africa is a vibrant land, boundless in spirit, buoyed by nearly two decades of release from repression and segregation, yet still suffering deep scars and facing daunting challenges that threaten its future success. In myriad facets, its striking diversity and bold experiments in new governance provide rich fodder for the inquisitive mind to critically evaluate its dynamic policy landscape.

My first path to South Africa was serendipitous. Following graduation from a wide-ranging B.Sc., I spent months each spring applying for countless youth internships sponsored by the Canadian International Development Agency, hoping to get the international work experience that would give me a sheen of credibility in applying to internationally-focused, research-based Master's programs. Undaunted by my meager Spanish, my goal was South America; Africa was not on the radar.

It was then a bittersweet morning when I finally woke to not one, but two offers: New Caledonia or Pretoria. A tropical paradise of coral reefs and sandy beaches, or an unknown city high on the South African plains, bordering a megalopolis reputed to be one of the most dangerous in the world. Why not the more challenging option? Not for one moment have I regretted that decision. South Africa is arguably one of the most interesting policy making contexts in the world.

South Africa's grand experiments in governance, rich cultural diversity, and enormous socioeconomic and environmental challenges provide limitless opportunities for policy-relevant research. Post-Apartheid South Africa may indeed be unique in the scale of its policy projects – where else has a country undertaken such dramatic changes in governance with such rich human, economic and institutional resources in such a short time?

Major challenges (PDF) in health, water, land, energy, housing, education, employment, crime and economic disparity have prompted sweeping and innovative reforms. While some have yielded promising results, historical geographies and rapid urbanization continue to thwart policy-makers' best intentions. Such a fundamental re-imagining of the country's constitution and governance has inevitably encountered setbacks, but the government appears to remain committed to progressive and reformative acts. The country's policy landscape remains highly dynamic, making insightful and policy-relevant research crucial to the success of current and future governance.

Now pursuing a Ph.D., I have been inexorably drawn back to South Africa after five years away. My focus is on energy technologies and adaptation to climate change. In a country where water resources have already been over-allocated in many catchments, climate change is predicted to further stretch the government's ability to manage the competing needs of consumers, farmers, industry and thermal power plants. Simultaneously, the country's post-Apartheid water and land reform programs are providing new entrepreneurial opportunities to thousands of previously disadvantaged farmers.

Unfortunately, these emerging agriculturalists are suffering from significantly lower productivity than their long-established counterparts, in part because they have less expertise and fewer resources at their disposal. In a country where nearly 90 percent of electricity is generated in coal-fired power plants and electricity tariffs are rising to pay for long-delayed new generating capacity, renewable energy technologies may provide part of the solution. This would allow emerging farmers to affordably and reliably access the groundwater to which they have rights, without depending on an increasingly overextended power sector. South Africa's water-energy relationship is of acute importance, yet is just one of many pressing issues demanding innovative governance.

Fortunately, while the vibrant optimism of the post-apartheid Mandela era has, in some quarters, given way to pragmatism or cynicism, South Africa retains an undercurrent of willful determination. It is crucial that we bear witness to this transformation and enable solutions to these challenges – both so that South Africans may evaluate their own governance and for the country to lead by example as the continent's most powerful economy.

A.2 Climate Change Adaptation: Business-as-Usual (27 August 2012)

CAPE TOWN – When adaptation is business-as-usual, it's very difficult to tease out the climate change thread. But people are always willing to talk about the weather!

Climate has been both the subject of my inquiry and a nagging nuisance, tugging at my coat and my mind. Cape Town can be cold, rainy and windy in the winter. Having grown up in Saskatchewan (sometimes reaching minus forty degrees Celsius on the coldest winter nights) I feel a bit treacherous in saying so, but the chill of the Capetonian winter has seeped into my bones. Without Canadian-scale insulation and central heating, ten degrees here has far more impact on my lifestyle and state of mind than did ten degrees at home.

Climate has proven less forthcoming in my work. Climate change will definitely have an impact on the operations of South Africa's farmers, yet it is interwoven with existing risks with which farmers have had to deal throughout their careers. Some risks from climate change are unique, but many are already factored into agricultural decision-making. In the Western Cape, climate change is expected to reduce rainfall and surface water availability, yet farmers there have dealt with water scarcity and competing water user demands for centuries. These competing demands have not been static – total demand and relative prioritization are dynamic variables. In this sense, farmers have continuously adapted to changes in climate-linked risks, because those same risks are well linked to other drivers, including weather, input costs, availability of financing and market fluctuations.

Of course, these complexities are not unique to the study of climate change adaption. Research design necessarily accounts for such confounding factors. The difficulty in separating them is simply multiplied when using semi-structured interviews to characterize the system and risks. In each interview, it takes time, patience, and a bit of artistic flair to find an honest answer to the question you wish answered, without asking it directly. And each interview is unique; the same technique and style will not work over and over again. Instead it must be adapted– through sensitivity to verbal and non-verbal cues, self-reflection, experience and flexibility.

Instead of approaching climate change adaptation directly, I've therefore opted to investigate the adoption of practices associated with conservation agriculture, both in terms of motivations and outcomes. Such adoption is happening now among a growing set of large-scale commercial farmers in South Africa, and will increase their resilience to the impacts of climate change. I hope to learn lessons that will contribute to policy development to support them in this shift and to provide small-scale farmers with the resources and knowledge necessary to adopt similar practices where suitable.

Of course, with weather as wacky as it has been this winter, people aren't shy to talk about increasing climate variability. Earlier this month, South Africa had snow in all nine provinces simultaneously for the first time in recorded history! The major national highway between Durban and Johannesburg was closed for days and the army was called upon to rescue stranded motorists. Not something that one would normally expect while working in Africa.

As I write this from a coffee shop in the Southern Suburbs, another fierce storm has rolled across Table Mountain, rattling the windows and viciously lashing the city with sheets of rain. I'm thankful for the roof over my head, and I'll put on another sweater.

A.3 Rebooting Fieldwork: the Upside of Failure (31 January 2013)

CAPE TOWN – I failed.

My proposed research project evaporated almost immediately upon my arrival in South Africa, the unintended victim of the shifting research priorities of my local partner. I immediately booked meetings with all of my local contacts. Was the project still feasible? With another partner? A different study site? Where and with whom?

Despite the obvious and overwhelming challenges, however, failure can provide a healthy dose of opportunity — a crucial breath in which to boost the relevance and impact of your work. Fieldwork is so intensive that many benefits are easily lost in the race to gather data. It is too often portrayed solely as a means of data collection, when in truth it provides myriad opportunities for learning, self-reflection and interaction that can dramatically alter your perspective. It is an intensive education requiring months to fully process – a sensory smorgasbord replete with informal learning experiences: lectures; critical discussions; endless evolving presentations; and lonely angst-filled nights in which to ponder your purpose.

Fieldwork is simultaneously the most stressful and most rewarding experience for graduate students. At no other time in a Master's or Ph.D. program will you have an experience as rich, dense, exhilarating, confusing, prolific, challenging, fascinating and all-consuming. Pulled from the relative familiarity of coursework and proposal writing, you are thrust forth to grapple, largely unaided, with innumerable trials demanding determination and flexibility.

Those profound research questions you so painstakingly crafted, word-by-word, during months of preparation? That informative and transformative methodology you lit upon half-asleep at 3:00 am, gently nursed from brief spark to bright flame? The mutually beneficial partnerships that you negotiated through conscientiously structured e-mails and well-enunciated video calls? Throw them upon the mercy of the unsympathetic unknown — comfort and encouragement are now distant, electronic, impersonal shadows of their former selves.

Having previously worked in South Africa, and with positive feedback from my local contacts, I arrived in 2012 with a measure of confidence in my proposed project. But after speaking with upwards of 80 experts and stakeholders, I have since concluded that my original proposal was neither well attuned to the needs of local decision-makers, nor would it likely have had a significant impact on the well-being of my participants. I would, of course, have attempted to adapt both the methodology and the dissemination of results to increase its relevance and impact, but my awareness of the shortcomings of the study would likely have accrued much later in the trip, and would have been incorporated with more difficulty.

Distantly-designed research has serious potential weaknesses — the most conscientious of scholars is shackled by the topical limitations and timeliness of the literature, the relevance and scope of their past experiences, and the effort committed by their local partners in helping to plan the project. There is no substitute for the direct input of local experts and stakeholders to ensure your research questions truly speak to substantive problems or priorities; they should be as relevant in the harsh light of day as they are in Times New Roman.

Though most students will incorporate some element of local expertise in the planning of their study, constraints on time and funding will normally limit this to a small sample of partners prior to departure or to pilot interviews immediately upon arrival. Early context-specific feedback from local experts and stakeholders is particularly important for graduate students, since we are more likely than seasoned researchers to be flexible, agile and receptive to new input. Of equal importance, these interactions strengthen the perceived legitimacy of the work, build awareness of the underlying problems, engage policy-makers and create a sense of investment among stakeholders – all of which help to increase the impact of the study's findings or recommendations.

In the end, my research in South Africa had greater stakeholder involvement in planning and execution than expected, with a stronger sense of investment by my newest partners and more potential for impact on policy and practice. Fieldwork failure will never be intentional — it creates staggering challenges and has a devastating effect on morale — but it can enable a depth of immersive understanding and a breadth of local participation that are otherwise elusive.

A.4 The Complexities of Climate Change Adaptation in South African Agriculture (Backgrounder No. 50)

AFRICAPORTAL
a project of the africa initiative

BACKGROUNDER
NO. 50 > JANUARY 2013

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THE COMPLEXITIES OF CLIMATE CHANGE ADAPTATION IN SOUTH AFRICAN AGRICULTURE

KIERAN FINDLATER

SUMMARY

- Agriculture is a complex and politically contentious industry in South Africa, given its connection to food security, water, health and land reform, and the historic resource imbalances between black and white farmers.
- As a large country with many fully allocated water basins, different parts of South Africa will face unique challenges related to climate change.
- Given the varying levels of adaptive capacity between large-scale commercial operations and emerging smallholder farms, South Africa's national policy response must be prioritized to ensure cohesive and nuanced support for climate change adaptation.

BACKGROUND

Given its wide-ranging impact on food security, water, health and land reform, the strength of South Africa's agricultural sector is of strategic importance to the nation (Republic of South Africa [RSA], 2011a). As a climate-dependent industry in a water-scarce region, however, South African farming is also vulnerable to the variations in weather patterns associated with changes in global temperatures.

Although the agricultural sector is dominated by industrial farming operations, small-scale and subsistence farmers are of outsized political importance — a reflection of national redress policies following the end of Apartheid (Atuahene, 2012; Lahiff and Cousins, 2005). As compared to small scale farmers, commercial farmers have greater resources at their disposal and tend to not only be more resilient to climate variability ,but also better equipped to adapt. (Challinor et al., 2007). Since each group has different tool adaptation sets,

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however, differentiated support policies are also required to deliver effective programs in response (Wreford et al., 2010).

CLIMATE CHANGE IN SOUTH AFRICA

South Africa is considered a semi-arid country, receiving an average of only 450mm of precipitation per year. High temporal and regional variability in rainfall results in scarce surface and groundwater resources, which are already fully allocated in many basins (RSA, 2011d). Exacerbating this sensitivity, Kruger and Shongwe (2004) suggest that South Africa has experienced measurable warming since the early 1980s, with higher mean temperatures that result in greater heat stress and higher rates of evapo-transpiration — the sum of evaporation and plant transpiration from the Earth's land surface to atmosphere.

Future precipitation trends are less certain, though broad patterns can be considered likely. In keeping with existing regional variability, South Africa is expected to experience regional differences in future precipitation change. Most of eastern South Africa, roughly coinciding with the summer rainfall area, is expected to experience similar or increased median precipitation, becoming more variable and resulting in frequent and more severe flood and drought events. In contrast, the country's winter rainfall area, in the west, is expected to experience a significant decrease in precipitation (RSA, 2011d).

These changes in temperature and precipitation patterns are projected to affect South African agriculture directly through changes in rainfall, temperature and CO_2 fertilization, and indirectly via changes in the incidence of pests and disease, and loss of ecosystem services such as pollination (Smit and Pilifosova, 2007). Both challenges will require adaptation in agricultural systems and cropping patterns to ensure the sector's stability and the country's food security.

ADAPTATION IN SOUTH AFRICAN AGRICULTURE

South African farmers are necessarily adaptive as they face variable weather. It is therefore difficult to distinguish between climate change adaptation and routine actions that increase resilience to climate variability. Unplanned adaptation is likely to occur spontaneously and privately, with decisions taken at the farm level in response to weather trends and short-term forecasts (Thomas et al., 2011; Wreford et al., 2010). The nature and success of these private responses may have important national and regional implications for food, water, energy and land reform. Cohesive public policies are therefore needed to align private adaptation (both spontaneous and planned) with national priorities in these related sectors (Howden et al., 2007).

The scarcity of South Africa's freshwater resources contributes to the country's agricultural vulnerability. There is little capacity, for example, to increase the amount of water used for irrigation to help mitigate increased evapotranspiration and heat stress. While agricultural land accounts for 82 percent of the South Africa's total land area, only 1.3 percent of agricultural land is under irrigation, with the remainder dependent on rainfall (RSA, 2012). Despite the small proportion of irrigated land, however, the overall agricultural sector accounts for 62 percent of the country's water withdrawals while irrigated lands generate 30 percent of the gross value of South African crop production (RSA, 2011d).

The enormous diversity of South Africa's agricultural sector makes it difficult to characterize typical adaptive capacity and strategies. The sector includes large-scale commercial producers, either under private or corporate ownership, and small-scale farmers, with either subsistence or emerging commercial aspirations (Thomas et al., 2011). Because large-scale producers have more substantial resources, larger cash flows and greater diversification, they typically have much longer planning horizons and are able to access credit, make capital investments and respond to market fluctuations. Small-scale producers typically have fewer resources and less diversification, requiring much quicker returns on investments and increasing vulnerability to short-term market fluctuations (Wreford et al., 2010).

Large and small-scale farmers therefore adapt to climate changes using very different strategies. The commercial sector may respond through technology development and adoption, crop shifting and diversification, insurance, and improved financial management, while small-scale farmers may respond through employment diversification, communal risk sharing and low-cost water-saving measures (Challinor et al., 2007; Wreford et al., 2010). Adaptation also involves both short-term and long-term components. Near-term strategies include changes in irrigation techniques, tilling practices, planting dates and crop varieties, while longer-term plans include technology and infrastructure investments, crop switching and diversification (Wreford et al., 2010).

POLICY IMPLICATIONS

The South African government has competing agriculture policy objectives. On one hand, the government would like to promote land reform — the transfer of land from historically wealthy commercial farmers to previously disadvantaged groups. For example, South Africa's National Development Plan for 2030 emphasizes the expansion of both dryland and irrigated agriculture, "beginning with smallholder farmers where possible" (RSA, 2011b). On the other, the government's National Climate Change Response Paper acknowledges that emerging farmers — recipients during the land reforms — are less resilient to climate change because they are resource poor and constrained in their ability to invest in longer-term planning (RSA, 2011a).

It is critically important that South Africa's agricultural policies are harmonized to clarify the relative importance of competing objectives. Prioritizing the transfer of ownership to small-scale farmers should be contextualized by the tradeoffs that it may require. Without sufficient extension programs, a policy-driven shift toward small-scale agriculture risks increasing the sector's vulnerability to climate change, as production is transferred from commercial to small-scale operations. Adaptation may still take place largely through spontaneous private responses to perceived trends, but will certainly require substantial public policy support for resource management, climate monitoring and forecasting, technology development and infrastructure investment, as well as targeted capacity building for farmers with low adaptive potential.

The cross-sectoral implications of climate change are also important. For example, increased irrigation pumping will draw more electrical power from the national grid, requiring the need for further generation capacity. South Africa's power sector is currently dominated by thermal coal power plants that require water for cooling, creating further competition for water between the power and agricultural sectors (Smit and Pilifosova, 2007).

CONCLUSION

Adaptation policies must be flexible and multi-targeted, with separate measures set out for large and small-scale farmers that account for differences in available resources and planning horizons. Policy makers should also be aware of regional differences in climate change predictions, with adaptation policy differentiating for needs of farmers who may experience increased variability versus others who will face chronic water shortages. It may also be useful to emphasize the co-benefits of adaptation measures, including cost reductions, improved resource management, water and energy savings, and climate change mitigation benefits (Smit and Pilifosova, 2007).

Policy support for climate change adaptation in agriculture will require a nuanced, multi-faceted approach, accounting for the diversity of operations and the motivations that farmers have typically exhibited in adopting new measures to make their operations more resilient to existing climate variability. The agricultural sector will undoubtedly respond to climate change, just as it has always reacted to changing resource availabilities, input costs and market fluctuations, but the overall success of the sector will depend on coherent policies to encourage, guide and support private adaptation. The various national and provincial policies affecting the agricultural sector need to be harmonized to prioritize and reduce competition among stated policy objectives. Integrated adaptation planning will help insure South Africa's food security, enable politically and culturally important small-scale farmers to succeed, improve environmental sustainability and contribute to policy objectives in other sectors.

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A.5 Conservation Agriculture: South Africa's New Green Revolution? (Backgrounder No. 61)

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BACKGROUNDER
NO. 61 > AUGUST 2013

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CONSERVATION AGRICULTURE: SOUTH AFRICA'S NEW GREEN REVOLUTION?

KIERAN FINDLATER

SUMMARY

- Conservation Agriculture (CA) has the potential to greatly improve the sustainability of South African crop production.
- Targeted and effective policy support is necessary to sustain the momentum behind CA, and to ensure that consistent techniques are properly applied, maximizing benefits and reducing the risk of poor outcomes.

BACKGROUND

As farmers move from conventional to conservation farming, agricultural production becomes more resilient to climate variability, and therefore to at least some aspects of anticipated climate change (FAO, 2011a). The components comprising Conservation Agriculture (CA) (a trifecta of no-till or minimum-till farming, permanent soil cover and crop rotations) have existed for nearly a century, but uptake has generally been slow and uneven (FAO, 2011a; Knowler and Bradshaw, 2007). Though adoption of no-till farming has been widespread in South America, rates in sub-Saharan Africa (including South Africa) remain particularly low (McCarthy et al., 2012), necessitating government support through targeted and integrated policy-making.

DRIVERS

The adoption of CA has generally been driven by necessity (Huggins and Reganold, 2008). First arising in the aftermath of the 1930s "dust bowl" in the United States, no-till and minimum-till farming evolved as a way to curb soil erosion (Hobbs et al., 2008). Though farm-level decision-making is difficult to

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disentangle, major drivers of no-till uptake include soil degradation, erosion and water scarcity, exacerbated by rising input costs, globalized markets and lower profit margins (Hardy et al., 2011; Knowler and Bradshaw, 2007).

In South Africa, an accelerated shift towards conservation farming began largely as a result of market deregulation that accompanied the end of apartheid. The withdrawal of protective price controls sparked a dramatic change in South African agriculture. Vast swaths of marginal agricultural land were abandoned as it became economically detrimental to continue its cultivation (Hardy et al., 2011). To offset diminished revenues, farmers were quickly forced to become more efficient, driving a technological shift as well as rapid consolidation within the industry. Crop switching occurred on a wide scale, as farmers were forced to adopt more climatically suitable, while also switching some cropland to pasture for livestock (Hardy et al., 2011).

COMPONENTS

A concept developed and promoted largely by the Food and Agriculture Organization of the United Nations (FAO), CA comprises three major practices: no-till farming, permanent soil cover, and crop rotations (FAO, 2011b).

1. No-till farming: To the greatest extent possible, the soil should not be disturbed (e.g., through plowing). This allows for the soil ecosystem and structure to return to a more natural state.

2. Permanent soil cover: To the greatest extent possible, the soil surface should not be left bare – most easily achieved by leaving crop stubble and residues on the field after harvest. This reduces the soil's exposure to environmental degradation and increases soil moisture retention.

3. Crop rotation: Crops should be grown in rotation, rather than in a monoculture. Crop rotation systems increase the diversity of production; intensive, nutrient-depleting crops are interspersed with more soil-friendly crops in short or long-term cycles. This may necessitate planting beneficial cover crops, rather than simply fallowing (resting) land. For example, farmers will no longer plant

wheat following a wheat harvest, but may instead rotate wheat with canola, grasses or nitrogen-fixing legumes.

BENEFITS

CA, when practiced in a comprehensive way, improves crop yields over time and reduces the required quantity of most inputs (FAO, 2011b). As the soil recovers from decades of tillage, and cover crops and residues add organic matter and nutrients, soil fertility, soil moisture, the system's resilience to environmental pressures improves dramatically (Hobbs et al., 2008).

CA increases soil organic matter content, soil moisture retention, while sharply reducing run-off (and therefore chemical pollution of nearby waterways), erosion by wind and water, and soil surface temperatures (helping to protect soil biota from extreme heat). As the health of soil fauna improves, soil organisms naturally till the soil, drawing nutrients from the surface down into the root zone, reducing soil compaction (thereby facilitating root penetration and water infiltration) and breaking down organic matter to make nutrients readily available for crops (Hobbs et al., 2008).

CA also reduces input costs by cutting fuel consumption in mechanized systems (planting is done using single-pass machinery), seed costs (due to direct planting) and fertilizer inputs, though herbicide use may increase (Knowler and Bradshaw, 2007). Crop rotations also allow for the inclusion of crops that contribute to increased soil fertility (e.g., nitrogen-fixing legumes). Pesticide use may also decrease – crop rotation systems under no-till are particularly resistant to pests and disease, since those that are crop specific have no host in the intervening years, and because robust soil biota increase the soil's resistance to pathogens (Hobbs et al., 2008).

The practice specifically decreases the farm system's sensitivity to weather variability and extremes (e.g., improving both water-logging and drought performance over time) (Holland, 2004; Thierfelder and Wall, 2010). For example, improved soil moisture retention makes for more reliable planting conditions, while single-pass techniques allow for planting to be completed within a much shorter timeframe. Planting under the CA approach therefore requires less rainfall and a smaller window of good weather, improving the farmer's ability to optimally time planting relative to the growing season (Hobbs, 2007).

In non-mechanized systems, CA may reduce labour inputs, though this finding has been variable across different studies (FAO, 2010; Giller et al., 2009). At the very least, CA requires less animal traction and may allow for labour inputs to be spread over a larger timeframe, since permanent soil cover reduces erosion between preparation and planting, allowing for earlier preparation.

Aggregate or off-farm benefits include increased food security, improved water quality through reductions in the agricultural pollution and sedimentation of water bodies, more regular and predictable river flows, increased soil biodiversity, lower greenhouse gas emissions from diesel use and soil processes, increased carbon sequestration in soil organic matter and higher soil albedo (reducing surface temperatures) (Holland, 2004; Knowler and Bradshaw, 2007).

COSTS AND CHALLENGES

No-till equipment is costly, making capital input an important limiting factor in the adoption of CA in mechanized systems. Farmers need to invest in single-pass planters, and despite the fact that no-till systems require fewer tractors because of reduced traffic, no-till planters may require more powerful tractors (Knowler and Bradshaw, 2007).

There may be an early reduction in yields and profit until natural soil fertility improves, leading to financial losses. This may necessitate the application of higher volumes of mineral fertilizer due to immobility of nutrients in the crop residue for the first few years (Giller et al., 2009).

CA may also increase the incidence of weed infestation, requiring more herbicide or more labour for weeding (Giller et al., 2009). Where conventional tillage or residue burning may have previously provided regular non-chemical weed control, farmers may increase their use of chemical herbicides under CA (Jat et al., 2012).

In mixed crop-livestock systems, there may be competition for crop residues between soil cover and animal feed – or fuel, where residues are used as an energy source. Farmers may be unwilling or unable to buy feed externally, and may therefore allow their animals to feed on residues (Giller et al., 2009). This can result in reduced soil cover late in the dry season, affecting soil moisture retention, temperature and erosion.

Animals may also compact the soil surface if they are left to roam freely, requiring loosening of the soil prior to planting (Hobbs et al., 2008).

There is anecdotal evidence that CA's improved water retention may lead to water-logging of the soil under some conditions, though over time water infiltration should improve, reducing this risk. Additionally, if some measure of soil erosion continues to occur, drainage gullies may get deeper over time, since they are not fixed each season through plowing. In some circumstances, these factors may necessitate drainage infrastructure improvements under CA (Jat et al., 2012).

The benefits of CA only fully accrue through years of rigorous application of the underlying principles. Some farmers may not apply the techniques consistently and may therefore risk jeopardizing the accrued benefit. For example, if a farmer is not consistent in minimizing tillage, soil fertility may be reduced through rapid mineralization of soil nutrients after plowing (Jat et al., 2012). This is of greater risk where farmers lack information and training, or where extension officers are poorly trained, themselves. Poor training can result in the incomplete application of CA techniques and may lead to lower yields than in conventional agriculture (Hobbs et al., 2008; Knowlder and Bradshaw, 2007).

CLIMATE SMART AGRICULTURE

The concept of Climate Smart Agriculture (CSA) builds on CA in many ways, and emerged in preparations for the climate negotiations at Durban, South Africa, in December 2011 (Beddington et al., 2012). CSA was promoted as a way to accrue multiple concurrent benefits by encouraging farmers to switch to production methods that both mitigate climate change and increase agricultural resilience to climate variability. With a primary focus on increasing soil carbon sequestration, farmers might thereby be able to sell carbon credits in foreign carbon markets (McCarthy et al., 2011).

Unfortunately, the costs and uncertainty in measuring soil carbon sequestration would likely make it financially unfeasible for small-scale farmers to participate in foreign carbon markets. Widespread implementation of CSA might therefore drive further consolidation in the agricultural sector by creating another revenue source that benefits from economies of scale (McCarthy et al., 2011). CSA may still provide incentives and additional policy tools to promote the adoption of CA practices, but at present, the cost of carbon accounting and the volatility of carbon markets largely preclude the use of CSA to promote CA adoption in South Africa.

POLICY IMPLICATIONS

The factors driving adoption of conservation farming techniques in South Africa are dynamic, and the agricultural sector continues to evolve as a result. The geography of production will continue to shift – in sectors with substantial infrastructure, high capital costs and long lead times (e.g., wine grapes), the effect has been delayed, and the impact has not yet fully been revealed. These shifts can be expected to continue as the climate changes.

CA is generally of net benefit, both at the farm scale and regionally (Knowler and Bradshaw, 2008). Policy-makers should increase support for farmers who would like to switch from conventional agriculture, but are limited by access to financing for new equipment or by lack of knowledge and training. For non-mechanized agriculture, further research and development must drive technological improvement to make CA more feasible for small-scale farmers. Crop rotation systems must be optimized for local climatic and soil conditions.

As with all agricultural policy in southern Africa, extension services for information and training are crucial. Current levels of extension and resources for training are insufficient (FAO, 2011b), especially as South Africa undertakes land reform, increasing the number of inexperienced farmers. Provincial agricultural departments should also focus on developing specific and localized crop rotation systems, since their development is particularly resource-intensive and their benefits widespread.

CA may also concurrently benefit from and help to imbue a sense of stewardship, as farmers become more explicitly aware of the role of ecosystem services in the success of their operations (Kassam et al., 2009). With facilitative policies, government may harness this emerging awareness to draw farmers into related conservation programs, and help farmers to prepare for climate change. Provincial agricultural policies need to be better integrated with land reform and climate change policies, to ensure the success of each program and encourage approaches that will result in comprehensive benefits.

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Appendix B: Research Protocols

B.1 Structured Interview Protocol

Interviewer: Kieran Findlater, PhD Candidate from the University of British Columbia

Participants: Commercial grain farmers in the Western Cape province of South Africa who appeared on the contact lists of the cooperatives and agribusinesses that market grain grown in the province.

Sampling Method: Geographically stratified random sampling

Interview Location: Participant's home, office, or other normal place of work

Materials:

- Two large white boards
- Sticky notes
- Erasable markers
- Two voice recorders

Setup:

- Introduce self
- Confirm participant's availability
- Obtain informed consent
- Lay out white boards and other materials
- Start voice recorders

Preamble:

- I use a standard set of questions, so that they're the same across all of my interviews. Some of the questions are broad, and some are specific, but I'm not looking for particular answers – just for your thoughts. The questionnaire should take about an hour, but that depends a bit on how much you talk. Some of the farmers have been quite talkative – farmers like to talk – so some of my interviews have gone over by (quite) a bit! But we'll just see how it goes. Is that alright? Do you have any questions for me before we begin?

Farming Experience:

- First, I'd like to talk to you about your farm and about your farming experience.
- How long have you farmed? Did you grow up on a/the farm? Where would you say you *learned* to farm?
- Did you study after matric? What did you study? Where? How long was the program?
- Do you own the farm? Is it in your name, in a trust, or something else?
- Do you manage the farm yourself? Is there anyone else who helps with management decisions?

Farm Characteristics:

- How big is your farming area? Is that the workable area or the total? Do you hire other farms?
- What are your farming activities? Which crops do you grow? How many hectares of each?
- Do you have any animals? How many head of each? How many ewes? How many cows? How many cows in milk?
- Do you have any *other* activities on the farm? Do you have any land under irrigation?
- Any other sources of income off the farm or apart from the farm?
- How many workers do you have on the farm? Permanent and full-time?

Future orientation:

- What plans do you have for the *future* of the/your farm? Do you have any other specific targets for improvement or change on the farm?
- Do you think that you'll continue to farm until you retire? What do you think will happen to the farm when you retire?
- Do you have any children? How old are they? Have they shown an interest in farming?

Risk elicitation:

- Next, I'd like to talk to you about the risks or concerns that you face as a farmer. I'm going to use these yellow sticky notes to organize our conversation. I've just written down a few things you've already said, [____], [____] and [____]. Beyond these – apart from these – I'd like you to please just start by listing risks or concerns that you face as a farmer. They might be of concern this week, next month, next year, or in ten or twenty years. Anything will do, and we'll just talk about them as they come up!

  [Lengthy pause.]

- You've mentioned [____] and [____], which are probably short-term risks. Can you think of any *other* short-term risks?
- You've mentioned [____] and [____], which are probably long-term risks. Can you think of any *other* long-term risks?
- What about any other risks to do with crop production or crop failure? Any other risks to do with weather? Anything else to do with politics? Anything else to do with economics? Anything else to do with the environment? Anything else to do with water, soil or inputs?
- And [____]? What makes that a problem? Why does that happen? [For risks where the cause was unclear.]

Manageability of risks:

- It sounds like some of these risks are probably manageable and some of them are probably unmanageable. I'd just like your help in quickly sorting them into those categories. I'm going to label this board manageable and the other board unmanageable, and you can just grab the sticky notes and move them around as you see fit. Remember, this is from your perspective – manageable or unmanageable from your side.

[Lengthy pause.]

- What makes these risks manageable? [One by one.]
- What makes these risks unmanageable? [One by one.]
- What can you do to manage these risks? And [____]? What can you do to manage that? And [____]? What makes that difficult to manage?
- On each side, one from manageable and one from unmanageable, what do you think will be the most important risk in the coming year?
- Which do you think will be the most important risks on each side in ten or twenty years?

Sources of information:

- In general, when you're trying to deal with risks on the farm, where do you find information or who do you talk to? What about information from other farmers? What about information from study groups – are you a part of a study group? What about information from the co-operative? What about information from other agricultural companies? What about information from the government? What about Elsenburg?[25] What about the Internet as a source of information?
- Who do you trust *most* to give you support or help when you're faced with a big challenge? What makes them trustworthy?

Specific concepts:

- I'd like to talk to you a bit more about your crop production now. I'm going to ask you a few questions that may seem a bit vague or broad, but just do your best to answer.

Crop Rotation:

- What comes to mind when you hear the term "crop rotation"? *Wisselbou*? [Afrikaans for crop rotation.]
- What is the effect of crop rotation? What are the benefits of crop rotation? What are the downsides? How does crop rotation interact with these risks on the board? Which of these risks does crop rotation make better or worse or more complicated?
- Would you say that you use crop rotations? For how many years have you done so? What is your current rotation? Has it changed over time? Do you have any plans to make (further) changes in the future?

[25] Elsenburg is the location of the main offices for the provincial Department of Agriculture, which conducts government-funded research and training.

Soil Disturbance:

- What comes to mind when you hear the term "soil disturbance"? Tilling or plowing? [If they misunderstood the concept.]
- What is the effect of soil disturbance? What are the benefits of *minimum* soil disturbance? What are the downsides of minimum soil disturbance? How does minimum soil disturbance interact with these risks on the board? Which of these risks does minimum soil disturbance make better or worse or more complicated?
- Would you say that you practice minimum soil disturbance? For how many years have you done so? What kind of implement do you use? Which model? How many years have you had that implement? What did you use before that? Do you have any plans to make changes to your implement? Do you ever disturb the soil in any other way, say by ripping or plowing?

Soil Cover:

- What comes to mind when you hear the term "permanent soil cover"? Crop residues, rests or stubble? [If they misunderstood the concept.]
- What is the effect of soil cover? What are the benefits of soil cover? What are the downsides? How does soil cover interact with these risks on the board? Which of these risks does soil cover make better or worse or more complicated?
- Would you say that you maintain permanent soil cover? To what extent? For how many years have you done so? Do you have any plans to make changes to your soil cover? Do you bale? When was the last time you burned a field? What proportion of your fields do you burn in a typical year? Do you put your animals on the crop fields in the summer? How much soil cover would there normally be left when you plant? After planting?

Conservation Agriculture:

- What comes to mind when you hear the term "conservation farming" or "conservation agriculture"? *Bewarings boerdery* or *bewarings landbou*? [Afrikaans for conservation farming or conservation agriculture.]
- How would you define conservation agriculture? *Definir*? [Afrikaans for define.] How would you describe it?
- Would you say that you practice conservation agriculture? To what extent?

Climate Change:

- We're almost done. Just a couple more questions.
- What comes to mind when you hear the term "climate change"? Do you think that the climate will or will not change on your farm? Do the potential effects of climate change concern you? Would you say that the climate has or has not changed since you started farming?
- Would you say that the risk of climate change, the effects of climate change on your farm, is a manageable risk or an unmanageable risk? What can you do to manage it? How would you say that the risk of climate change, the effects of climate change, interacts with

these other risks on the board? (If the climate changes), which of these risks will it/climate change make better or worse or more complicated?

Systemic Change:

- When you consider all of these risks together, what might cause you to make a major change in your farming system? What might cause you to sell your farm?

Request for Records and Concluding Remarks:

- May I ask how old you are?

- We're done the questionnaire. I just had one more thing I wanted to ask you before we wrap up. I'm told that many farmers keep pretty good records of things like crop yields (production per hectare) and inputs (input costs). Do you keep that kind of thing?
- It would help me better understand the context of your answers if I better understood that side, as well. Would you be willing to share that with me? You may send it to me by email.

- If I have any small follow-up questions or clarifications, may I contact you again? Would you prefer by phone or by email? Would you please just write your email address at the bottom of the form? Do you have a landline number as well?
- Would you be interested in my findings? May I send them by email?

Generic follow-ups, used throughout:

Standard form: Repeat participant's word/statement, then ask for clarification, elaboration or cause-and-effect.

- e.g., "You mentioned [____]. What do you mean by that?"

Examples of Follows-ups:

- What? Why? How? How much? When? Where? Who?
- In what sense/way?
- What do you mean by that?
- What causes that? What effect does that have?
- How/why does that work/happen?
- How/why do you do that?
- What helps you do that? What stops you from doing that?
- What makes that easier/harder/more important/less important?
- What can you do about that?

B.2 Survey Instrument

Study: Improving South African Grain Farming

Please choose a language. / Kies asseblief jou taal van voorkeur.

◉ English

○ Afrikaans

Preliminary Information

University of British Columbia

<u>**Study: Improving South African Grain Farming**</u>
University of British Columbia
Vancouver, Canada

With in-kind support from Grain SA

Thank you for your help with this study. This questionnaire should take approximately 10 minutes to complete.

Your participation will help us to better understand ongoing trends in South African grain production practices. A summary of the findings will be shared with our partners at Grain SA to better inform the products and services that they provide to their members.

Please review the following information about your consent to participate, and then ***click the "Next" button*** at the bottom of the page to proceed to the first question. Please answer each question from memory as accurately as possible.

Study and Consent Information

Purpose: You have been invited to participate in this study because you make management decisions in your farming business. If you are not involved in decisions about the grain farming part of your business, please pass the survey link along to someone who helps to make those decisions.

This survey is being conducted as part of Kieran Findlater's doctoral studies at the University of British Columbia, in Vancouver, Canada. The study will examine ongoing changes in key production practices in South African grain farming, as well as the impact that these changes will have on the future resilience of the sector. The results of the study will enable more appropriate support for farmers in dealing with emerging challenges in the agricultural sector. There are no anticipated risks from your participation in this study.

Confidentiality: Your privacy is of the utmost importance, and no identifying information will be collected. Your answers will be combined with those of other grain farmers from across South Africa, and will contribute to the publication of a doctoral thesis, reports, and academic journal articles. The survey is being conducted using the ESurveyCreator.com software, operated in Austria by Enuvo. During the open survey period, your answers will be stored and accessed on the company's servers in Ireland, and will be subject to European data protection laws. Your computer's IP address will be recorded, but it will not be associated with your answers. You may find further information at https://www.esurveycreator.com/?url=datenschutz. At the end of the survey period, the survey data will be downloaded, encrypted and stored on a password-protected computer at the University of British Columbia in Vancouver, Canada. The data will then be deleted from the server.

Research Team:
Investigators: Dr. Milind Kandlikar, Professor (Phone: +1.604.822.5918); and Mr. Kieran Findlater, PhD Candidate (Phone: +1.778.987.0100, Email: k.findlater@alumni.ubc.ca). Institute for Resources, Environment & Sustainability (IRES), University of British Columbia, Vancouver, Canada.

Co-Investigator: Dr. Mark New, Director. African Climate & Development Initiative, University of Cape Town, South Africa (Phone: +27.21.650.5598).

Funding: This study is supported by funding from the University of British Columbia (Vancouver, Canada), the Government of Canada, and the Centre for International Governance Innovation (Ontario, Canada).

Contact: If you have any questions or concerns about what we are asking of you, please contact Dr. Milind Kandlikar or Mr. Kieran Findlater. Their names and telephone numbers are listed above. If you have any concerns or complaints about your rights as a research participant and/or your experiences while participating in this study, contact the Research Participant Complaint Line in the UBC Office of Research Ethics at +1-604-822-8598 or by e-mail at RSIL@ors.ubc.ca.

Consent: Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time.

By clicking the button labeled "Next", you indicate your consent to participate in this study, and you will be taken to the first question.

Farm Characteristics

These questions are about the type of farm that you manage.

In which province do you farm? *

If you farm in more than one province, select the province in which most of your grain farming takes place.

(Please choose...)

If you also farm in other provinces, select them below.

☐ Gauteng	☐ North West
☐ KwaZulu-Natal	☐ Eastern Cape
☐ Limpopo	☐ Free State
☐ Mpumalanga	☐ Western Cape
☐ Northern Cape	☐ *None. I farm in only one province*

What is the total area of land on the farms that you manage? *

If the number varies by year, indicate approximately how many hectares you managed this past year.

☐ Hectares

Of the total area mentioned above, approximately how many hectares are there of each of the following land uses -- irrigated and not irrigated?

If the number varies by year, indicate approximately how many hectares of each land use you managed this past year.

	Hectares (not irrigated)	Hectares (irrigated)
Annual crops		
Plantations or permanent crops		
Planted pastures (or forage)		
Natural pastures (or rangeland)		

Is there more than one growing season on any part of your farms? *

For example, with two growing seasons, you might plant and harvest irrigated forage in the same field twice in one year.

- ○ No
- ○ Yes

Farm Characteristics (2)

Which of the following grains, oilseeds and annual legumes did you grow this past year? *

☐ Maize, for market	☐ Canola
☐ Maize, for silage	☐ Sunflower
☐ Wheat	☐ Groundnuts
☐ Barley	☐ Other oilseeds
☐ Oats, for market	☐ Soya bean
☐ Oats, for silage	☐ Dry bean / sugar bean
☐ Oats, for grazing	☐ Other annual legumes
☐ Sorghum	☐ *None. I did not grow any grains, oilseeds or annual legumes this past year.*
☐ Other grains	

Which of the following grains, oilseeds and annual legumes did you grow this past year, during your first growing season? *

☐ Maize, for market	☐ Canola
☐ Maize, for silage	☐ Sunflower
☐ Wheat	☐ Groundnuts
☐ Barley	☐ Other oilseeds
☐ Oats, for market	☐ Soya bean
☐ Oats, for silage	☐ Dry bean / sugar bean
☐ Oats, for grazing	☐ Other annual legumes
☐ Sorghum	☐ *None. I did not grow any grains, oilseeds or annual legumes in the first growing season.*
☐ Other grains	

Which of the following __grains, oilseeds and annual legumes__ did you grow this past year, during your __second__ growing season? *

☐ Maize, for market	☐ Canola
☐ Maize, for silage	☐ Sunflower
☐ Wheat	☐ Groundnuts
☐ Barley	☐ Other oilseeds
☐ Oats, for market	☐ Soya bean
☐ Oats, for silage	☐ Dry bean / sugar bean
☐ Oats, for grazing	☐ Other annual legumes
☐ Sorghum	☐ *None. I did not grow any grains, oilseeds or annual legumes in the second growing season.*
☐ Other grains	

Which of the following __other__ crops did you plant this past year? *

☐ Grapes

☐ Other Fruit

☐ Vegetables

☐ Industrial crops

☐ *None. I did not grow any other crops this past year.*

☐ Other

Which of the following __other__ crops did you plant this past year, during your __first__ growing season? *

☐ Grapes

☐ Other Fruit

☐ Vegetables

☐ Industrial crops

☐ *None. I did not grow any other crops in the first growing season.*

☐ Other

Which of the following __other__ crops did you plant this past year, during your __second__ growing season? *

☐ Grapes

☐ Other Fruit

☐ Vegetables

☐ Industrial crops

☐ *None. I did not grow any other crops in the second growing season.*

☐ Other

Which of the following __perennial planted pasture__ (forage) types did you grow this past year? *

☐ Legumes, for grazing

☐ Legumes, for silage

☐ Grasses, for grazing

☐ Grasses, for silage

☐ *None. I did not grow any perennial planted pasture (forage) this past year.*

☐ Other

Farm Characteristics (3)

You said that you grew the following <u>grains, oilseeds and annual legumes</u> this past year. On approximately how many hectares did you grow each crop?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Maize, for market *{{crop_selection_no}}*		
Maize, for silage *{{crop_selection_no}}*		
Wheat *{{crop_selection_no}}*		
Barley *{{crop_selection_no}}*		
Oats, for market *{{crop_selection_no}}*		
Oats, for silage *{{crop_selection_no}}*		
Oats, for grazing *{{crop_selection_no}}*		
Sorghum *{{crop_selection_no}}*		
Other grains *{{crop_selection_no}}*		
Canola *{{crop_selection_no}}*		
Sunflower *{{crop_selection_no}}*		
Groundnuts *{{crop_selection_no}}*		
Other oilseeds *{{crop_selection_no}}*		
Soya bean *{{crop_selection_no}}*		
Dry bean / sugar bean *{{crop_selection_no}}*		
Other annual legumes *{{crop_selection_no}}*		
None. I did not grow any grains, oilseeds or annual legumes this past year. *{{crop_selection_no}}*		

You said that you grew the following grains, oilseeds and annual legumes this past year, during your first growing season. On approximately how many hectares did you grow each crop in the first growing season?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Maize, for market *{{crop_selection_first}}*	☐	☐
Maize, for silage *{{crop_selection_first}}*	☐	☐
Wheat *{{crop_selection_first}}*	☐	☐
Barley *{{crop_selection_first}}*	☐	☐
Oats, for market *{{crop_selection_first}}*	☐	☐
Oats, for silage *{{crop_selection_first}}*	☐	☐
Oats, for grazing *{{crop_selection_first}}*	☐	☐
Sorghum *{{crop_selection_first}}*	☐	☐
Other grains *{{crop_selection_first}}*	☐	☐
Canola *{{crop_selection_first}}*	☐	☐
Sunflower *{{crop_selection_first}}*	☐	☐
Groundnuts *{{crop_selection_first}}*	☐	☐
Other oilseeds *{{crop_selection_first}}*	☐	☐
Soya bean *{{crop_selection_first}}*	☐	☐
Dry bean / sugar bean *{{crop_selection_first}}*	☐	☐
Other annual legumes *{{crop_selection_first}}*	☐	☐
None. I did not grow any grains, oilseeds or annual legumes in the first growing season. *{{crop_selection_first}}*	☐	☐

You said that you grew the following grains, oilseeds and annual legumes this past year, during your second growing season. On approximately how many hectares did you grow each crop in the second growing season?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Maize, for market *{{crop_selection_second}}*		
Maize, for silage *{{crop_selection_second}}*		
Wheat *{{crop_selection_second}}*		
Barley *{{crop_selection_second}}*		
Oats, for market *{{crop_selection_second}}*		
Oats, for silage *{{crop_selection_second}}*		
Oats, for grazing *{{crop_selection_second}}*		
Sorghum *{{crop_selection_second}}*		
Other grains *{{crop_selection_second}}*		
Canola *{{crop_selection_second}}*		
Sunflower *{{crop_selection_second}}*		
Groundnuts *{{crop_selection_second}}*		
Other oilseeds *{{crop_selection_second}}*		
Soya bean *{{crop_selection_second}}*		
Dry bean / sugar bean *{{crop_selection_second}}*		
Other annual legumes *{{crop_selection_second}}*		
None. I did not grow any grains, oilseeds or annual legumes in the second growing season. *{{crop_selection_second}}*		

You said that you grew the following other crops this past year. On approximately how many hectares did you grow each crop?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Grapes *{{other_crop_selection_no}}*		
Other Fruit *{{other_crop_selection_no}}*		
Vegetables *{{other_crop_selection_no}}*		
Industrial crops *{{other_crop_selection_no}}*		
None. I did not grow any other crops this past year. *{{other_crop_selection_no}}*		

You said that you grew the following other crops this past year, during your first growing season. On approximately how many hectares did you grow each crop in the first growing season?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Grapes *{{other_crop_selection_first}}*		
Other Fruit *{{other_crop_selection_first}}*		
Vegetables *{{other_crop_selection_first}}*		
Industrial crops *{{other_crop_selection_first}}*		
None. I did not grow any other crops in the first growing season. *{{other_crop_selection_first}}*		

You said that you grew the following other crops this past year, during your second growing season. On approximately how many hectares did you grow each crop in the second growing season?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Grapes *{{other_crop_selection_second}}*		
Other Fruit *{{other_crop_selection_second}}*		
Vegetables *{{other_crop_selection_second}}*		
Industrial crops *{{other_crop_selection_second}}*		
None. I did not grow any other crops in the second growing season. *{{other_crop_selection_second}}*		

You said that you grew the following perennial planted pasture (forage) types this past year. On approximately how many hectares did you grow each type?

Enter an approximate number of hectares from memory.

	Hectares (not irrigated)	Hectares (irrigated)
Legumes, for grazing *{{forage_selection_no}}*		
Legumes, for silage *{{forage_selection_no}}*		
Grasses, for grazing *{{forage_selection_no}}*		
Grasses, for silage *{{forage_selection_no}}*		
None. I did not grow any perennial planted pasture (forage) this past year. *{{forage_selection_no}}*		

Approximately how many adults of each of the following livestock types did you have on your farms this past year?

If the number varied during the year, what was the approximate average?

	Number of Adults
Cattle (meat)	☐
Cattle (dairy)	☐
Sheep (meat)	☐
Sheep (wool)	☐
Sheep (mixed meat and wool)	☐
Goats	☐
Pigs	☐
Poultry (chickens)	☐
Ostriches	☐
Game	☐

Cropping Practices

These questions are about your method of grain farming.

Approximately what fraction of the soil surface is covered with crop residue (including stubble) after planting?

- ◯ Less than 15%
- ◯ 15 to 30%
- ◯ 30 to 60%
- ◯ More than 60%

During planting, approximately what percent of the soil surface is disturbed by the planter?

- ◯ Less than 15%
- ◯ 15 to 25%
- ◯ More than 25%

How often do you include *perennial* (ley) cover crops in your grain cropping system?

Cover crops are those planted primarily to control weeds or to improve soil fertility, and not primarily for harvest or grazing.

For example, you might usually grow perennial cover crops for one or more full years in between rotations of commercial crops.

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ Very often
- ◯ Always

How often do you include *annual* cover crops in your grain cropping system?

Cover crops are those planted primarily to control weeds or to improve soil fertility, and not primarily for harvest or grazing.

For example, you might usually grow annual cover crops for a few months in between commercial growing seasons.

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ Very often
- ◯ Always

How many types of crops do you rotate in your grain cropping system, excluding cover crops?

For example, you might usually plant wheat the first year, canola the second year, and oats the third year. This rotation would then include three crops.

- ◯ One crop (no rotation)
- ◯ Two crops
- ◯ Three crops
- ◯ More than three crops

Which of the following implements do you use for *primary* tillage?

Select one or more.

- ☐ Mouldboard plough
- ☐ Disc plough
- ☐ Chisel plough
- ☐ Heavy-duty offset disc
- ☐ Offset disc harrow
- ☐ Tandem disc harrow
- ☐ Ripper
- ☐ *None. I do not use primary tillage.*
- ☐ Other ____________

Which of the following implements do you use for *secondary* tillage?

Select one or more.

- ☐ Rotary tiller
- ☐ Tined cultivator
- ☐ Tandem disc harrow
- ☐ Row weeder
- ☐ *None. I do not use secondary tillage.*
- ☐ Other ____________

Which of the following implements do you use for planting?

Select one or more.

- ☐ Conventional planter
- ☐ No-till planter fitted with tine opener
- ☐ No-till planter fitted with disc opener
- ☐ Other ______

Which of the following implements do you use for cultivating (weed control) during the growing season?

Select one or more.

- ☐ Rigid tine cultivator
- ☐ Spring loaded cultivator
- ☐ *None. I do not use a cultivator during the growing season.*
- ☐ Other ______

Cropping Practices (2)

On the previous page, you said that you include *perennial* (ley) cover crops in your grain cropping system.

How long is your typical *perennial* (ley) cover crop period?

______ years

On the previous page, you said that you include *annual* cover crops in your grain cropping system.

How long is your typical *annual* cover crop period?

______ months

How many times per growing season do you usually apply *pre-emergence* herbicide?

- ○ *None. I do not usually apply a pre-emergence herbicide.*
- ○ Once
- ○ Twice
- ○ More than twice

How many times per growing season do you usually apply *post-emergence* herbicide?

- ○ *None. I do not usually apply a post-emergence herbicide.*
- ○ Once
- ○ Twice
- ○ More than twice

How often do you burn crop residues on the field?

- ○ Never
- ○ Rarely
- ○ Sometimes
- ○ Very often
- ○ Always

Which term do you think *best* describes your method of grain farming?

If more than one term applies to your method of grain farming, please choose the method that you prioritize.

- ○ Biological
- ○ Conservation
- ○ Conventional
- ○ Organic
- ○ Precision
- ○ Progressive

For how long have you farmed in the above manner?

- ○ Less than 5 years
- ○ 5 to 10 years
- ○ 10 to 20 years
- ○ More than 20 years

Management Decisions

These questions are about the way that you make management decisions about your farm.

What portion of your farm's management decisions do you make?

- ○ None
- ○ About one quarter (25%)
- ○ About one half (50%)
- ○ About three quarters (75%)
- ○ All (100%)

What portion of the land on which you farm do you own?

- ○ None. I manage the farm, but do not own it.
- ○ None. I hire or borrow all of the land on which I farm.
- ○ About one quarter (25%)
- ○ About one half (50%)
- ○ About three quarters (75%)
- ○ All (100%)

On average, approximately how much profit does your business earn each year?

Including farming activities, other on-farm businesses, and business beyond the farm (if applicable).

- ○ Less than R10,000
- ○ R10,000 to R50,000
- ○ R50,000 to R100,000
- ○ R100,000 to R250,000
- ○ R250,000 to R500,000
- ○ R500,000 to R1 million
- ○ R1 million to R5 million
- ○ More than R5 million
- ○ I would prefer not to say

Of the above total, approximately what percentage of your business' profit is earned from each of the following?

Enter values between 0 and 100%. The sum of all values should not exceed 100%.

	Percent of Total Profit (0 to 100%)
Grain crops	
Other crops	
Livestock	
Game farming	
Other on-farm activities	
Other business beyond the farm	

Future Success

These questions are about how you view threats to the future success of your farming business.

From the following list, select the five (5) factors that pose the greatest threats to the future success of your farming business. *

- ☐ Availability of information
- ☐ Availability of new technology
- ☐ Climate change
- ☐ Input costs
- ☐ Labour
- ☐ Land reform or claims
- ☐ Markets
- ☐ Personal health or family
- ☐ Pests
- ☐ Plant diseases
- ☐ Soil quality or health
- ☐ Weather
- ☐ Weeds

Future Success (2)

You selected the following five factors as threats to the future success of your farming business. Please rank them from highest threat (1) to lowest threat (5) by entering values between 1 and 5 beside each category.

Enter values from 1 to 5. Do not use the same value twice.

	Rank (1 to 5)
Availability of information *{{risk_selection}}*	☐
Availability of new technology *{{risk_selection}}*	☐
Climate change *{{risk_selection}}*	☐
Input costs *{{risk_selection}}*	☐
Labour *{{risk_selection}}*	☐
Markets *{{risk_selection}}*	☐
Personal health or family *{{risk_selection}}*	☐
Land reform or claims *{{risk_selection}}*	☐
Weather *{{risk_selection}}*	☐
Soil quality or health *{{risk_selection}}*	☐
Pests *{{risk_selection}}*	☐
Plant diseases *{{risk_selection}}*	☐
Weeds *{{risk_selection}}*	☐

How strongly do you agree or disagree with the following statements about climate change (also known as global warming)?

	Strongly disagree -2	-1	Neutral 0	+1	Strongly agree +2
Climate change is already happening	○	○	○	○	○
Climate change is caused primarily by human action	○	○	○	○	○
Climate change is of serious concern for South African agriculture	○	○	○	○	○
Climate change is of serious concern for my farming business	○	○	○	○	○
I need to consider the effects of climate change on my farm as I plan for the next 5 to 10 years	○	○	○	○	○

Demographic Information

This is the last section. Please make sure to click "Done" when you complete it!

On the first page of this questionnaire, you indicated that you farm in Eastern Cape. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Free State. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Gauteng. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in KwaZulu-Natal. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Limpopo. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Mpumalanga. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in North West. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Northern Cape. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

On the first page of this questionnaire, you indicated that you farm in Western Cape. In which of the municipalities listed below do you farm?

If you farm in more than one municipality, please select one municipality near which most of your grain farming takes place.

(Please choose...)

What is your gender?

- ○ Male
- ○ Female

What is your age?

- ◯ Less than 21 years
- ◯ 21 to 30 years
- ◯ 31 to 40 years
- ◯ 41 to 50 years
- ◯ 51 to 60 years
- ◯ 61 to 70 years
- ◯ 71 to 80 years
- ◯ More than 80 years

For how many years have you farmed, either for yourself or for someone else?

- ◯ Less than 5 years
- ◯ 5 to 10 years
- ◯ 10 to 20 years
- ◯ 20 to 30 years
- ◯ 30 to 40 years
- ◯ More than 40 years

What is the highest level of education that you have completed?

- ◯ I did not attend school
- ◯ I attended school, but did not matriculate
- ◯ I matriculated from secondary school
- ◯ One or two year post-secondary certificate or degree at a college or university
- ◯ Four year post-secondary degree at a college or university
- ◯ Master's or Doctoral degree

How would you generally describe your political outlook?

- ◯ Very liberal
- ◯ Somewhat liberal
- ◯ Moderate
- ◯ Somewhat conservative
- ◯ Very conservative
- ◯ I would prefer not to say

You have completed the survey. Thank you very much for your time.

For more information about this study, or to request a copy of the study's findings upon completion, please contact Mr. Kieran Findlater at k.findlater@alumni.ubc.ca. For more information about the University of British Columbia, please visit http://www.ubc.ca.

You may now close this window.

Appendix C: Sample mental models

Figure C.1: Sample mental model, demonstrating model complexity with reference to problems of weather and climate variability. Node shape corresponds to mental model section (cause, problem, effect, response, mediator), while edge colour corresponds to the sign of the mediator (green is positive, red is negative).

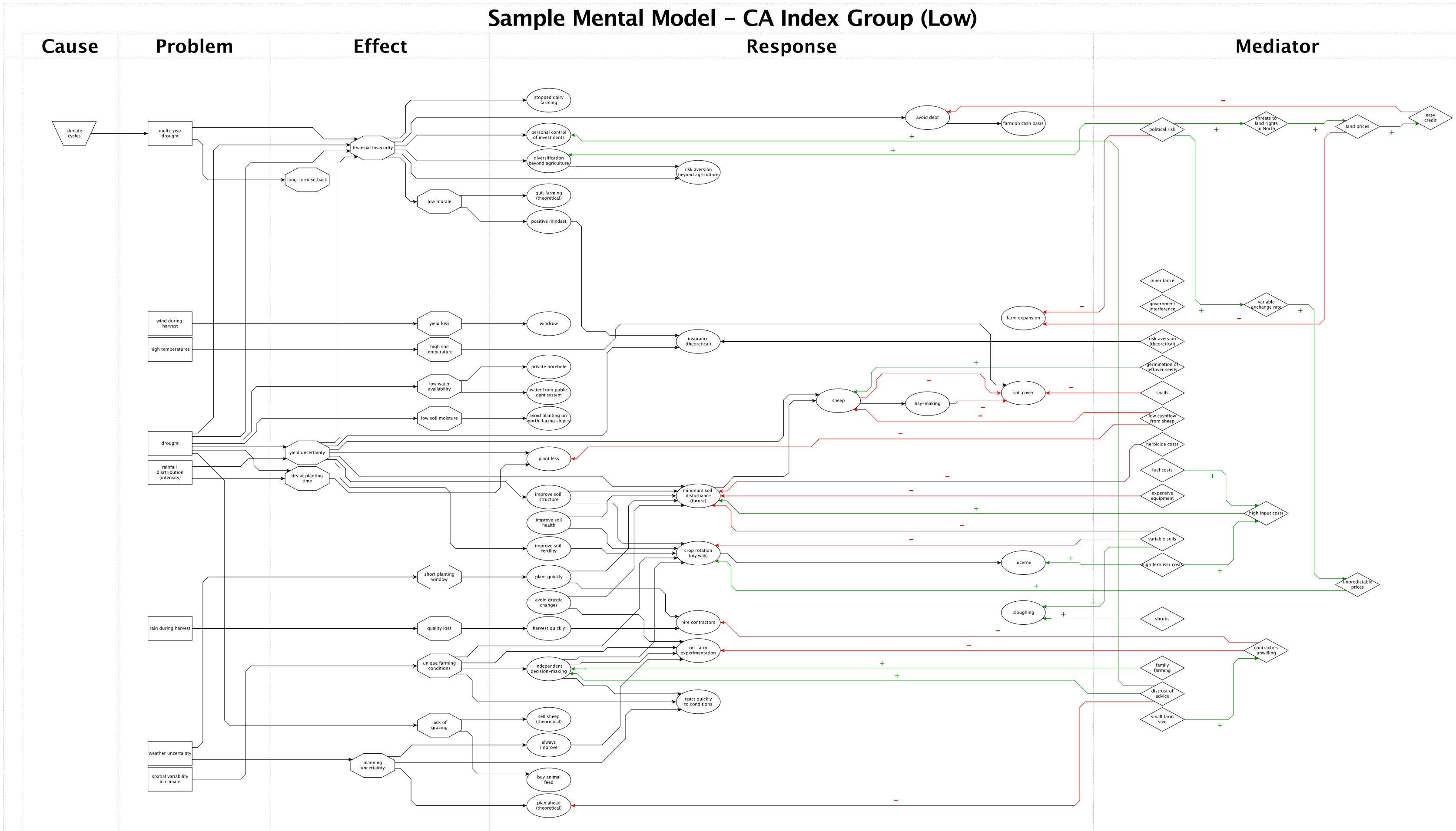
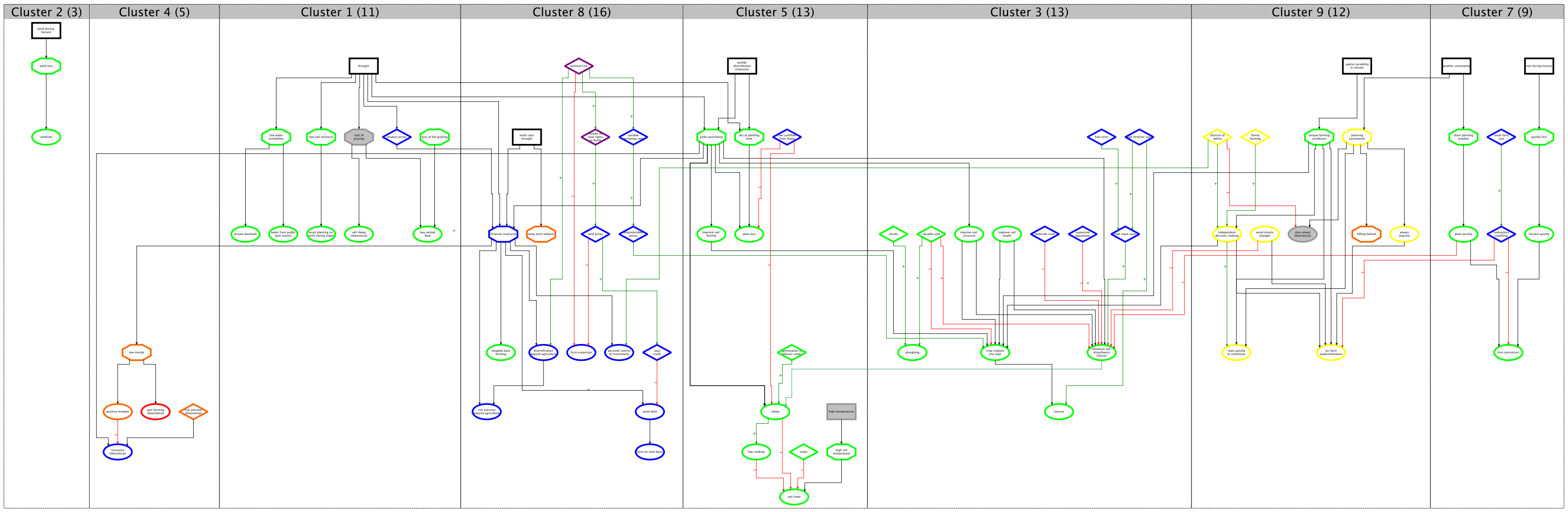


Figure C.2: Sample clustered mental model of a participant from the low-adopting CA index group. The nodes were coded for language type and clustered automatically using an algorithm based on edge betweenness to demonstrate the natural clustering of language types. Languages are represented by colour: agricultural (green), cognitive (yellow), economic (blue), emotional (orange), survival (red) and political (purple).



Appendix D: List of unique elicited risks

Table D.1: Unique risks elicited during mental models interviews. These 81 unique risks were derived from those raised by participants in the risk elicitation exercise at the beginning of each interview. The percentage of participants who raised each risk is indicated. This table is continued on the two pages that follow.

Unique risk	Risk category	Percentage of participants
Input Costs (General)	Economic	80
Product Prices (General)	Economic	64
Land Reform or Land Rights	Political	63
Exchange Rate	Economic	58
Climate Change	Weather and Climate	57
Farm Size	Economic	52
Rainfall	Weather and Climate	47
Politics (General)	Political	44
Chemical Resistance	Technological	42
Weather (General)	Weather and Climate	39
Product Prices (Imports)	Economic	37
Weeds	Crop (excluding Weather)	37
Labour (Skill or Reliability)	Labour (excluding Cost)	32
Transport Costs	Economic	32
Pests	Crop (excluding Weather)	31
Crime	Societal	29
Drought	Weather and Climate	28
Government (General)	Political	28
Input Costs (Equipment)	Economic	28
Research (Cultivars)	Technological	28
Labour (General)	Labour (excluding Cost)	22
Labour Costs	Economic	22
Product Prices (Foreign Subsidies)	Economic	22
Research (General)	Technological	18
Wind	Weather and Climate	18
Labour (Availability)	Labour (excluding Cost)	17
Diseases	Crop (excluding Weather)	14
Government (Services or Support)	Political	14

Table continued on next page…

Unique risk	Risk category	Percentage of participants
...Table continued from previous page.		
Marketing System	Economic	12
Economy or Markets (General)	Economic	10
Financial Viability	Economic	10
Climate	Weather and Climate	9
Decision-making	Personal	9
Input Costs (Fuel)	Economic	9
Strikes	Societal	9
Water (Availability)	Weather and Climate	9
Regulation	Political	8
Soil (Health)	Crop (excluding Weather)	8
Water (Quality)	Weather and Climate	8
Debt	Economic	7
Input Costs (Water)	Economic	7
Interest Rates	Economic	7
Livestock Mortality	Livestock	7
Personal Health	Personal	7
Cold	Weather and Climate	6
Government (Understanding of Farmers)	Political	6
Infrastructure	Logistical	6
Input Costs (Electricity)	Economic	6
Taxes	Economic	6
Diversification	Economic	4
Food Security	Societal	4
Helping People	Societal	4
Labour (Laws)	Political	4
New Technologies (Availability)	Technological	4
Table continued on next page…		

Unique risk	Risk category	Percentage of participants
...Table continued from previous page.		
Government (Trust)	Political	3
Hail	Weather and Climate	3
Morale	Personal	3
Veterinary Services	Livestock	3
Water (Rights)	Political	3
Weather (Extremes)	Weather and Climate	3
Yield or Quality	Crop (excluding Weather)	3
Availability of Information	Other	2
Fire	Weather and Climate	2
Inflation	Economic	2
Mining (Rights)	Political	2
Other Logistical	Logistical	2
Other Societal	Societal	2
Other Technological	Technological	2
Population Growth	Societal	2
Research (Chemicals)	Technological	2
Soil (Other)	Crop (excluding Weather)	2
Soil Compaction	Livestock	2
Sustainability (Need)	Societal	2
Antibiotic Resistance	Technological	1
Government (Other)	Political	1
Knowledge	Personal	1
New Technologies (Risk)	Technological	1
Other Costs	Economic	1
Other Environmental	Other	1
Other Personal	Personal	1
Sustainability (Overemphasis)	Societal	1

Appendix E: Conservation Agriculture (CA) scoring and additional CA figures

Table E.1: Conservation Agriculture (CA) scoring criteria. These were used to code participants' performance towards each CA principle from the mental models interview data.

CA Principle	Score	Description
Crop Rotation	0.0	Mono-cropping; no fallowing, no legumes
	0.5	Rotation of one or two cash crops with fallowing; no legumes
	1.0	Rotation of one or two cash crops with a legume, with some rationale regarding natural fertilization and weed/disease control
	1.5	Haphazard rotation with a legume and a diversity of other crops, with some rationale regarding natural fertilization and weed/disease control
	2.0	Systematic rotation with a legume and other crops, with clear rationale regarding natural fertilization and weed control
Minimum Soil Disturbance	0.0	Ploughing and broadcasting of seeds
	0.5	Older tine implement, with broadcasting of seeds
	1.0	Newer tine planter, but still ripping (or open to it)
	1.5	Newer tine planter, no ripping (or strongly opposed to it)
	2.0	Newer disc planter, no ripping
Permanent Soil Cover	0.0	Burning residues or ploughing them under
	0.5	No/limited burning or ploughing under, but freely grazing or often baling
	1.0	Some attempt to control grazing of non-forage crop residues; some baling
	1.5	Strong attempt to control grazing of non-forage crop residues; no baling or burning
	2.0	No grazing, baling or burning of non-forage crop residues

Figure E.1: Boxplots of age and farm size (workable area) by CA index group (*n* = 30).

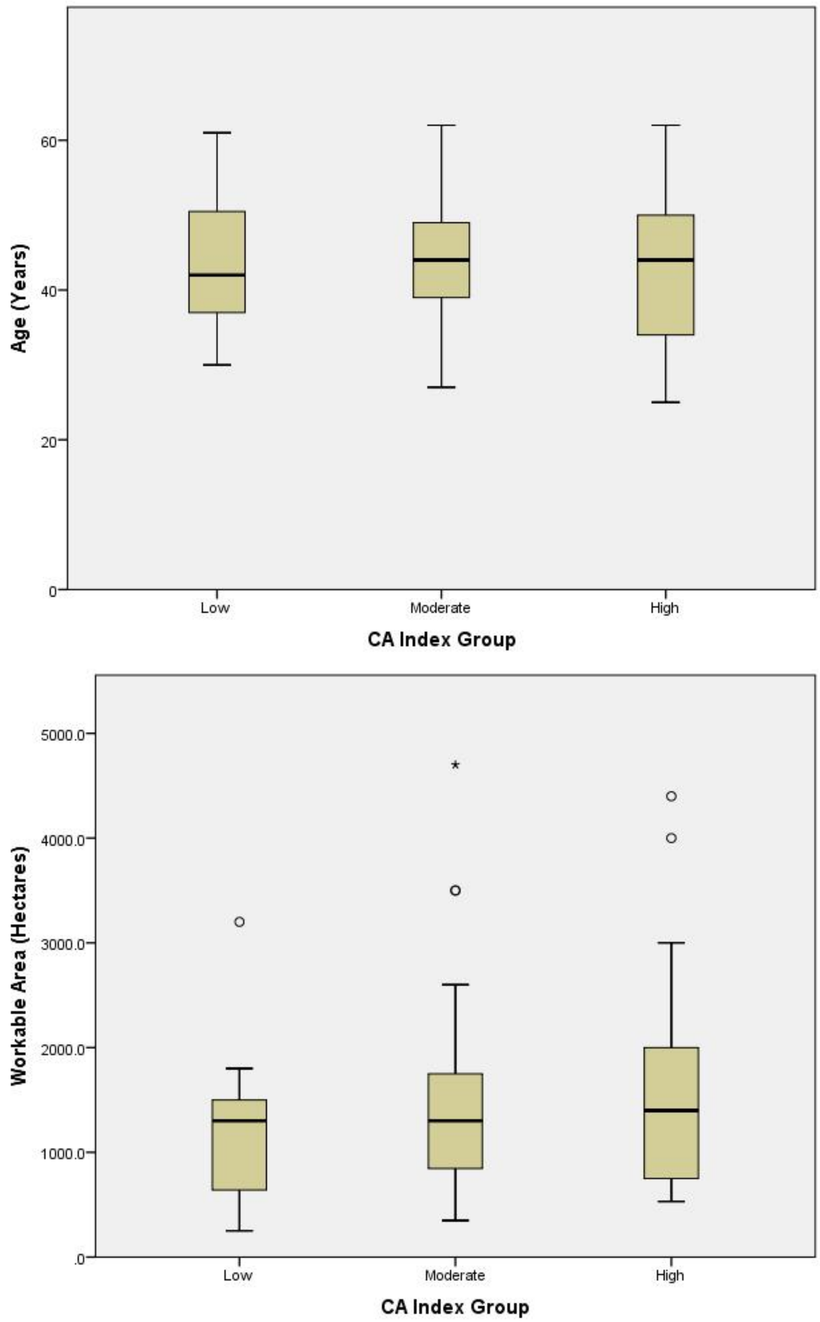
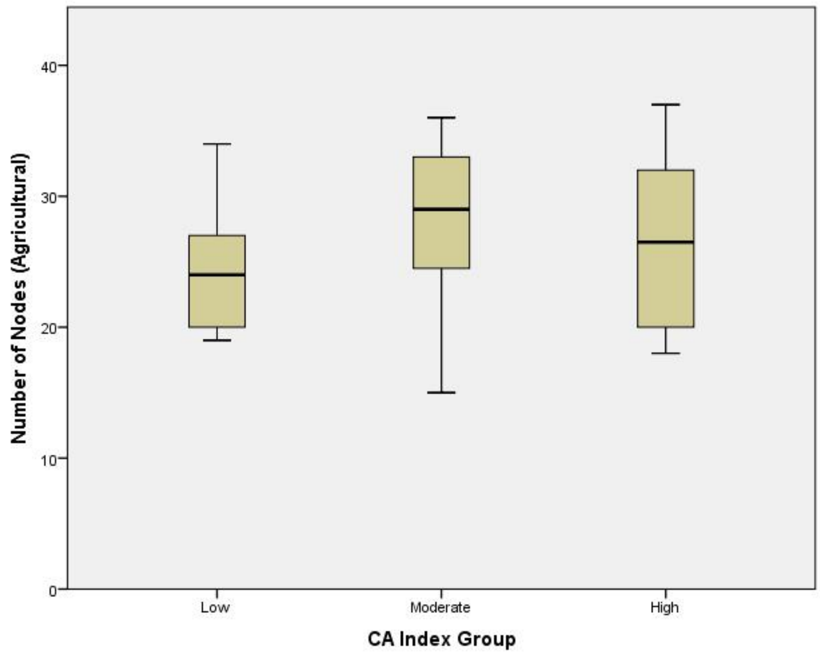
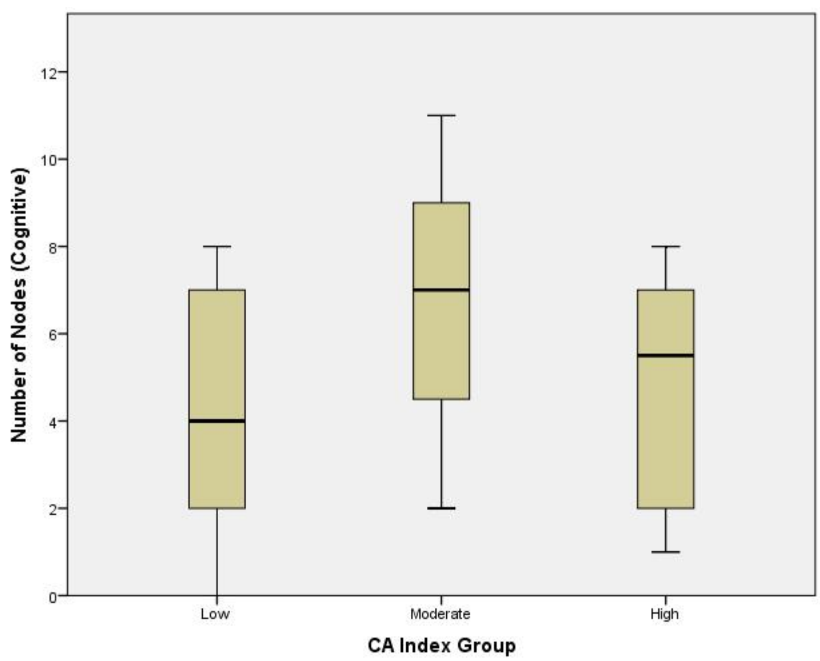
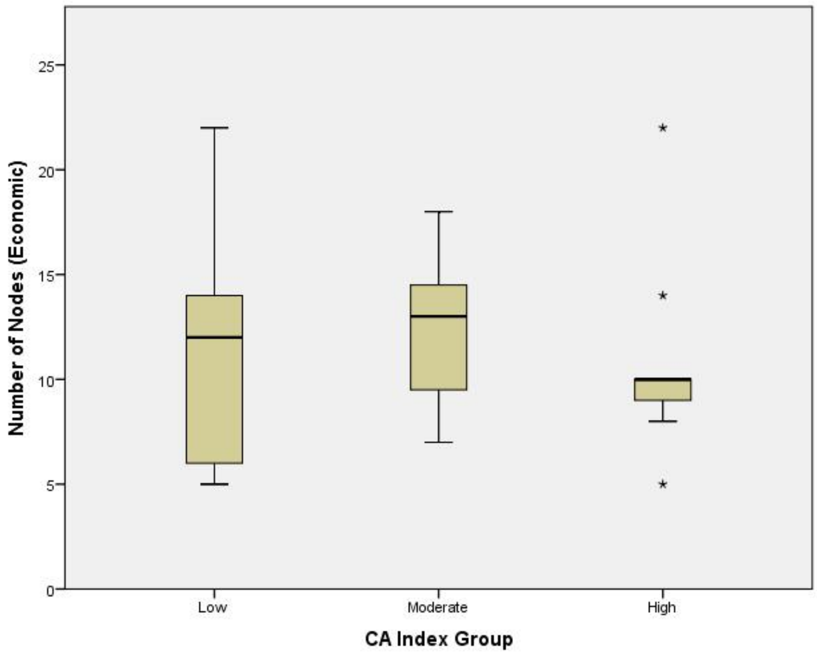


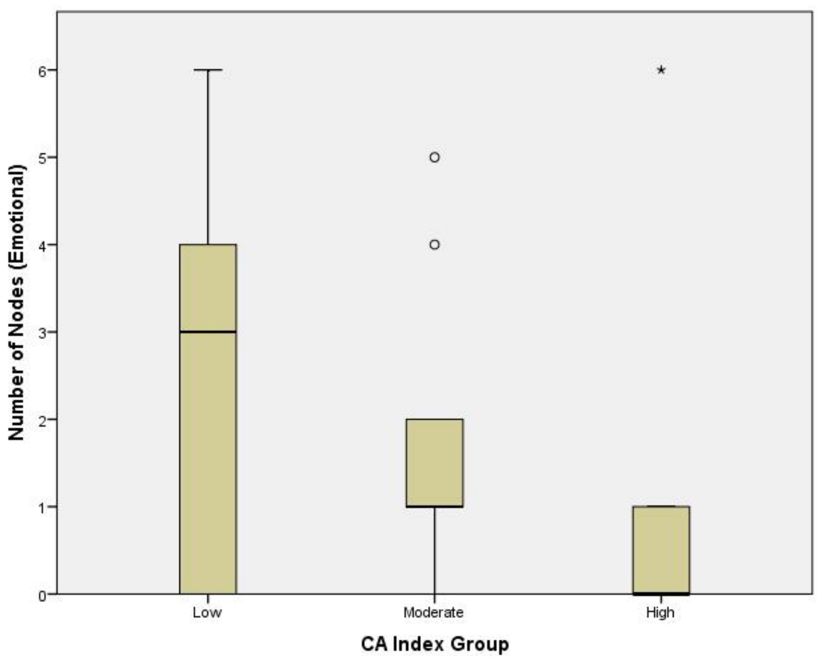
Figure E.2: Boxplots of language node frequencies by CA index group (*n* = 30).



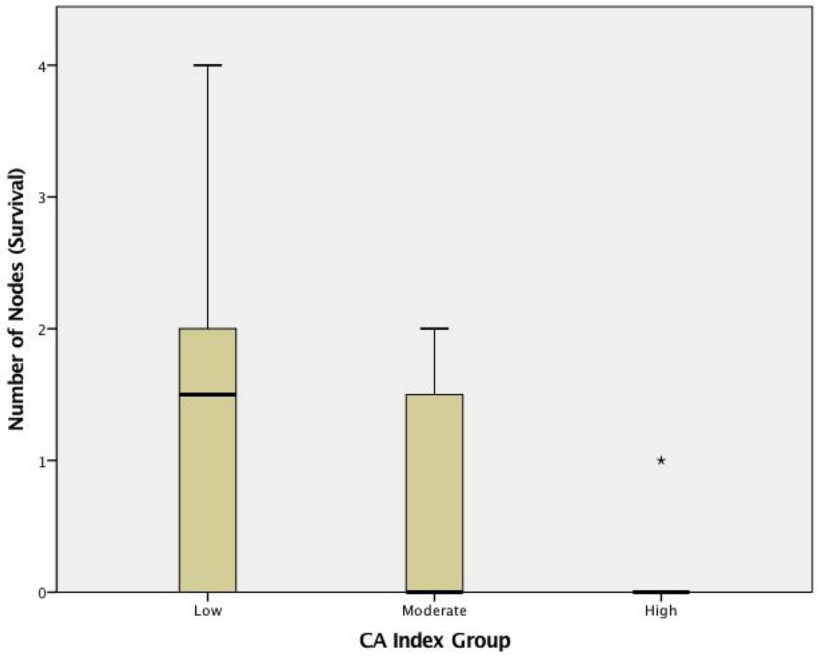




25
20
15
10
5
0
Number of Nodes (Economic)
Low
Moderate
High
CA Index Group



6
5
4
3
2
1
0
Number of Nodes (Emotional)
Low
Moderate
High
CA Index Group


Number of Nodes (Survival)
0
1
2
3
4
Low
Moderate
High
CA Index Group

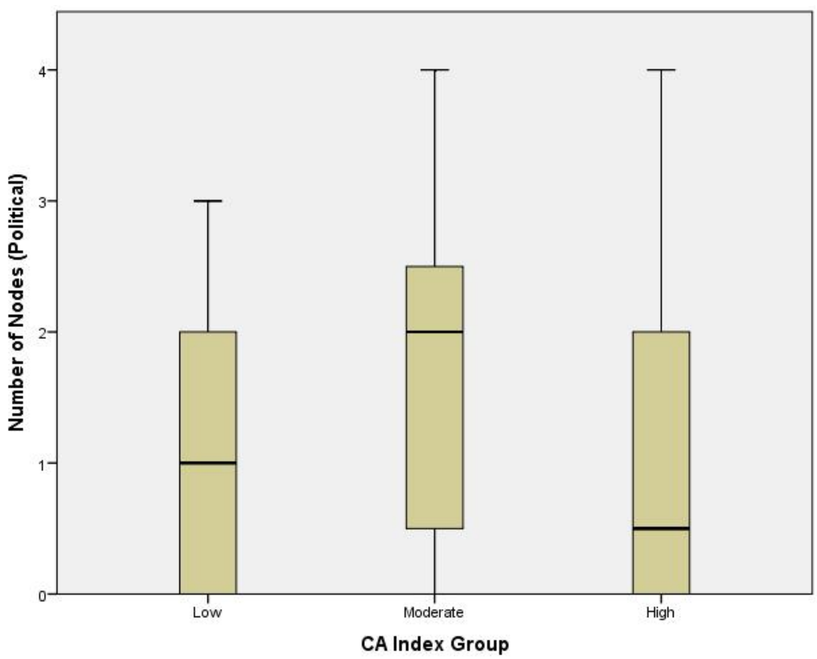
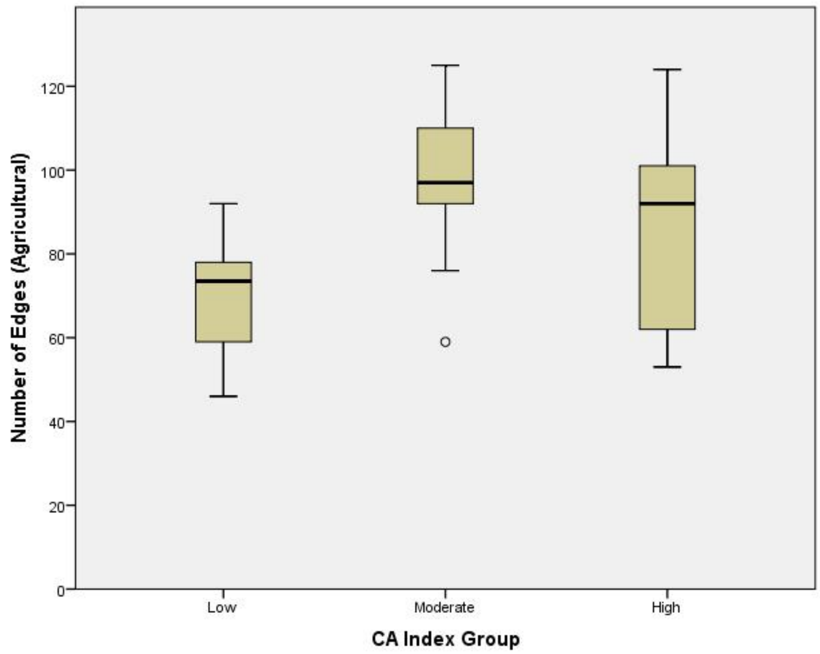
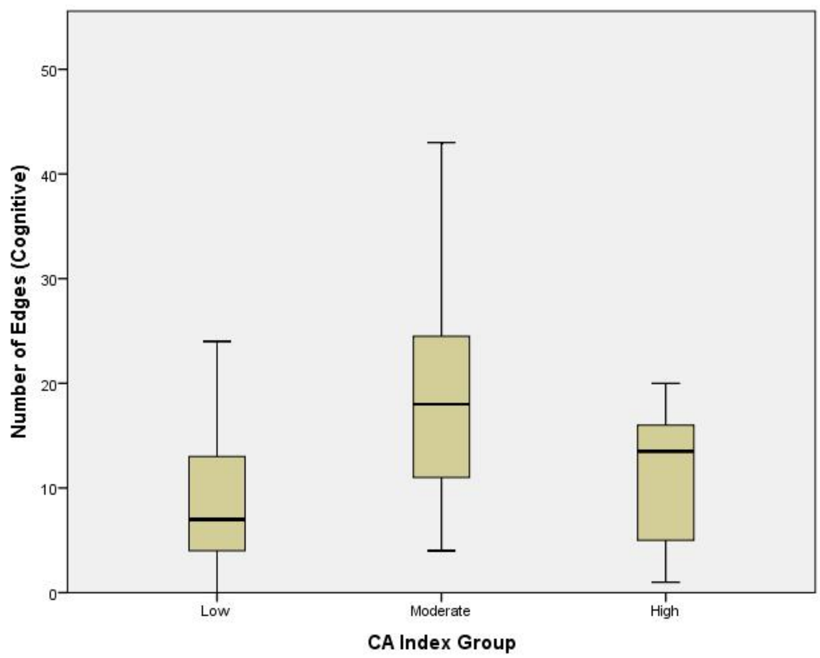
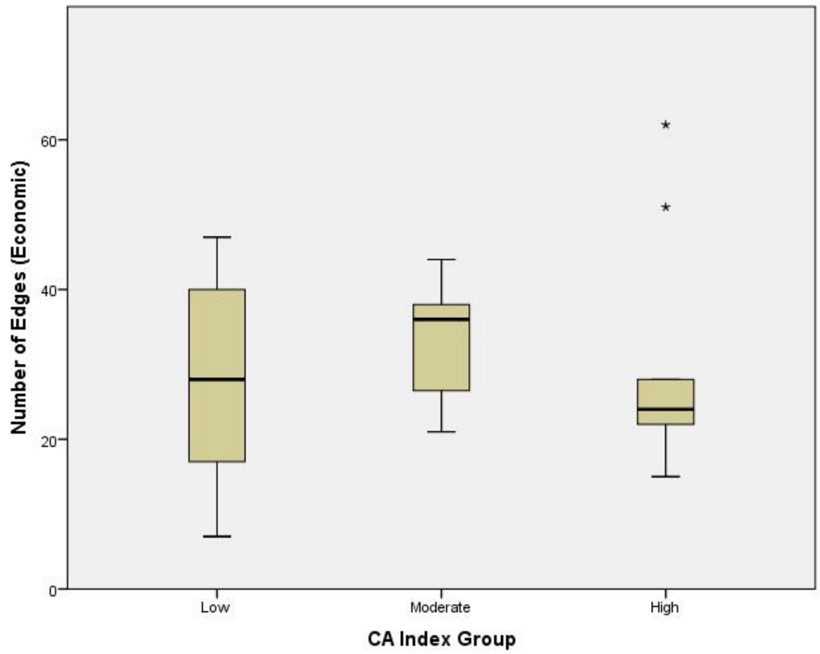

Number of Nodes (Political)
0
1
2
3
4
Low
Moderate
High
CA Index Group

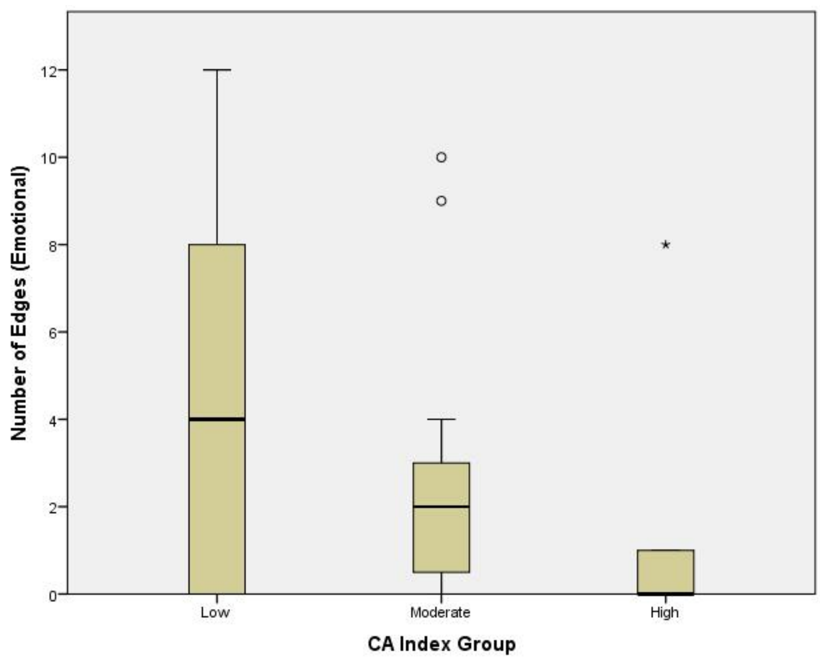
Figure E.3: Boxplots of language edge frequencies by CA index group (n = 30).



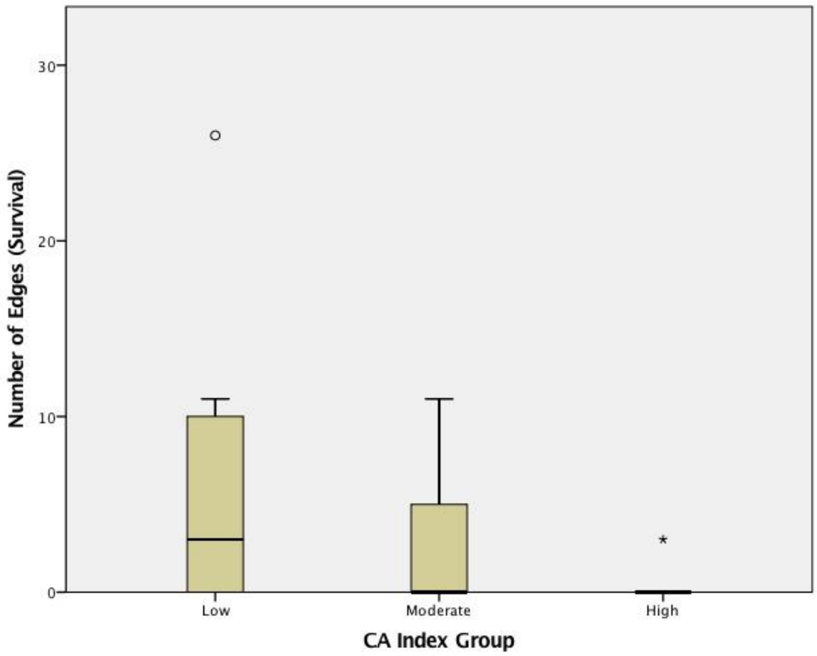




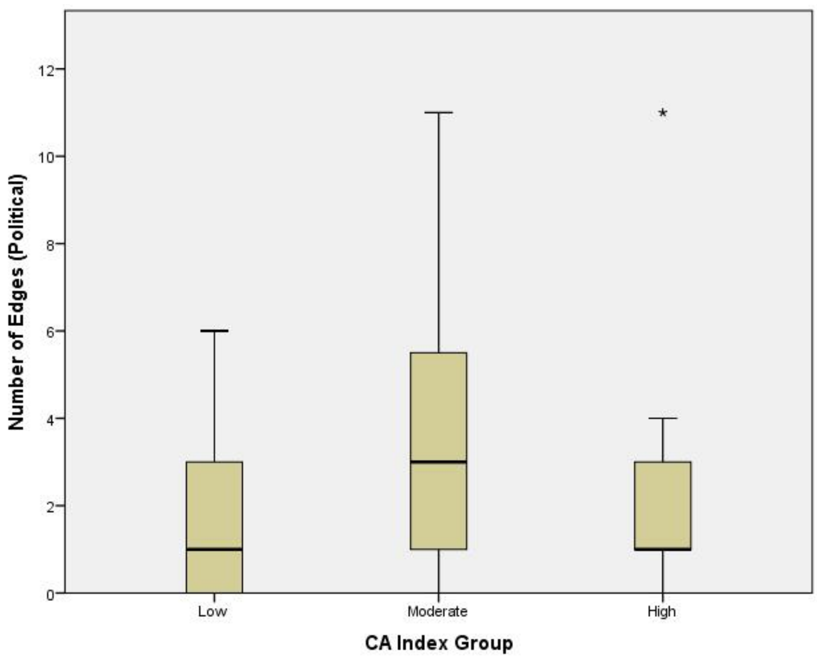
Number of Edges (Economic)
0
20
40
60
Low
Moderate
High
CA Index Group



Number of Edges (Emotional)
0
2
4
6
8
10
12
Low
Moderate
High
CA Index Group



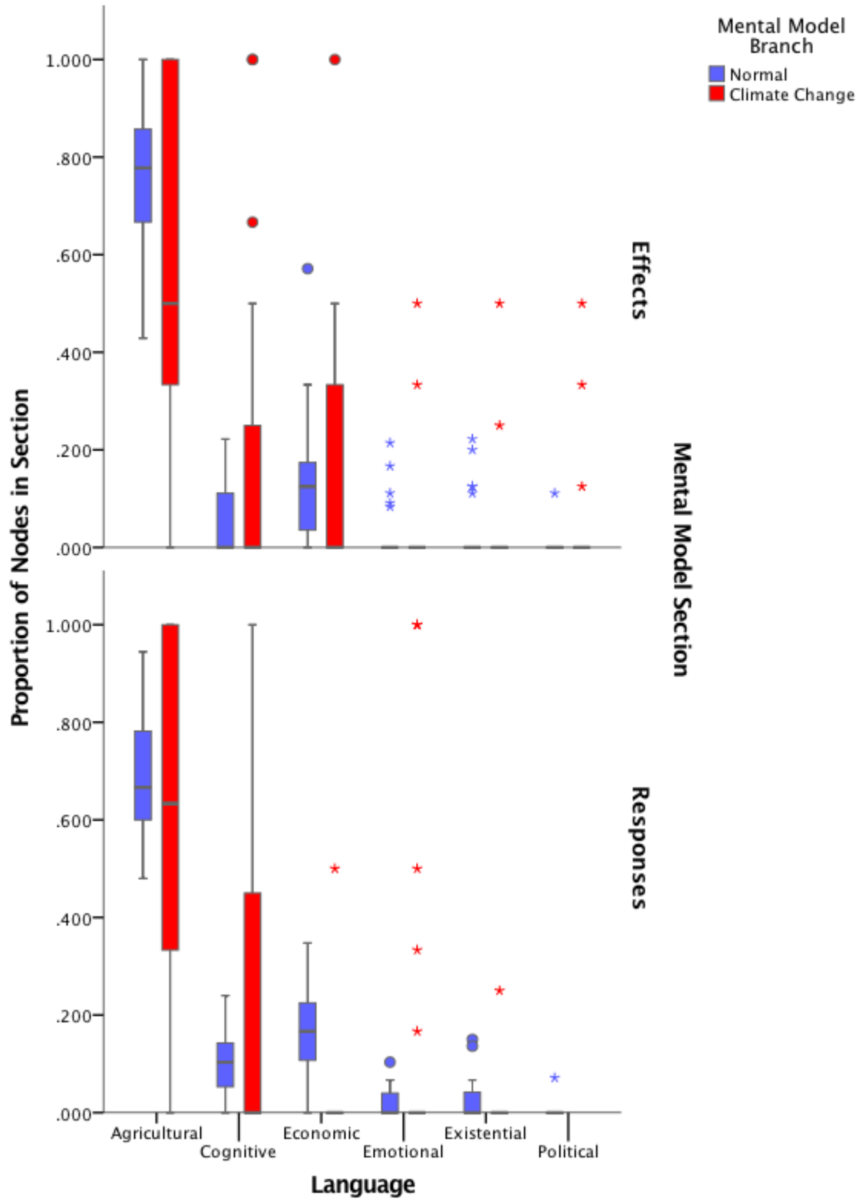
Number of Edges (Survival)
30
20
10
0
Low
Moderate
High
CA Index Group



Number of Edges (Political)
12
10
8
6
4
2
0
Low
Moderate
High
CA Index Group

Appendix F: Additional boxplots of language frequencies

Figure F.1: Boxplot of language proportions by mental model section and branch (i.e., normal and climate change) (n = 30).



Appendix G: Detailed regression analyses

G.1 Conservation Agriculture (CA) outcomes and related practices

Table G.1: Test of model effects for ordinal and binary regression analyses of CA outcomes and related variables. Descriptions of each independent variable may be found below Table 4.2.

Tests of Model Effects (from GZLM): Conservation Agriculture Outcomes and Related Practices

		CA Index		**Soil Cover**		**Minimum Soil Disturbance**		**Crop Rotation**		**Low-Tillage Implements**		**No Residue Burning**	
Independent variable	*df*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*
Age	2	4.535	0.104	1.664	0.435	0.402	0.818	1.775	0.412	0.061	0.970	0.586	0.746
Education	1	1.297	0.255	2.573	0.109	0.005	0.944	1.043	0.307	0.064	0.801	0.748	0.387
Age x Education	2	0.654	0.721	6.493	0.039	5.874	0.053	3.658	0.161	2.538	0.281	1.962	0.375
Political identity	2	0.537	0.764	5.856	0.054	1.125	0.570	1.119	0.572	0.082	0.960	1.541	0.463
Political identity x Education	2	8.373	0.015	2.716	0.257	**14.973**	**0.001**	0.828	0.661	6.317	0.042	4.554	0.103
Crop cluster	3	**24.220**	**0.000**	**12.287**	**0.006**	1.682	0.641	**39.529**	**0.000**	**35.282**	**0.000**	21.634	**0.000**
Rainfall variability	1	1.389	0.239	1.253	0.263	0.038	0.846	1.984	0.159	4.739	0.029	5.918	0.015
Crop cluster x Rainfall variability	3	8.222	0.042	1.719	0.633	0.175	0.981	**12.147**	**0.007**	10.066	0.018	1.604	0.659
Farm size (annual crops < 500 ha)	1	5.571	0.018	0.903	0.342	0.765	0.382	**16.864**	**0.000**	3.923	0.048	0.137	0.711
Percentage of profit from grain	1	**12.708**	**0.000**	**8.690**	**0.003**	3.683	0.055	1.358	0.244	1.968	0.161	1.823	0.177
Model summaries													
Regression type			Ordinal		Ordinal		Ordinal		Binary		Ordinal		Binary
-2 log-likelihood (-2LL)			300.252		309.652		310.649		161.236		271.047		112.804
Likelihood ratio chi-square			64.436		42.408		33.878		90.756		90.951		85.485
Degrees of freedom			18		18		18		18		18		18
Model significance (p)			**0.000**		**0.001**		0.013		**0.000**		**0.000**		**0.000**
Sample size (N)			305		308		307		306		297		309

Significance	
p > .10	p < .05
p < .10	**p < .01**

Table G.2: Odds ratio estimates for ordinal regression analyses of CA index and soil cover. Descriptions of each independent variable may be found below Table 4.2.

Parameter Estimates (from GZLM): CA Index and Soil Cover

	CA Index			Soil Cover		
Independent variables	*B*	*Exp(B)*	*Sig.*	*B*	*Exp(B)*	*Sig.*
Age						
Younger	0.292	1.339	0.501	-0.146	0.864	0.734
Middle-aged	-0.331	0.718	0.375	-0.407	0.666	0.274
Older	Ref	Ref	Ref	Ref	Ref	Ref
Education	-1.236	0.291	0.020	-1.017	0.362	0.048
Age x Education						
Younger x Education	0.342	1.408	0.501	0.254	1.289	0.614
Middle-aged x Education	0.337	1.400	0.428	0.906	2.476	0.033
Older x Education	Ref	Ref	Ref	Ref	Ref	Ref
Political identity						
Conservative	-0.262	0.769	0.472	-0.352	0.703	0.328
Moderate	-0.131	0.878	0.689	0.301	1.351	0.343
Liberal	Ref	Ref	Ref	Ref	Ref	Ref
Political identity x Education						
Conservative x Education	**1.318**	**3.735**	**0.004**	0.690	1.993	0.125
Moderate x Education	1.048	2.852	0.014	0.286	1.331	0.488
Liberal x Education	Ref	Ref	Ref	Ref	Ref	Ref
Crop cluster						
Mixed	1.220	3.388	0.074	1.252	3.496	0.067
Irrigation	0.998	2.713	0.015	0.755	2.129	0.061
Dry wheat	**1.958**	**7.089**	**0.000**	**1.259**	**3.520**	**0.001**
Dry maize	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability	-0.009	0.991	0.977	0.048	1.049	0.869
Crop cluster x Rainfall variability						
Mixed x Rainfall var.	0.929	2.533	0.292	0.677	1.968	0.441
Irrigation x Rainfall var.	0.708	2.029	0.151	0.351	1.421	0.468
Dry wheat x Rainfall var.	-0.435	0.647	0.247	-0.110	0.896	0.765
Dry maize x Rainfall var.	Ref	Ref	Ref	Ref	Ref	Ref
Farm size						
Annual crops < 500 ha	-0.646	0.524	0.018	-0.256	0.774	0.342
Annual crops > 500 ha	Ref	Ref	Ref	Ref	Ref	Ref
Percentage of profit from grain	**0.487**	**1.628**	**0.000**	**0.392**	**1.481**	**0.003**

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Table G.3: Odds ratio estimates for ordinal regression analysis of minimum soil disturbance and binary regression analysis of crop rotation. Descriptions of each independent variable may be found below Table 4.2.

Parameter Estimates (from GZLM): Minimum Soil Disturbance and Crop Rotation

	Minimum Soil Disturbance			Crop Rotation		
Independent variables	*B*	*Exp(B)*	*Sig.*	*B*	*Exp(B)*	*Sig.*
Age						
Younger	-0.217	0.805	0.617	0.391	1.478	0.462
Middle-aged	-0.234	0.791	0.527	-0.109	0.897	0.811
Older	Ref	Ref	Ref	Ref	Ref	Ref
Education	-0.766	0.465	0.144	-0.089	0.914	0.892
Age x Education						
Younger x Education	-0.120	0.887	0.813	0.707	2.028	0.261
Middle-aged x Education	-0.805	0.447	0.058	1.004	2.728	0.059
Older x Education	Ref	Ref	Ref	Ref	Ref	Ref
Political identity						
Conservative	-0.135	0.874	0.710	0.438	1.550	0.342
Moderate	-0.315	0.730	0.335	0.146	1.157	0.728
Liberal	Ref	Ref	Ref	Ref	Ref	Ref
Political identity x Education						
Conservative x Education	**1.575**	**4.831**	**0.001**	-0.250	0.779	0.664
Moderate x Education	**1.690**	**5.419**	**0.000**	-0.459	0.632	0.394
Liberal x Education	Ref	Ref	Ref	Ref	Ref	Ref
Crop cluster						
Mixed	-0.278	0.757	0.686	2.227	9.271	0.011
Irrigation	-0.161	0.851	0.690	**1.792**	**6.003**	**0.000**
Dry wheat	-0.496	0.609	0.198	**3.495**	**32.938**	**0.000**
Dry maize	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability	0.086	1.090	0.765	-0.241	0.786	0.514
Crop cluster x Rainfall variability						
Mixed x Rainfall var.	-0.258	0.773	0.772	2.262	9.601	0.043
Irrigation x Rainfall var.	0.110	1.116	0.821	0.975	2.652	0.098
Dry wheat x Rainfall var.	-0.001	0.999	0.999	-0.519	0.595	0.265
Dry maize x Rainfall var.	Ref	Ref	Ref	Ref	Ref	Ref
Farm size						
Annual crops < 500 ha	-0.233	0.792	0.382	**-1.550**	**0.212**	**0.000**
Annual crops > 500 ha	Ref	Ref	Ref	Ref	Ref	Ref
Percentage of profit from grain	0.248	1.282	0.055	0.197	1.217	0.244

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Table G.4: Odds ratio estimates for ordinal regression analysis of low-tillage implements and binary regression analysis of soil residue burning. Descriptions of each independent variable may be found below Table 4.2.

Parameter Estimates (from GZLM): Low-Tillage Implements and No Residue Burning

	Low-Tillage Implements			No Residue Burning		
Independent variables	*B*	*Exp(B)*	*Sig.*	*B*	*Exp(B)*	*Sig.*
Age						
Younger	-0.013	0.987	0.978	-0.050	0.951	0.937
Middle-aged	-0.073	0.930	0.851	0.265	1.303	0.640
Older	Ref	Ref	Ref	Ref	Ref	Ref
Education	-0.188	0.829	0.716	-0.168	0.845	0.851
Age x Education						
Younger x Education	-0.733	0.480	0.158	-0.903	0.405	0.246
Middle-aged x Education	-0.645	0.525	0.132	-0.902	0.406	0.169
Older x Education	Ref	Ref	Ref	Ref	Ref	Ref
Political identity						
Conservative	-0.069	0.934	0.855	-0.201	0.818	0.763
Moderate	-0.098	0.906	0.776	-0.576	0.562	0.305
Liberal	Ref	Ref	Ref	Ref	Ref	Ref
Political identity x Education						
Conservative x Education	0.718	2.050	0.118	0.245	1.278	0.772
Moderate x Education	1.077	2.934	0.013	1.208	3.347	0.118
Liberal x Education	Ref	Ref	Ref	Ref	Ref	Ref
Crop cluster						
Mixed	-0.452	0.636	0.614	-1.847	0.158	0.035
Irrigation	0.936	2.549	0.027	**-2.480**	**0.084**	**0.000**
Dry wheat	**2.546**	**12.752**	**0.000**	**-2.187**	**0.112**	**0.000**
Dry maize	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability	**-0.930**	**0.395**	**0.002**	-0.686	0.504	0.275
Crop cluster x Rainfall variability						
Mixed x Rainfall var.	-0.938	0.391	0.409	-1.470	0.230	0.331
Irrigation x Rainfall var.	0.803	2.232	0.116	0.032	1.033	0.968
Dry wheat x Rainfall var.	**1.142**	**3.134**	**0.005**	0.250	1.284	0.717
Dry maize x Rainfall var.	Ref	Ref	Ref	Ref	Ref	Ref
Farm size						
Annual crops < 500 ha	-0.568	0.567	0.048	0.155	1.168	0.711
Annual crops > 500 ha	Ref	Ref	Ref	Ref	Ref	Ref
Percentage of profit from grain	0.192	1.211	0.161	-0.269	0.764	0.177

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

G.2 Farming identity: Conservation versus conventional

Table G.5: Test of model effects for drivers of "conservation" farming identity in binary logistic regression. To reveal the implicit definition of conservation farming in contrast with conventional farming, those who broadly identified their farming practices as "conservation" were coded as "1", and those who identified themselves as "conventional" farmers were coded as "0". Descriptions of each independent variable may be found below Table 4.2 and Table 4.3.

Tests of Model Effects (from GZLM): Cons. vs. Conv. Farming

		Reduced Model		**Full Model**	
Independent variables	*df*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*
Age	2	0.926	0.629	1.936	0.380
Education	1	0.379	0.538	0.421	0.517
Political identity	1	0.836	0.361	0.644	0.422
Crop cluster	3	1.470	0.689	1.165	0.761
Farm size (annual crops < 500 ha)	1	**10.874**	**0.001**	**9.141**	**0.002**
More soil cover	1	2.579	0.108	3.466	0.063
Less soil disturbance	1	2.311	0.128	2.612	0.106
More crops in rotation	1	**7.332**	**0.007**	3.647	0.056
Low-tillage implements	1	**37.027**	**0.000**	**29.415**	**0.000**
Never burn crop residues	1	**7.814**	**0.005**	3.905	0.048
Age x Education	2			1.276	0.528
Political x Education	1			0.770	0.380
Rainfall variability	1			0.083	0.773
Crop cluster x Rainfall var.	3			4.937	0.176
% profit from grain	1			0.024	0.878
Model summaries					
Regression type			Binary		Binary
-2 log-likelihood (-2LL)			87.907		74.020
Likelihood ratio chi-square			132.016		136.292
Degrees of freedom			13		21
Model significance (p)			**0.000**		**0.000**
Sample size (N)			244		218

Significance	
p > .10	p < .05
p < .10	**p < .01**

Table G.6: Odds ratio estimates for drivers of "conservation" farming identity in binary logistic regression. To reveal the implicit definition of conservation farming in contrast with conventional farming, those who broadly identified their farming practices as "conservation" were coded as "1", and those who identified themselves as "conventional" farmers were coded as "0". Odds ratios above 1 indicate a greater likelihood of identifying as a "conservation" farmer, while odds ratios below 1 indicate a greater likelihood of identifying as a "conventional" farmer. Descriptions of each independent variable may be found below Table 4.2 and Table 4.3.

Parameter Estimates (from GZLM): Conservation vs. Conventional Farming

		Reduced Model			Full Model	
Independent variable	*B*	*Exp(B)*	*Sig.*	*B*	*Exp(B)*	*Sig.*
Age						
Younger	0.632	1.882	0.350	0.728	2.071	0.360
Middle-aged	0.229	1.258	0.665	-0.089	0.915	0.893
Older	Ref	Ref	Ref	Ref	Ref	Ref
Education	0.140	1.150	0.538	0.331	1.392	0.619
Political identity	-0.273	0.761	0.361	-0.272	0.762	0.422
Crop cluster						
Mixed	0.399	1.490	0.613	0.546	1.727	0.723
Irrigation	0.784	2.190	0.239	-0.229	0.795	0.802
Dry wheat	0.359	1.432	0.628	0.897	2.453	0.419
Dry maize	Ref	Ref	Ref	Ref	Ref	Ref
Farm size						
Annual crops < 500 ha	**-1.469**	**0.230**	**0.001**	**-1.715**	**0.180**	**0.002**
Annual crops > 500 ha	Ref	Ref	Ref	Ref	Ref	Ref
More soil cover	0.363	1.438	0.108	0.520	1.682	0.063
Less soil disturbance	0.390	1.477	0.128	0.485	1.624	0.106
More crops in rotation	**0.967**	**2.630**	**0.007**	0.774	2.169	0.056
Low-tillage implements	**2.219**	**9.202**	**0.000**	**2.564**	**12.987**	**0.000**
Crop residue burning						
Never burn	**1.624**	**5.074**	**0.005**	1.361	3.902	0.048
Sometimes or always burn	Ref	Ref	Ref	Ref	Ref	Ref
Age x Education						
Younger x Education				-0.588	0.556	0.517
Middle-aged x Education				0.228	1.256	0.755
Older x Education				Ref	Ref	Ref
Political identity x Education				0.354	1.425	0.380
Rainfall variability				0.625	1.869	0.269
Crop cluster x Rainfall variability						
Mixed by Rainfall var.				1.707	5.512	0.586
Irrigation by Rainfall var.				-1.631	0.196	0.219
Wheat by Rainfall var.				-1.599	0.202	0.039
Maize by Rainfall var.				Ref	Ref	Ref
Percentage of profit from grain				-0.039	0.961	0.878

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

G.3 Climate change and weather ranks

Table G.7: Test of model effects for independent predictors of climate change rank. These were obtained using ordinal regression (i.e., generalized linear model with cumulative logit link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3.

Tests of Model Effects (from GZLM): Climate Change Ranks

		Demographics		Crop Cluster		Farm Characteristics		Farming Practices		Full Model without Practices		Full Model	
Independent variables	*df*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*
Age	2	4.097	0.129							2.627	0.269	2.215	0.330
Education	1	0.448	0.503							0.874	0.350	0.893	0.345
Age x Education	2	0.527	0.769							0.923	0.630	1.521	0.467
Political identity	1	1.435	0.231							4.400	0.036	3.907	0.048
Political x Education	1	**8.337**	**0.004**							**8.368**	**0.004**	**8.309**	**0.004**
Crop cluster	3			**12.933**	**0.005**	6.324	0.097			6.255	0.100	5.823	0.121
Rainfall variability	1					1.569	0.210			1.914	0.166	2.949	0.086
Crop cluster x Rainfall variability	3					6.323	0.097			7.222	0.065	7.814	0.050
Farm size (annual crops < 500 ha)	1					1.728	0.189			1.476	0.224	2.974	0.085
Total profit	1					3.450	0.063			3.697	0.054	3.307	0.069
More rotations crops	1							0.754	0.385			1.068	0.301
Low-tillage implements	1							1.916	0.166			0.548	0.459
Never burn crop residues	1							**14.415**	**0.000**			**9.417**	**0.002**
Model summaries													
Regression type			Ordinal		Ordinal		Ordinal		Ordinal		Ordinal		Ordinal
-2 log-likelihood (-2LL)			81.711		23.187		256.464		103.635		282.310		281.002
Likelihood ratio chi-square			16.499		13.108		25.563		21.720		42.689		53.622
Degrees of freedom			7		3		9		3		16		19
Model significance (p)			0.021		**0.004**		**0.002**		**0.000**		**0.000**		**0.000**
Sample size (N)			246		246		246		246		246		246

Significance	
p > .10	p < .05
p < .10	**p < .01**

Table G.8: Test of model effects for independent predictors of weather rank. These were obtained using ordinal regression (i.e., generalized linear model with cumulative logit link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3.

Tests of Model Effects (from GZLM): Weather Ranks

		Demographics		Crop Cluster		Farm Characteristics		Farming Practices		Full Model without Practices		Full Model	
Independent variables	*df*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*
Age	2	0.861	0.650							0.292	0.864	0.148	0.929
Education	1	5.268	0.022							6.304	0.012	6.254	0.012
Age x Education	2	4.795	0.091							5.732	0.057	5.696	0.058
Political identity	1	0.835	0.361							1.653	0.199	2.107	0.147
Political x Education	1	0.659	0.417							0.253	0.615	0.164	0.685
Crop cluster	3			**12.752**	**0.005**	**14.367**	**0.002**			**16.105**	**0.001**	**22.017**	**0.000**
Rainfall variability	1					0.002	0.961			0.012	0.915	0.015	0.902
Crop cluster x Rainfall variability	3					6.353	0.096			7.256	0.064	11.226	0.011
Farm size (annual crops < 500 ha)	1					0.774	0.379			2.195	0.138	2.883	0.090
Total profit	1					0.075	0.784			0.233	0.630	0.361	0.548
More rotations crops	1							0.526	0.468			0.022	0.883
Low-tillage implements	1							1.223	0.269			3.196	0.074
Never burn crop residues	1							0.498	0.481			**9.384**	**0.002**
Model summaries													
Regression type			Ordinal		Ordinal		Ordinal		Ordinal		Ordinal		Ordinal
-2 log-likelihood (-2LL)			96.093		26.075		279.043		117.500		304.976		303.193
Likelihood ratio chi-square			10.510		13.879		20.472		1.957		32.217		44.101
Degrees of freedom			7		3		9		3		16		19
Model significance (p)			0.161		**0.003**		0.015		0.581		**0.009**		**0.001**
Sample size (N)			246		246		246		246		246		246

Significance	
p > .10	p < .05
p < .10	**p < .01**

Table G.9: Test of model effects for independent predictors of the distance between climate change and weather ranks. These were obtained using multivariate linear regression (i.e., generalized linear model with identity link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3.

Tests of Model Effects (from GZLM): Distance Between Climate Change and Weather Ranks

		Demographics		**Crop Cluster**		**Farm Characteristics**		**Farming Practices**		**Full Model without Practices**		**Full Model**	
Independent variables	*df*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*	*Wald Chi-Square*	*Sig.*
Age	2	0.644	0.725							0.538	0.764	0.276	0.871
Education	1	4.964	0.026							5.668	0.017	5.535	0.019
Age x Education	2	5.295	0.071							6.661	0.036	7.535	0.023
Political identity	1	0.265	0.607							0.475	0.491	0.291	0.589
Political x Education	1	2.357	0.125							2.766	0.096	3.156	0.076
Crop cluster	3			6.732	0.081	8.762	0.033			10.009	0.018	**19.073**	**0.000**
Rainfall variability	1					0.254	0.614			0.212	0.646	0.497	0.481
Crop cluster x Rainfall variability	3					1.765	0.623			1.921	0.589	4.278	0.233
Farm size (annual crops < 500 ha)	1					1.624	0.203			2.639	0.104	6.191	0.013
Total profit	1					1.724	0.189			2.172	0.140	2.099	0.147
More rotations crops	1							0.492	0.483			2.230	0.135
Low-tillage implements	1							2.086	0.149			3.805	0.051
Never burn crop residues	1							**7.332**	**0.007**			**16.789**	**0.000**
Model summaries													
Regression type			Linear		Linear		Linear		Linear		Linear		Linear
-2 log-likelihood (-2LL)			566.341		568.006		566.291		565.220		560.463		549.772
Likelihood ratio chi-square			9.972		6.641		10.072		12.214		21.728		43.110
Degrees of freedom			7		3		9		3		16		19
Model significance (p)			0.190		0.084		0.345		**0.007**		0.152		**0.001**
Sample size (N)			246		246		246		246		246		246

Significance	
p > .10	p < .05
p < .10	**p < .01**

Table G.10: Odds ratio estimates for independent predictors of climate change rank. These were obtained using ordinal regression (i.e., generalized linear model with cumulative logit link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3. The table is continued on the following page.

Parameter Estimates (from GZLM): Climate Change Ranks

	Demographics				Crop Cluster				Farm Characteristics			
Independent variables	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*
Age												
Younger	0.913	0.363	2.299	0.847								
Middle-aged	1.672	0.783	3.570	0.184								
Older	Ref	Ref	Ref	Ref								
Education	0.731	0.327	1.635	0.445								
Age x Education												
Younger x Education	1.245	0.418	3.705	0.694								
Middle-aged x Education	1.378	0.573	3.312	0.473								
Older x Education	Ref	Ref	Ref	Ref								
Political identity	1.258	0.864	1.831	0.231								
Political identity x education	**0.502**	**0.314**	**0.801**	**0.004**								
Crop cluster												
Mixed					1.367	0.506	3.694	0.537	4.466	0.975	20.464	0.054
Irrigation					0.661	0.315	1.386	0.273	0.888	0.368	2.141	0.791
Dry wheat					**0.377**	**0.214**	**0.665**	**0.001**	0.592	0.267	1.315	0.198
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability									0.906	0.499	1.645	0.745
Crop cluster x Rainfall variability												
Mixed by Rainfall var.									10.513	1.172	94.284	0.036
Irrigation by Rainfall var.									0.945	0.321	2.781	0.918
Wheat by Rainfall var.									0.701	0.318	1.544	0.378
Maize by Rainfall var.									Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha									0.681	0.384	1.208	0.189
Annual crops > 500 ha									Ref	Ref	Ref	Ref
Total profit									0.779	0.599	1.014	0.063
More rotation crops												
Low-tillage implements												
Crop residue burning												
Never burn												
Sometimes or always burn												

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Parameter Estimates (from GZLM): Climate Change Ranks

Independent variables	Farming Practices *Exp(B)*	*Low CI*	*High CI*	*Sig.*	Full Model without Practices *Exp(B)*	*Low CI*	*High CI*	*Sig.*	Full Model *Exp(B)*	*Low CI*	*High CI*	*Sig.*
Age												
Younger					0.859	0.328	2.248	0.756	0.894	0.339	2.359	0.820
Middle-aged					1.459	0.658	3.234	0.353	1.448	0.650	3.226	0.366
Older					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Education					0.702	0.312	1.579	0.392	0.621	0.273	1.412	0.256
Age x Education												
Younger x Education					1.115	0.362	3.433	0.850	1.345	0.428	4.225	0.612
Middle-aged x Education					1.462	0.600	3.561	0.403	1.726	0.698	4.270	0.238
Older x Education					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Political identity					1.518	1.028	2.243	0.036	1.485	1.003	2.197	0.048
Political identity x education					**0.495**	**0.308**	**0.797**	**0.004**	**0.491**	**0.303**	**0.796**	**0.004**
Crop cluster												
Mixed					4.524	0.987	20.732	0.052	6.272	1.288	30.551	0.023
Irrigation					0.947	0.385	2.331	0.906	1.784	0.668	4.765	0.248
Dry wheat					0.590	0.262	1.331	0.204	1.215	0.425	3.474	0.717
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability					0.874	0.479	1.596	0.661	0.843	0.451	1.574	0.592
Crop cluster x Rainfall variability												
Mixed by Rainfall var.					11.862	1.355	103.831	0.025	15.819	1.715	145.902	0.015
Irrigation by Rainfall var.					1.139	0.378	3.430	0.818	1.461	0.465	4.588	0.516
Wheat by Rainfall var.					0.694	0.311	1.550	0.373	0.751	0.325	1.732	0.501
Maize by Rainfall var.					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha					0.692	0.382	1.253	0.224	0.574	0.306	1.079	0.085
Annual crops > 500 ha					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Total profit					0.769	0.588	1.005	0.054	0.779	0.594	1.020	0.069
More rotation crops	0.897	0.703	1.146	0.385					0.849	0.622	1.158	0.301
Low-tillage implements	0.844	0.664	1.073	0.166					0.901	0.683	1.188	0.459
Crop residue burning												
Never burn	**3.196**	**1.754**	**5.823**	**0.000**					**2.921**	**1.473**	**5.791**	**0.002**
Sometimes or always burn	Ref	Ref	Ref	Ref					Ref	Ref	Ref	Ref

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Table G.11: Odds ratio estimates for independent predictors of weather rank. These were obtained using ordinal regression (i.e., generalized linear model with cumulative logit link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3. The table is continued on the following page.

Parameter Estimates (from GZLM): Weather Ranks

	Demographics				Crop Cluster				Farm Characteristics			
Independent variables	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*
Age												
Younger	1.526	0.622	3.748	0.356								
Middle-aged	1.316	0.623	2.778	0.472								
Older	Ref	Ref	Ref	Ref								
Education	2.078	0.936	4.614	0.072								
Age x Education												
Younger x Education	0.918	0.318	2.650	0.874								
Middle-aged x Education	0.467	0.196	1.112	0.085								
Older x Education	Ref	Ref	Ref	Ref								
Political identity	1.186	0.822	1.712	0.361								
Political identity x education	0.829	0.528	1.303	0.417								
Crop cluster												
Mixed					0.881	0.327	2.374	0.802	0.716	0.168	3.050	0.651
Irrigation					**0.233**	**0.104**	**0.523**	**0.000**	**0.165**	**0.065**	**0.421**	**0.000**
Dry wheat					0.711	0.418	1.211	0.210	0.792	0.369	1.701	0.550
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability									1.701	0.940	3.079	0.079
Crop cluster x Rainfall variability												
Mixed by Rainfall var.									0.709	0.096	5.218	0.735
Irrigation by Rainfall var.									0.410	0.131	1.279	0.124
Wheat by Rainfall var.									0.389	0.183	0.826	0.014
Maize by Rainfall var.									Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha									1.284	0.736	2.241	0.379
Annual crops > 500 ha									Ref	Ref	Ref	Ref
Total profit									1.037	0.800	1.345	0.784
More rotation crops												
Low-tillage implements												
Crop residue burning												
Never burn												
Sometimes or always burn												

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Parameter Estimates (from GZLM): Weather Ranks

	Farming Practices				Full Model without Practices				Full Model			
Independent variables	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*	*Exp(B)*	*Low CI*	*High CI*	*Sig.*
Age												
Younger					1.250	0.492	3.177	0.639	1.183	0.459	3.051	0.728
Middle-aged					1.058	0.484	2.310	0.888	1.052	0.479	2.314	0.899
Older					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Education					2.407	1.062	5.454	0.035	2.434	1.066	5.554	0.035
Age x Education												
Younger x Education					0.819	0.272	2.466	0.722	0.808	0.263	2.485	0.710
Middle-aged x Education					0.402	0.164	0.984	0.046	0.397	0.161	0.984	0.046
Older x Education					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Political identity					1.283	0.878	1.875	0.199	1.328	0.905	1.947	0.147
Political identity x education					0.888	0.560	1.409	0.615	0.908	0.569	1.449	0.685
Crop cluster												
Mixed					0.633	0.147	2.724	0.539	0.684	0.155	3.029	0.617
Irrigation					**0.138**	**0.052**	**0.364**	**0.000**	**0.079**	**0.027**	**0.229**	**0.000**
Dry wheat					0.739	0.341	1.603	0.444	0.444	0.161	1.222	0.116
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability					1.793	0.985	3.265	0.056	2.027	1.088	3.778	0.026
Crop cluster x Rainfall variability												
Mixed by Rainfall var.					0.756	0.100	5.706	0.786	0.797	0.103	6.153	0.828
Irrigation by Rainfall var.					0.406	0.125	1.315	0.133	0.326	0.099	1.082	0.067
Wheat by Rainfall var.					**0.357**	**0.167**	**0.766**	**0.008**	**0.263**	**0.119**	**0.585**	**0.001**
Maize by Rainfall var.					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha					1.547	0.869	2.757	0.138	1.710	0.921	3.175	0.090
Annual crops > 500 ha					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Total profit					1.067	0.820	1.389	0.630	1.086	0.831	1.419	0.548
More rotation crops	0.916	0.724	1.160	0.468					0.977	0.720	1.327	0.883
Low-tillage implements	1.141	0.903	1.441	0.269					1.283	0.976	1.686	0.074
Crop residue burning												
Never burn	0.823	0.478	1.415	0.481					**0.358**	**0.185**	**0.690**	**0.002**
Sometimes or always burn	Ref	Ref	Ref	Ref					Ref	Ref	Ref	Ref

Odds Ratio	Significance	
Exp(B) < 1	p < .10	p < .05
Exp(B) > 1	p < .10	p < .05

Table G.12: Parameter estimates for independent predictors of the distance between climate change and weather ranks. These were obtained using multivariate linear regression (i.e., generalized linear model with identity link) (n = 246). Descriptions of each independent variable may be found below Figure 6.3. The table is continued on the following page.

Parameter Estimates (from GZLM): Distance Between Climate Change and Weather Ranks

	Demographics				Crop Cluster				Farm Characteristics			
Independent variables	*B*	*Low CI*	*High CI*	*Sig.*	*B*	*Low CI*	*High CI*	*Sig.*	*B*	*Low CI*	*High CI*	*Sig.*
Age												
Younger	-0.181	0.262	2.660	0.759								
Middle-aged	0.162	0.450	3.069	0.741								
Older	Ref	Ref	Ref	Ref								
Education	-0.834	0.159	1.190	0.105								
Age x Education												
Younger x Education	-0.105	0.231	3.517	0.880								
Middle-aged x Education	0.919	0.830	7.560	0.103								
Older x Education	Ref	Ref	Ref	Ref								
Political identity	0.127	0.700	1.843	0.607								
Political identity x education	-0.466	0.346	1.138	0.125								
Crop cluster												
Mixed					0.374	-0.965	1.713	0.584	1.026	-0.919	2.971	0.301
Irrigation					1.031	0.056	2.007	0.038	1.474	0.320	2.628	0.012
Dry wheat					-0.343	-1.058	0.373	0.348	-0.326	-1.349	0.698	0.533
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability									-0.406	-1.196	0.384	0.314
Crop cluster x Rainfall variability												
Mixed by Rainfall var.									1.236	-1.436	3.909	0.365
Irrigation by Rainfall var.									0.575	-0.843	1.993	0.427
Wheat by Rainfall var.									0.578	-0.413	1.568	0.253
Maize by Rainfall var.									Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha									-0.479	-1.216	0.258	0.203
Annual crops > 500 ha									Ref	Ref	Ref	Ref
Total profit									-0.229	-0.572	0.113	0.189
More rotation crops												
Low-tillage implements												
Crop residue burning												
Never burn												
Sometimes or always burn												

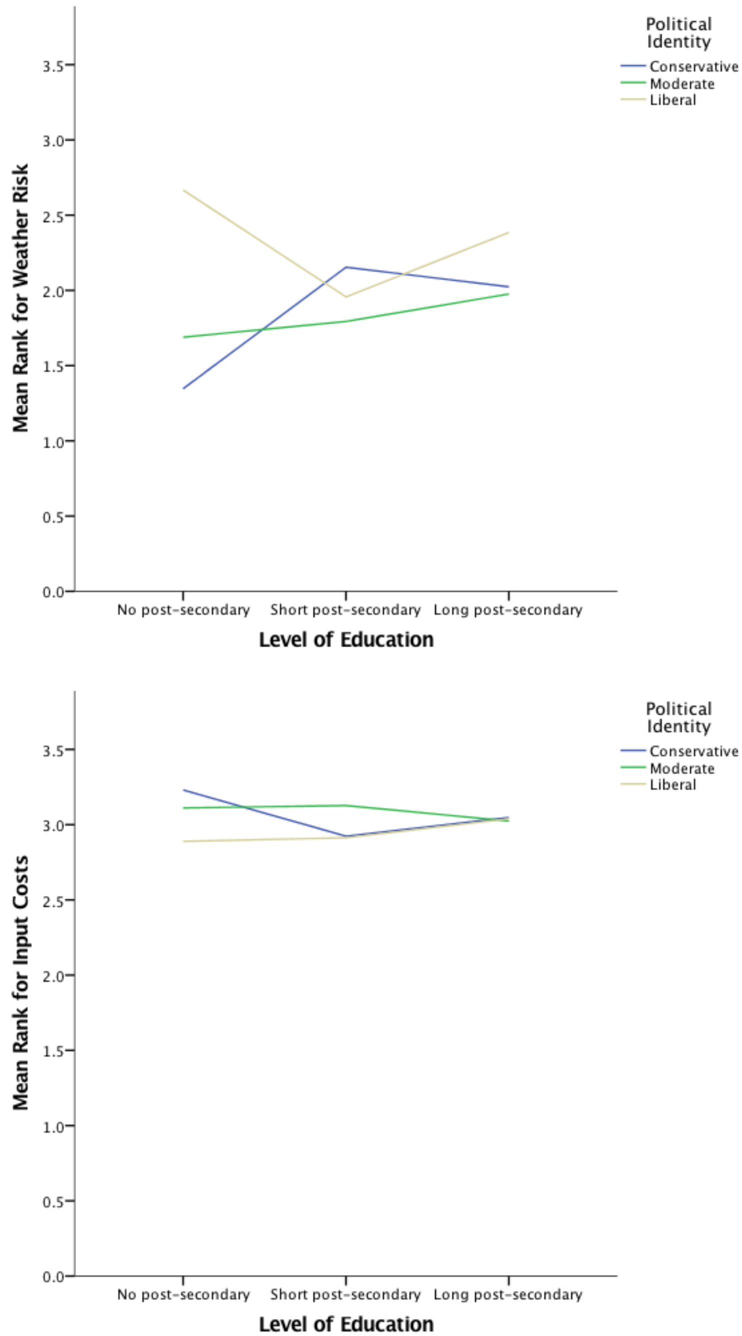
Par. Est.	Significance	
B < 0	p < .10	p < .05
B > 0	p < .10	p < .05

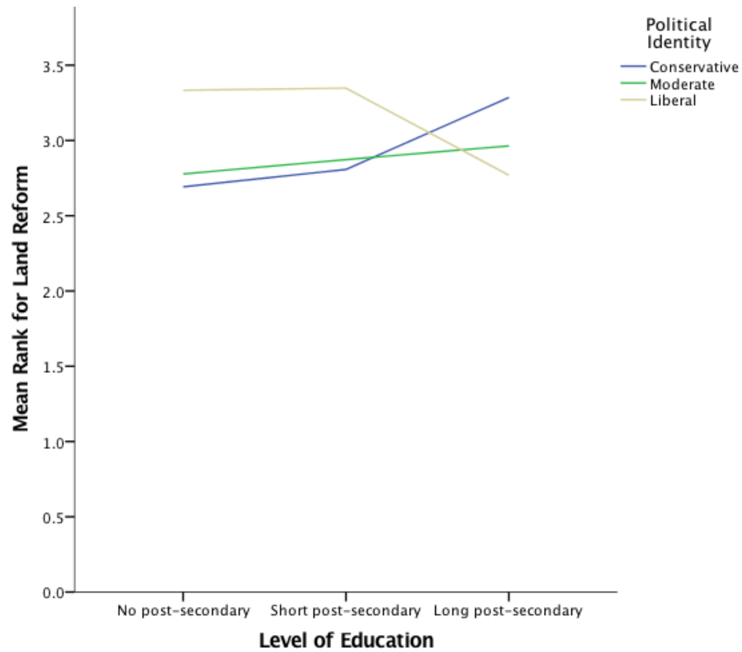
Parameter Estimates (from GZLM): Distance Between Climate Change and Weather Ranks

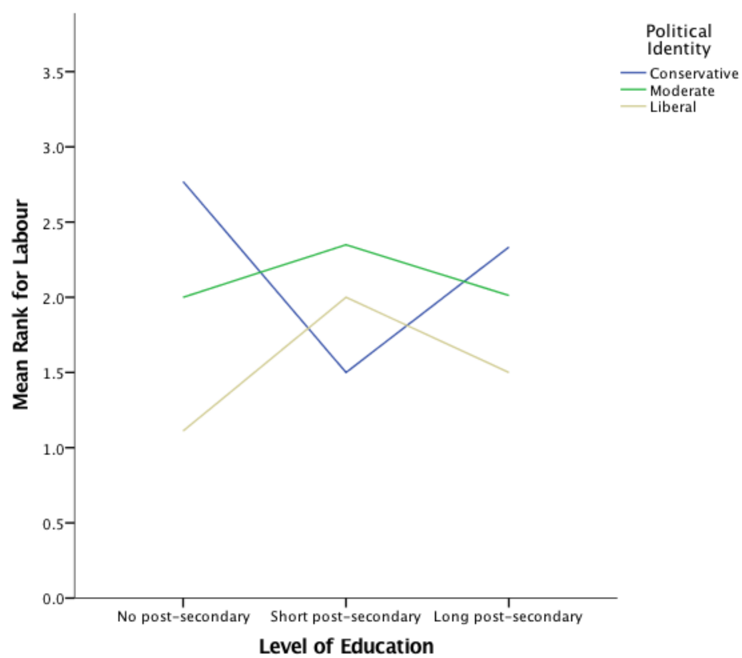
Independent variables	Farming Practices B	Low CI	High CI	Sig.	Full Model without Practices B	Low CI	High CI	Sig.	Full Model B	Low CI	High CI	Sig.
Age												
Younger					-0.035	-1.189	1.119	0.952	0.084	-1.026	1.194	0.882
Middle-aged					0.239	-0.723	1.201	0.626	0.220	-0.702	1.142	0.640
Older					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Education					-0.909	-1.900	0.082	0.072	-1.014	-1.969	-0.059	0.037
Age x Education												
Younger x Education					-0.089	-1.446	1.268	0.897	0.163	-1.151	1.476	0.808
Middle-aged x Education					1.035	-0.057	2.127	0.063	1.189	0.133	2.245	0.027
Older x Education					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Political identity					0.169	-0.313	0.652	0.491	0.127	-0.335	0.589	0.589
Political identity x education					-0.496	-1.080	0.088	0.096	-0.510	-1.073	0.053	0.076
Crop cluster												
Mixed					1.083	-0.823	2.988	0.265	1.420	-0.429	3.270	0.132
Irrigation					**1.596**	**0.454**	**2.738**	**0.006**	**2.590**	**1.413**	**3.767**	**0.000**
Dry wheat					-0.262	-1.268	0.744	0.610	1.029	-0.198	2.256	0.100
Dry maize					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rainfall variability					-0.445	-1.220	0.329	0.260	-0.605	-1.367	0.158	0.120
Crop cluster x Rainfall variability												
Mixed by Rainfall var.					1.257	-1.370	3.885	0.348	1.480	-1.051	4.011	0.252
Irrigation by Rainfall var.					0.627	-0.771	2.026	0.379	1.099	-0.273	2.472	0.116
Wheat by Rainfall var.					0.582	-0.390	1.554	0.241	0.860	-0.100	1.820	0.079
Maize by Rainfall var.					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Farm size												
Annual crops < 500 ha					-0.610	-1.345	0.126	0.104	-0.942	-1.684	-0.200	0.013
Annual crops > 500 ha					Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Total profit					-0.253	-0.589	0.083	0.140	-0.238	-0.560	0.084	0.147
More rotation crops	-0.112	-0.425	0.201	0.483					-0.278	-0.643	0.087	0.135
Low-tillage implements	-0.229	-0.539	0.082	0.149					-0.330	-0.663	0.002	0.051
Crop residue burning												
Never burn	**0.999**	**0.276**	**1.722**	**0.007**					**1.618**	**0.844**	**2.392**	**0.000**
Sometimes or always burn	Ref	Ref	Ref	Ref					Ref	Ref	Ref	Ref

Par. Est.	Significance	
B < 0	p < .10	p < .05
B > 0	p < .10	p < .05

Figure G.1: The interaction effect of education and political identity on the ranks assigned to weather, input costs, land reform, labour and markets.




Political Identity
Conservative
Moderate
Liberal
Mean Rank for Land Reform
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
No post-secondary
Short post-secondary
Long post-secondary
Level of Education


Political Identity
Conservative
Moderate
Liberal
Mean Rank for Labour
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
No post-secondary
Short post-secondary
Long post-secondary
Level of Education

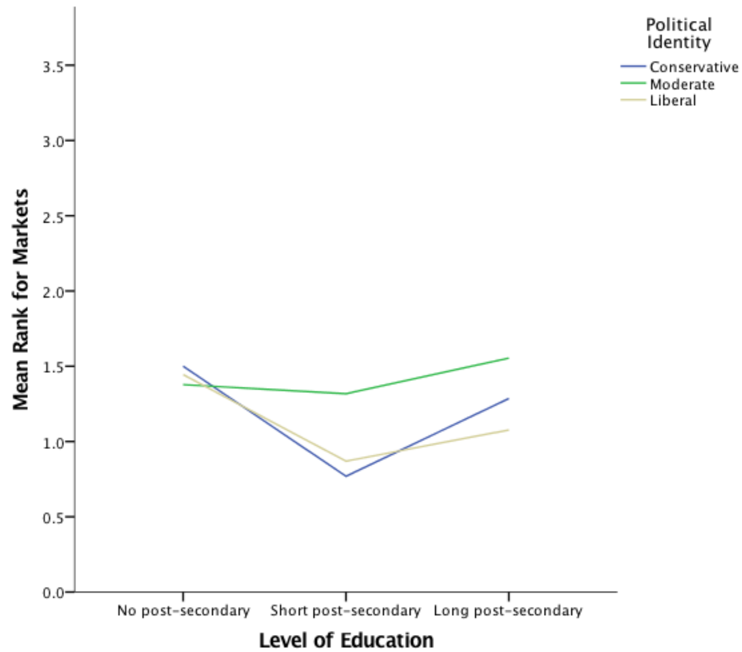
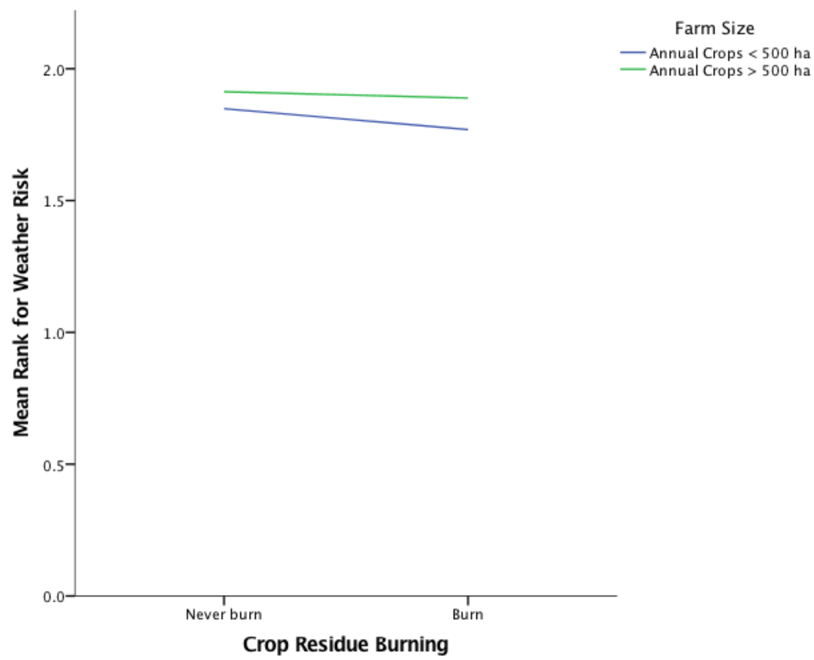
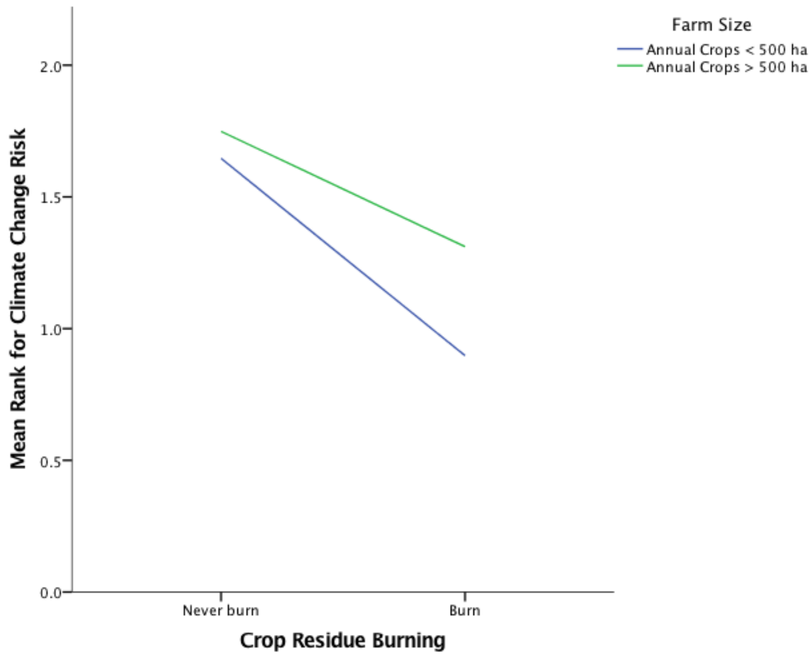
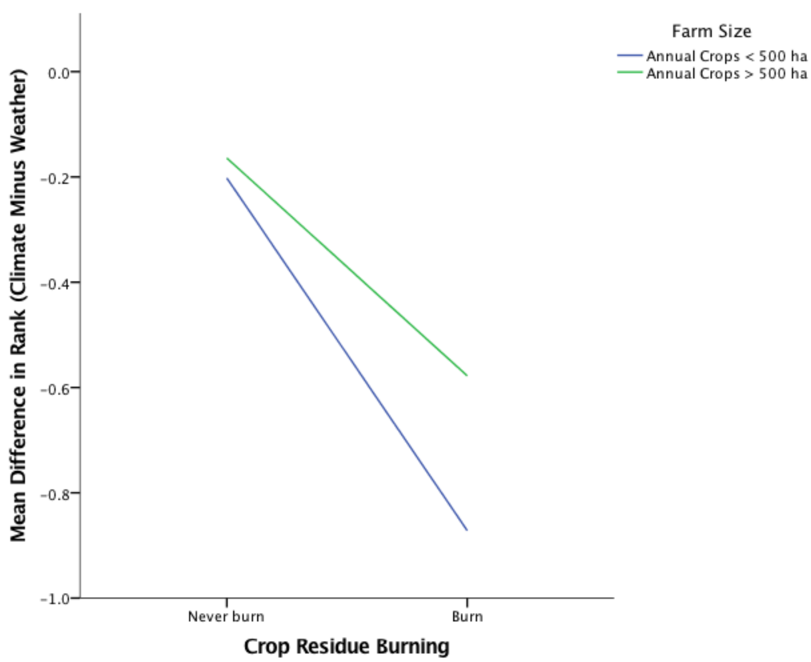


Figure G.2: The interaction effect of farm size and crop residue burning on the ranks assigned to weather and climate change, as well as their difference.




Farm Size
Annual Crops < 500 ha
Annual Crops > 500 ha
Mean Rank for Climate Change Risk
2.0
1.5
1.0
0.5
0.0
Never burn
Burn
Crop Residue Burning


Farm Size
Annual Crops < 500 ha
Annual Crops > 500 ha
Mean Difference in Rank (Climate Minus Weather)
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
Never burn
Burn
Crop Residue Burning