RESILIENCE OF MONTANA'S AGROECOSYSTEMS

TO ECONOMIC AND CLIMATIC CHANGE

by

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DEDICATION

I dedicate the work in this dissertation to my daughter Hazel, who will inherit a world that is transformed by the technologies used to complete the research. I hope for her sake that future agricultural systems, and civilization in general, are able to balance the power of automation with environmental quality, social justice, and peace.

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TABLE OF CONTENTS

TABLE OF CONTENTS – CONTINUED

TABLE OF CONTENTS – CONTINUED

TABLE OF CONTENTS – CONTINUED

LIST OF TABLES

LIST OF FIGURES

LIST OF FIGURES – CONTINUED

LIST OF FIGURES – CONTINUED

ABSTRACT

Semiarid dryland agricultural systems in the western United States are faced with a highly uncertain production environment that complicates decision-making and makes static agronomic prescriptions unreliable for maintaining sustainability. The primary sources of uncertainty for farmers are weather, fluctuations in prices, and site-specific environmental and ecological variability, some of which may be amplified by climate change. To effectively respond to the risks posed by these uncertainties requires knowledge of the vulnerability of these agricultural systems. The aim of this dissertation was to meet this need for Montana by analyzing the economic resilience of the state's dryland agricultural systems at site-specific and county-wide scales.

To begin, a framework was created to integrate weather, prices, nitrogen inputs, and spatial soil variability within a statistical model for site-specific crop responses and net returns. Simulations suggest that six crop years of simulated data collection and parameter tuning were required to derive an accurate model, suggesting that an extended period of observation and targeted nitrogen rate experimentation was required to optimize spatial fertilizer management. The framework was subsequently applied to a spatiotemporal precision agricultural dataset from a farm near Great Falls, MT, and was modified to account for several crop rotations and different farmer risk preferences. Regardless of farmers' level of risk aversion, winter wheat-pea rotations resulted in higher value (utility) for the farmer than winter wheat-fallow and continuous winter wheat rotations. For most levels of risk adversity, it was also optimal to apply no nitrogen fertilizer. Net returns at the field site were always threatened by drought.

Subsequently, a qualitative analysis of farmer adaptability in Montana based on survey and interview data determined that farmers had few options for responding to drought but were more adaptable to high input prices. On-farm experimentation and crop rotations could greatly increase adaptability in the future. Finally, simulations of alternative price, precipitation, and crop rotation scenarios were completed. The most resilient agricultural systems were located in northeastern Montana where pulses have been more widely adopted; systems in north-central Montana were less resilient. State-wide, over 50% of dryland farmers may not be resilient to future economic or climatic variability.

CHAPTER ONE

INTRODUCTION

Prologue

If I had to summarize the discourse surrounding agriculture in the 21st century, I would simplify it to one simple sound bite: "feeding 9 billion people with fewer resources". Inevitably it seems as if all of the agronomic complexities, all of the environmental pressures, and all of the social nuances are obliterated with that simple utterance. And of course the logical follow-up to that statement is one of: "how can we increase productivity, and how can we do it *right now*?" Although it may seem obvious that the reality underlying this need to produce more food is incredibly complicated, the sound bite, nevertheless, imposes a feeling of relentless pressure that must be relieved at all costs.

I firmly believe that this moral imperative needs to be discarded. First, the vast amount of food waste (40% in the US) that has been recently highlighted in academic journals (Hall *et al.* 2009) and the popular press casts serious doubt on emphasizing productivity increases over supply chain efficiency. Second, the discussion about increasing yields tends to focus on commodity crops, and omits much discussion of quality. Humans need to consume a wide variety of plants to achieve healthy lives: nutritional variety cannot be replaced by providing numerous processed derivatives of a small number of crops such as corn, as evidenced by the obesity epidemic in the US. Third, the discussion tends to lead towards land sparing vs. land sharing (intensive agriculture on smaller areas of land vs. environmentally "sustainable" agriculture over larger areas; Phalan *et al.* 2011), which at best is a false dichotomy, and at worse disregards the incredible amount of regional specificity in productivity, sustainability, and social justice associated with food production (Ostrom 2009). It is simply not reasonable to expect that choices between land-sparing and land-sharing will be made globally, let alone nationally or even regionally.

Instead, while we must acknowledge the global market forces that have an outsized impact on food production (at least in moderately and highly-developed countries), we must accept that the solutions to food insecurity, environmental degradation associated with agriculture, food quality, and resilience to climate change will all be found at a more localized scale (Suppe 1987). Bioclimatic variation alone dictates that a one-size-fits-all approach to food production will be sub-optimal. What works in one region won't necessarily work in the next. Blanket guidelines for agricultural production, despite their efficiency from an information dissemination standpoint, are a relic from the 20th century and sorely need updating.

This project has been a study in how we might shift away from those recommendations. Making the transition to localized agricultural management is a challenging task, and requires careful attention to the biophysical, economic, and social factors that impact farms and community at small scales, all while recognizing the forces operating at larger scales. To make the transition, a shift in mindset is required that parallels recent changes in the news industry, from a model of centralized media control to one of distributed and democratic news generation. In agriculture, the analogous entities are universities/industry and individual farmers, with the former currently situated as the authoritative source for agronomic knowledge, and the latter often perceived as consumers of recommendations.

In the new agriculture, I hypothesize that farmers will serve as the distributed nodes of agricultural knowledge creation. Universities and industry will still play a substantial role in mediating the discussion and generating fundamental understanding, but they will no longer hold exclusive rights to the truth (Carolan 2006), and must adapt to fulfill different roles. This new regime empowers farmers and can be thought of as the informational equivalent of land races: localized management derived from a common stock of first principles, appropriate for one place, one time, and one farmer.

Understanding this new system will be difficult because it requires transdisciplinary understanding, and as such will confound the aggregate statistics of economists, the environmental indicators of ecologists, and the policy goals of bureaucrats. It will require sensitivity to the shifting forms of knowledge, the unique social characteristics of individuals, and the intimate physical landscapes that underlay each individual agricultural setting. Of course, this localized specificity has existed all along, but the excuses for ignoring its importance are vanishing as site-specific data and management improve daily. Adapting to this reality will be challenging for disciplinary scientists, but it is an opportunity to pursue a more holistic understanding of socio-ecological systems that has been distant in modern conceptions of reductionist science.

Meeting this challenge has been the focus of my dissertation. I do not pretend to have come close to a solution, and indeed the challenges of interdisciplinary work

(MacMynowski 2007, Strang 2007) have, at many points, nearly prevented me from finishing. Despite this, I have tried my best to make small steps in this direction, with the goal of helping to produce food, but in a manner that considers location, climate, and ultimately the farmer.

Justification and Research Question

Dryland farmers in the Northern Great Plains (NGP) face a multitude of challenges including drought (Nielsen *et al.* 2005), soil loss (Tanaka *et al.* 2010), reduction in crop yields from weed pressure (Maxwell and O'Donovan 2006), price fluctuations of inputs and prices received (Henderson *et al.* 2011, Boehlje *et al.* 2013), and difficulties associated with family farming (Marotz-Baden 1988). In addition, society places responsibility on farmers to minimize environmental pollution (Diaz and Rosenberg 2008) and protect other valuable ecosystem services (Power 2010), all while producing an abundance of inexpensive food (Tilman *et al.* 2002). Although farmers must juggle these competing demands, researchers have been slow to adopt an analytical perspective that acknowledges this complexity of interconnected problems. Complex Socio-Ecological Systems are not easily understood using the traditional quantitative methods of agricultural science without resorting to reductionism. Consequently, there is little comprehensive understanding of the overall welfare of the region's farmers and whether their farms will remain viable in the future (NRC 1989 in Kloppenburg 1991), especially in the face of unprecedented global change.

My research question addressing this need was as follows: *Are Montana's dryland small-grain farms resilient (resilience defined below) under current management regimes given economic and climate variability, and how/why might that change in the future?* My overarching hypothesis is that *the cost of inputs along with uncertainty in prices and driving environmental variables coupled with current decision-making processes will make these agricultural systems less resilient.*

This research project had the additional goal of providing insight into whether and how farmers might increase resilience under conditions of drought and unfavorable prices. I examined the multiplicity of factors that affected the profitability of large-scale dryland farms, using data collected at local and regional scales.

As a conceptual framework to guide this investigation, I relied on the recently popularized (Christopherson *et al.* 2010; Folke 2006) concept of resilience. Resilience has many conflicting definitions (Brand and Jax 2007), but for the purposes of this project, I defined resilience as *the ability of farmers to persist and to endure variability in wheat prices, costs of inputs and insurance, changes in governmental programs, climate uncertainty and social factors while continuing to produce crops as a primary source of livelihood*. The conceptual structure of resilience suggests that thresholds may exist beyond which the farms cannot return to profitability or productivity (Scheffer *et al.* 2001). However, depending upon the management and adaptability of the farmer, the proximity and severity of those thresholds may be reduced.

To examine the resilience of the farmers, I first assessed the quantitative environmental and economic factors that affected farmers at the farm and sub-farm scales. Drawing upon the data-rich environment of these large-scale operations, I extended recent work in precision agriculture (Anselin *et al.* 2004, Bongiovanni *et al.* 2007, Griffin *et al.* 2008, Jiang *et al.* 2008) to evaluate the variable response of crops and profitability to changes in inputs, climate and prices using a simulation study. Following validation of the methodology with simulation, the same process was expanded to account for alternative crop rotations and was used to analyze an eight-year precision agriculture dataset from a dryland farm located near Great Falls, Montana. The specific spatiotemporal responses from the long-term farm data were then used to understand the impacts of uncertainty and a number of alternative farmer risk preferences on optimal agronomic management. Unique risk preferences of farmers can lead to divergent choices to maximize benefits for the farmer, hence it was important to account for these differences.

Next, recognizing that farmer adaptability can alter the impacts of adverse conditions and can potentially minimize vulnerabilities, a qualitative analysis of farmer reactions to drought and economic uncertainty was implemented. The nuanced perceptions and reactions of farmers to historic and current stressors provided insight into the possible economic trajectories of semiarid dryland farms under novel conditions.

Finally, the results described above were integrated into a comprehensive assessment of resilience within the concluding chapter. Data at the site-specific scale were compared against county-level data from across Montana. The result was a broad overview of some of the challenges and opportunities for Montana's farms in the 21st century.

Research Objectives

1. Develop a quantitative framework for sub-field and whole-farm bio-economic analysis that explicitly accounts for spatial and temporal uncertainty in prices, costs of inputs and insurance, soil variability, climate, and crop responses. Enable calculation of economically optimal management under uncertainty and the ability to forecast responses under new economic or climatic scenarios.
2. Apply the developed framework to an empirical dataset to identify the optimal input and crop rotation strategies for a range of different farmer risk preferences. Assess the impacts of nitrogen fertilization rates and crop rotation strategies on net returns.
3. Evaluate the ability of the farmers to adapt to possible climatic and economic changes, especially how they learn new strategies for adaptation. Elicit farmers' knowledge to identify other factors that may threaten their farm's resilience. Finally, use the knowledge of adaptability to understand whether farmers are likely to maintain resilience under changing conditions.
4. Bring together the quantitative framework and decision-making assessment to form a complete resiliency and sustainability assessment of the farming systems under consideration.

References

Anselin, L., Bongiovanni, R., Lowenberg-DeBoer, J. 2004. A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. *American Journal of Agricultural Economics* 86: 675–687.

Boehlje, M.D., Gloy, B.A., Henderson, J.R. 2013. U.S. Farm Prosperity: the new normal or Reversion to the Mean. *American Journal of Agricultural Economics* 95:310-317.

Bongiovanni, R.G., Robledo, C.W., Lambert, D.M. 2007. Economics of site-specific nitrogen management for protein content in wheat. *Computers and Electronics in Agriculture* 58: 13–24.

Brand, F.S., Jax, K. 2007. Focusing the meaning (s) of resilience: resilience as a descriptive concept and a boundary object. *Ecology and Society* 12: 23.

Carolan, M.S., 2006. Do You See What I See? Examining the Epistemic Barriers to Sustainable Agriculture. *Rural sociology* 71: 232–260.

Christopherson, S., Michie, J., Tyler, P. 2010. Regional resilience: theoretical and empirical perspectives. *Cambridge Journal of Regions, Economy and Society* 3: 3–10.

Folke, C. 2006. Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change* 16: 253–267.

Griffin, T.W., Dobbins, C.L., Vyn, T.J., Florax, R.J.G.M., Lowenberg-DeBoer, J.M. 2008. Spatial analysis of yield monitor data: case studies of on-farm trials and farm management decision making. *Precision Agriculture* 9: 269–283.

Hall, K.D., Guo, J., Dore, M., Chow, C.C. 2009. The progressive increase of food waste in America and its environmental impact. *PLoS ONE* 4: 1-6.

Henderson, J., Gloy, B., Boehlje, M. 2011. Agriculture's Boom-Bust Cycles: Is This Time Different? *Economic Review of the Federal Reserve Bank of Kansas City, Fourth Quarter*: 83-105.

Jiang, P., He, Z., Kitchen, N.R., Sudduth, K.A. 2008. Bayesian analysis of within-field variability of corn yield using a spatial hierarchical model. *Precision Agriculture* 10: 111–127.

Kloppenburg, J. 1991. Social Theory and the De/Reconstruction of Agricultural Science: Local Knowledge for an Alternative Agriculture1. *Rural sociology* 56: 519–548.

MacMynowski, D.P. 2007. Pausing at the brink of interdisciplinarity: power and knowledge at the meeting of social and biophysical science. *Ecology and Society* 12: 20.

Marotz-Baden, R. 1988. Income, economic satisfaction, and stress in two-generational farm families. *Journal of Family and Economic Issues* 9: 331–356.

Maxwell, B.D., Luschei, E.C. 2005. Justification for site-specific weed management based on ecology and economics. *Weed Science* 53: 221–227.

Nielsen, D.C., Unger, P.W., Miller, P.R. 2005. Efficient water use in dryland cropping systems in the Great Plains. *Agronomy Journal* 97: 364–372.

Ostrom, E. 2009. A General Framework for Analyzing Sustainability of Social-Ecological Systems. *Science* 325:419-422.

Phalan, B., Onial, M., Balmford, A., Green, R.E. 2011. Reconciling food production and biodiversity conservation: land sharing and land sparing compared. *Science* 333: 1289-1291.

Power, A.G. 2010. Ecosystem services and agriculture: tradeoffs and synergies. *Philosophical Transactions of the Royal Society B: Biological Sciences* 365: 2959–2971.

Scheffer, M., Carpenter, S., Foley, J.A., Folke, C., Walker, B. 2001. Catastrophic shifts in ecosystems. *Nature* 413: 591–596.

Strang, V. 2009. Integrating the social and natural sciences in environmental research: a discussion paper. *Environment, Development and Sustainability* 11: 1-18.

Suppe, F. 1987. The limited applicability of agricultural research. *Agriculture and Human Values* 4: 4–14.

Tanaka, D.L., Schillinger, W.F., Papendick, R.I., McCool, D.K. 2010. Soil and water conservation advances in the semiarid northern great plains. Soil and Water Conservation Advances in the United States, pp. 47–79.

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S. 2002. Agricultural sustainability and intensive production practices. *Nature* 418: 671–677.

CHAPTER TWO

BACKGROUND

Integrated Agricultural Management in the Northern Great Plains

For over 100 years, farmers in the northern Great Plains (NGP) of Montana have continuously contended with the challenges of unpredictable drought, short, hot growing seasons, cold winters, highly variable soils (Padbury *et al.* 2002), and long distances from agricultural markets. These difficulties amplify the routine struggles that farmers must manage in wetter and milder regions, and serve to highlight the seemingly high resilience of farmers in the NGP. In this section, I outline some of the difficulties of farming in the NGP in historical and current contexts, and present the scientific concept of resilience as a way to advance an integrated, holistic understanding of agricultural systems in general.

Dryland Farming in the Northern Great Plains: Historical Context

Euro-American agriculture in the Northern Great Plains (NGP) began during the years 1880-1916, when the Homestead Act attracted large numbers of immigrants from the eastern U.S. to this region. Drawn by the promise of a new life on 160-320 acres of deeded land, entire families uprooted their lives and relocated out west, filing roughly one million homestead entries in the Great Plains region alone (GLO Records n.d.). Numerous challenges were faced by the settlers in this relatively undeveloped region, but plentiful land and abnormally favorable regional weather conditions greeted them and enticed them to set down roots (Hansen and Libecap 2004). The highly variable precipitation, long and cold winters, and short and hot summers that characterize the NGP (Padbury *et al.* 2002) were unusually mild during this period, prompting a rapid expansion of agricultural cultivation and production. Settlers brought agricultural practices and implements with them that were adapted to more humid, favorable climates, and began implementing them widely throughout the region (Tanaka *et al.* 2010)

In 1917, the streak of favorable climatic conditions was shattered, and a long, multi-year drought ensued. Large numbers of homestead farms failed, leading to the consolidation of original homesteads into larger parcels and towards the use of alternative agricultural practices that would be more resistant to drought (Campbell 1907, Wilson 1928). Some of the new practices included summerfallow (Larney *et al.* 1994), which historically required tillage for weed control, and less intensive cultivation (extending to no-till in the 1970s to 1990s), which uses chemicals for weed control during the fallow period, that are still in use today.

Drought has always been one of the most important drivers of agricultural production in the NGP (Nielsen *et al.* 2005). Fortunately, despite the high level of variability in precipitation, soils in this region are predominantly highly productive mollisols, typified by a high water storage capacity and high levels of organic matter, which help to retain moisture during periods of low precipitation (Padbury *et al.* 2002). However, these soil conditions are highly variable, and there are numerous locations where the depth, porosity, and biological activity of the soil are substantially less favorable as (Chapter Four).

Due to the semiarid nature of the NGP, with variable precipitation patterns and short growing seasons, spring and winter wheat (*Triticum aestivum* L.) have long been the dominant crops on the landscape, and were generally grown every other year after summerfallow. The primary management emphasis during the fallow phase was generally weed control in order to decrease moisture loss; decreasing moisture loss was emphasized to an even greater degree when chemical fallow was introduced. In addition to conserving moisture, summerfallow lends sufficient time for the mineralization of organic matter and crop residues to occur (Cochran *et al.* 2006), producing additional nutrients for the subsequent wheat crop. However, it also has significant negative effects on environmental quality such as depletion of soil organic matter under some circumstances (Janzen *et al.* 1998), nitrate leaching (Campbell *et al.* 2006) and soil erosion, particularly when weed control was achieved mainly through tillage (Lindstrom *et al.* 1992). Since 1971, however, the use of summerfallow has declined by 54% in the eastern half of the NGP (no decline in the Golden Triangle region north of Great Falls) and has been replaced to a significant extent by continuous cropping and crop rotations (Miller *et al.* 2015).

The other notable historical trends in the NGP have been changes in tillage, fertilizer usage, the use of rotational crops, and continued increase in average farm sizes. Originally, farmers would till the soil 7 – 15 times during the course of the growing season, pulverizing the soil structure in a technique referred to as 'dust mulching' (Salmon *et al.* 1953 in Tanaka *et al.* 2010). It wasn't long before the disadvantages of this approach with respect to capillarity and soil erosion were realized, leading to efforts to reduce tillage and promote surface residue (*Ibid*). In the 1970s to 1990s, no-tillage methods evolved, which involved seeding directly into the soil with minimum disturbance and drastically higher levels of crop residue retained on the soil surface. Estimates of no-till adoption in the NGP were as high as 50-90 % in 2012 (M. Friedrich, R. Bray, personal communication 2011 *in* Hansen *et al.* 2012).

Simultaneous to the reduction of tillage, farm sizes were continuing to expand at a rapid rate (Figure 2.1, USDA NASS 2011, 2015), with successful farmers purchasing land from neighbors who preferred to leave the profession to pursue more gainful employment or had failed to make ends meet. This expansion in farm size was paralleled by an increase in size of farm machinery and escalating quantities of applied fertilizer (Figure 2.2) and herbicides.

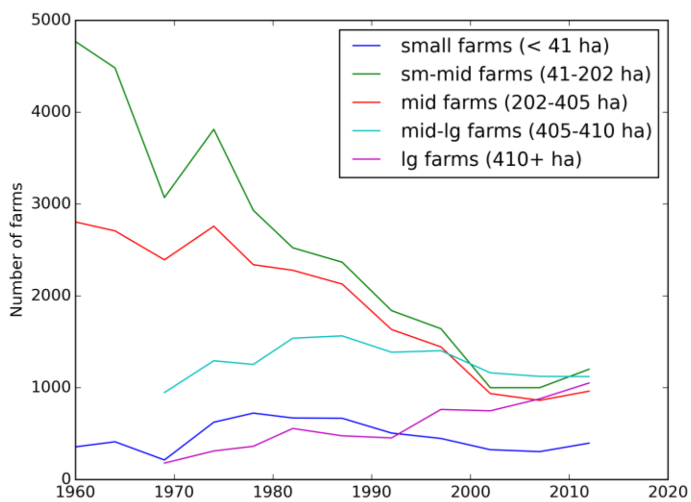

Figure 2.1. Numbers of farms in Montana by agricultural census size class, 1960-2012. Source: USDA NASS 2015.

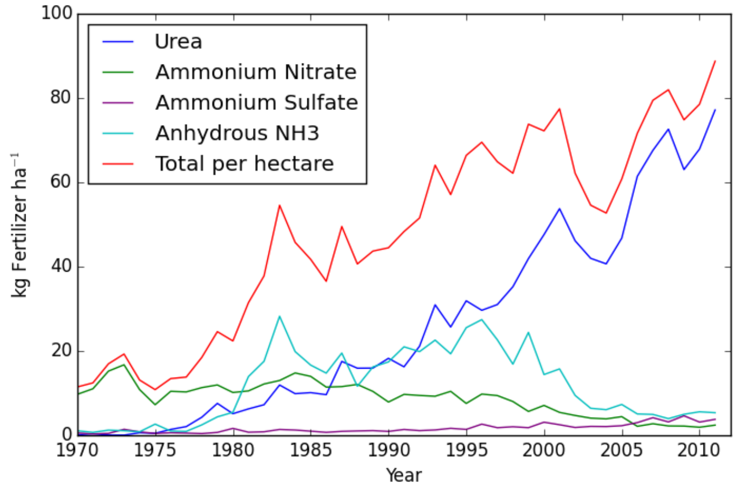

Figure 2.2. Fertilizer usage by type in Montana, 1970-2012. Source: USDA NASS/MDA 2011, USDA NASS 2015.

Finally, during the past 20 years, farmers in the NGP have been rapidly diversifying their rotations into alternative crops (Long *et al.* 2014). Diversification has created additional logistical challenges for farmers but has opened up marketing and agronomic opportunities that were not previously available. Furthermore, rotations often reduce weed and pest pressure and, in the case of legumes, increase the amount of nitrogen fixed from the atmosphere (Allen *et al.* 2011, O'Dea *et al.* 2015).

<u>Dryland Farming in the Northern Great Plains: Current Context and Challenges</u>

The biophysical characteristics of the NGP are relatively unchanged since the early 1900s. These sources of uncertainty can be grouped into factors that impact agricultural systems at the farm level, and those that impact agricultural systems at the sub-farm level. Although technological and agronomic tools to mitigate risk associated with uncertainty have improved, the underlying variability continues to be problematic for NGP farmers to this day.

Farm-Level Heterogeneity.

At the whole-farm scale, the primary sources of variability for dryland farmers are fluctuations in weather (precipitation and temperature) and fluctuations in prices. These impact the farm temporally rather than spatially; small-scale microclimatic variations between fields exist but are typically much smaller than inter-annual variations *(Sadler et al.* 2007).

At annual, decadal and centennial time spans, weather and climatic variation is controlled by a complex set of regional and global interacting factors. For farmers, the salient information about this variation is the degree to which it is predictable. The uncertainty and scale of the predictions are summarized in Figure 2.3.

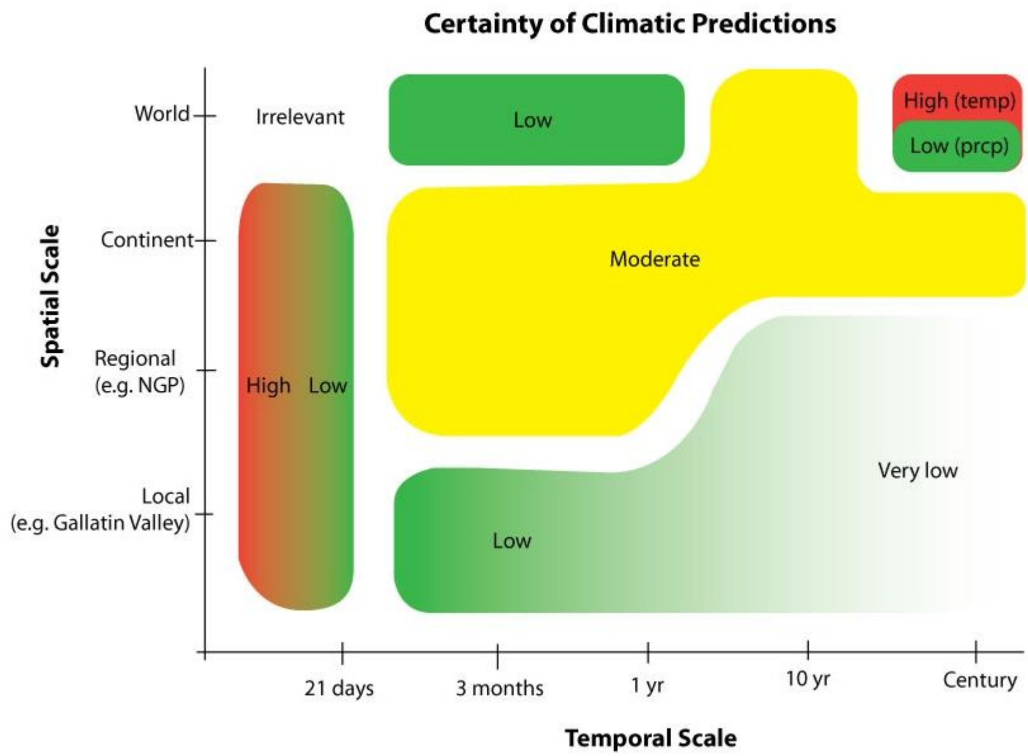

Figure 2.3. Certainty in weather and average climate predictions over a range of temporal and spatial scales.

At very short time scales (under 21 days), weather variation is dictated by meteorological processes (Lorenz 1963), but the chaotic nature of weather systems exponentially decreases confidence in predictions after each successive day (Simmons and Hollingsworth 2006). Between time scales of more than 21 days and less than one year, there is an increasing ability to predict aggregate climatic trends at regional or continental scales via knowledge of current Sea-Surface Temperatures (SST)/Sea-Level Pressure (SLP) anomalies, teleconnection indices and the autocorrelative properties of each of these phenomena (Schoennagel *et al.* 2005, Mo 2010), yet these predictions are still very coarse. At the decadal scale, the trends in temperature are relatively well known as indicated by successive IPCC reports. However, precipitation trends are generally irrelevant at the global scale, and there is little certainty at regional or local scales that would be relevant to the NGP (Sheffield *et al.* 2013, Dulière *et al.* 2013).

At the longest time scales, changes in the global climate caused by humans will likely impact crop production from changes in CO_2 fertilization, precipitation, temperature, and evapotranspiration (Hatfield *et al.* 2011). These impacts may be catastrophic when thresholds are crossed for important reproductive processes, such as anthesis, that determine yields (Lin *et al.* 2008), yet the frequency and severity of these impacts in the NGP are not yet clear. Temperatures have increased significantly in the NGP since 1950 (Cutforth *et al.* 1999, Cutforth and Judiesch 2012, Lanning *et al.* 2010), but the impacts on yields will become much more pronounced if temperatures consistently rise above 31 and 35 degrees C during spring wheat anthesis and grain fill, respectively, or significant periods of unpredictable drought are experienced (Hatfield *et al.* 2011). Unfortunately, historical trends of increased temperatures or fluctuations in precipitation are not necessarily indicative of future conditions (Percival and Rothrock 2005).

Prices are not subject to the same unpredictable biophysical influences as precipitation and temperature, yet they are still difficult to forecast (Wisner *et al.* 1998, Tomek and Peterson 2001, Kantanantha *et al.* 2010). The impact of fluctuations in the price of commodities can be mitigated by farmers through the use of hedging strategies, however less than 50% of farmers choose to do so (Mishra and El-Osta 2002, Velandia *et al.* 2009). Price fluctuations impact farms by creating uncertainty surrounding the most profitable (or unprofitable) agronomic choices, and can have a substantial impact on the economic trajectory of farms. Nitrogen fertilizer is the leading example of an unpredictable production factor; it is the largest energetic input used by farmers in the NGP (Burgess *et al.* 2012, Zentner *et al.* 2004), and is also the most costly variable input. Furthermore, it also has a very low (~50%) rate of recovery by the crop (Cassman *et al.* 2002; Crews and Peoples 2004). For all these reasons, nitrogen fertilizer is often the focus of efforts to increase energy efficiency and profitability on the farm (e.g. Burgess *et al*. 2012)

Sub-farm Heterogeneity (Site-Specificity)

Within each field on a farm there is a high degree of site-specific variation, and this is very evident in the NGP. Soil attributes such as soil texture and nitrate availability (Baxter *et al.*, 2003; Kerry and Oliver, 2003) can be completely reversed and intermixed between two ends of a field. These properties influence the water retention of the soil and growth of crops, often explaining variations in yield (Bourennane *et al.* 2004). Most physical soil properties cannot be easily altered by agricultural practitioners, however knowledge of their spatial variability can help optimize inputs such as fertilizer that are influenced by soil properties, and serve as a logical basis for identifying management zones (King *et al.* 2005, Khosla *et al.* 2008, Shahandeh 2005, Shahandeh 2011, Shaner 2008). In contrast, soil nutrients can often be manipulated, hence a plethora of literature exists evaluating the potential for site-specific phosphorus (Mallarino and Wittry 2004, McCormick *et al.* 2009) and nitrogen application (e.g. Anselin *et al.* 2004, Cao *et al.* 2012, Koch *et al.* 2004, Long *et al.* 2015, Meyer-Aurich *et al.* 2010, Thrikawala 1999).

The problem of spatial variation in soil properties is not new; in the very first meeting of professors of Land-Grant colleges in 1877, the first experimental subject proposed was crop variability due to soil heterogeneity (Hatch 1967 in Franzen and Peck, 1995), indicating its long-standing recognition as an agricultural challenge. However, the ability to quantify the spatial variability in soil properties and crop productivity in high resolution has only arisen in the last 20 years, and is rapidly expanding the possibilities for site-specific crop management and reduction of adverse environmental impacts (Berry *et al.* 2005).

In addition to soil properties, spatial variations in weed densities also have the potential to differentially impact crop production, as patches of highly clustered weeds can dramatically reduce yields (Maxwell and Luschei 2005). Several species of weeds may be present within a field, and the patterns of weed distribution provide an obvious means to maximize crop performance (Wiles 2009, Keller *et al.* 2013) and reduce herbicide costs. Anecdotally, few farmers in the NGP manage weeds site-specifically (Maxwell, *personal communication*, Sept 13, 2013), yet as technology improves for identifying weeds through image recognition (Ahmed *et al.* 2012) and other methods, adoption of site-specific weed management is likely to increase.

All of the site-specific factors that impact crop productivity and input-yield relationships can be, in theory, manipulated to optimize crop performance. The entire agricultural sub-discipline of precision agriculture is dedicated to this task. However, organizing and analyzing the high-volume data stream to achieve optimization is a difficult endeavor, and is a primary focus of this dissertation. The other difficulties are optimizing application maps given variable growing season conditions and volatile economic markets, as well as individual farmer's risk preferences – another major emphasis of the remainder of the dissertation.

Resilience as a Unifying Method of Inquiry

Managing the high levels of variability and uncertainty on dryland farms in the NGP is a challenging task that requires knowledge of climate, biology, soils, economics, logistical constraints, and sociology. Most research efforts only focus on one or a few of these factors in order to ensure controlled conditions and uniform results. Unfortunately, this narrow approach ignores the reality faced by farmers, who must manage all of these uncertainties simultaneously. "Integrated" agricultural systems analysis was a frontier for agricultural science three decades ago (Kunkel 1988), and it remains so in current times (Robertson and Swinton 2005).

The reasons for the lack of progress in generating a holistic understanding of agricultural systems are many. Within agronomic research, there is debate about the applicability of experimental trials to the vast landscapes that farms occupy (Suppe 1987). Economists are far from unified on how to account for externalities such as ecosystem services that may not appear in typical profitability analyses (Yang *et al.* 2010) but are important to the long-term viability of the farm, particularly as most farms remain within the family unless they become economically insolvent. Sociologists and others have divergent views about the role of reductionism versus holism in agricultural research (Odum 1989) and whether agricultural knowledge should be generated by the farmers themselves (Kloppenburg 1991). Put together, there is an overwhelming confusion about the goals of agricultural research, who it should benefit, who creates it, and what it should encompass.

Resilience is a relatively recent paradigm that may provide a means to address these questions. It has the ability to flexibly account for the complexities of socio-ecological systems (SES – such as farms), providing a common theme for integrating the disparate components. However, as will be shown, this flexibility needs to carefully managed to prevent interdisciplinary analyses from falling victim to ambiguity.

Introduced into the ecological literature in 1973 by C.S. Holling, resilience has become an increasingly popular research focus within the last decade in fields as diverse as ecology, economics and anthropology. In its original definition, it was described as a "*measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables"* (Holling 1973). This definition predicted that there would be non-linear thresholds on the boundaries of resilient systems, and that once a threshold was crossed the original relationships might never be recovered (May 1977). It would be more than another decade before this definition was extended to other descriptive contexts, including less precise terminology such as "identity" to describe the emergent aspects of a system that might persist. Even more broadly, resilience would be expanded to encompass complex SESs, and would recognize that a system's persistence could be affected by its ability to learn and adapt to changing conditions (Folke 2006). An excellent overview of the numerous descriptions of resilience is provided by Brand and Jax (2007), who convincingly argue that the imprecision of the term threatens its utility as a concept. The authors contend that resilience should either be used as a descriptive concept as related to ecological/ecosystem resilience, or that it should be utilized as a boundary object (means for interdisciplinary communication), for the purposes of transdisciplinary SES work.

Strunz (2012) elaborated on this idea of dual concepts for resilience by describing the trade-off between precision and vagueness (Table 2.1).

Precision	Vagueness
Scientific Method	Creativity
Establishing the validity of concepts	Inter and transdisciplinary communication
Empirical testability	Problem-solving instead of puzzle-solving

Table 2.1. Summary of arguments from philosophy of science in favor of precision and vagueness, respectively (Strunz 2012).

On the side of precision, there exists the Popperian ideal of falsifiability, testability, and empirical rigor (Popper 1959). In support of vagueness, benefits include the ability to focus on problems in a transdisciplinary manner and allowing creativity into the scientific process where precision would make it all but impossible to evaluate a complex SES. Strunz argues that researchers should choose a location between the two poles of precision and vagueness to fit the requirements of the research problem. In addition, he argues that the normative concept of resilience needs to be separated from the descriptive concept by using a structure that divides “resilience thinking” into (i) resilience as a descriptive concept, (ii) sustainability as a normative target, and (iii) adaptability and transformability that represent the changeability of resilience. By conceptually segregating the term, it is acknowledged that a resilient system might not be desirable, and that through adaptation, humans may influence the resilience of a system.

In the context of this project, resilience is outlined as a descriptive concept, specifically *the ability of farmers to persist and to endure variability in wheat prices, costs of inputs and insurance, climatic uncertainty, changes in governmental programs, and social factors while continuing to produce crops as a primary source of livelihood*. Given the inclusion of social factors, this description somewhat tends towards vagueness, however allowing for some ambiguity fits the transdisciplinary nature of this project. Although the resilience of crops and profits is somewhat quantifiable, social resilience is necessarily subjective and dependent upon interpretation.

Finally, by asking how/why the resilience of Montana's farms might change in the future I address adaptability, recognizing that the attitudes and practices of the farmers might change the future viability and sustainability of their farms.

Overview of Analytical Approach

Historically, agricultural research performed by universities and extension personnel has been focused at the farm level, seeking to provide management recommendations that could be generalized to the entire farm or region. This research was performed at centralized experiment stations that served the surrounding regions, with the expectation that principles discovered at the stations would be applicable to area farms (Odum 1989). Two assumptions were implicit in this model of "technology transfer". The first assumption was that the experimental stations were representative of the surrounding area. The second assumption was that first principles derived at the experiment stations could be applied uniformly over a whole field, farm and regional farming system minimizing environmental variation and eliciting relatively constant responses from the crops (Cambardella and Karlen 1999). Both assumptions were never rigorously tested, however research in site-specific agriculture have largely shown them to be at least somewhat incorrect (Mortensen 1999), and have emphasized the importance of sub-farm heterogeneity.

In contrast to the centralized approach of traditional agricultural research, this dissertation is focused on understanding the variability inherent to individual farming systems, within the context of broader agroeconomic and sociological trends. Adopting a methodologically pluralistic approach required flexibility and openness to a multitude of data sources, methodologies, and scientific disciplines, each with different norms and standards. During the course of analysis, I liberally borrowed concepts from ecology, soil science, hydrology, economics, sociology, political ecology, and agronomy. At the sub-farm level, precision agricultural data were compiled, cleaned, and analyzed using a wide variety of statistical methods. At the whole-farm level, data from weather stations were used to understand the impacts of precipitation variability on crop yields. At even broader scales, historical economic and census data provided insight into the impacts of price fluctuations and general agronomic trends. These data at the macroeconomic and whole-farm scales were compared with individual farmer interview and survey data to provide insight into the adaptability of NGP farmers to climatic or economic change.

In summary, the subject matter contained in this dissertation crossed spatial, temporal, and disciplinary boundaries to form an understanding of farmer resilience under current and a range of future conditions. The work contained herein delicately balances specificity with generalizability, which at times may provide for a limited scope, and at other times may be overly broad: the process of finding this equilibrium is indicative of the challenge at hand, and of the issues facing modern agriculture in the 21st century.

References

Ahmed F., Al-Mamun H.A., Hossain Bari A.S.M., Hossain E., & Kwan P. 2012. Classification of crops and weeds from digital images: a support vector machine approach. *Crop Protection* 40: 98-104.

Allen P.G. 1994. Economic forecasting in agriculture. *International Journal of Forecasting* 10: 81–135.

Anselin L., Bongiovanni R., & Lowenberg-DeBoer J. 2004. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *American Journal of Agricultural Economics* 86: 675–687.

Baxter S.J., Oliver M.A., & Gaunt J. 2003. A geostatistical analysis of the spatial variation of soil mineral nitrogen and potentially available nitrogen within an arable field. *Precision Agriculture* 4: 213–226.

Berry J.K., Delgado J.A., Pierce F.J., & Khosla R. 2005. Applying spatial analysis for precision conservation across the landscape. *Journal of Soil and Water Conservation* 60: 363–370.

Bourennane H., Nicoullaud B., Couturier A., & King, D. 2004. Exploring the spatial relationships between some soil properties and wheat yields in two soil types. *Precision Agriculture* 5: 521–536.

Brand F.S. & Jax K. 2007. Focusing the meaning (s) of resilience: resilience as a descriptive concept and a boundary object. *Ecology and Society* 12: 23.

Burgess M**.**, Miller P., & Jones C.A. 2012. Pulse crops improve energy intensity and productivity of cereal production in Montana, U.S.A. *Journal of Sustainable Agriculture* 36: 699-718.

Cambardella C.A. & Karlen D.L. 1999. Spatial analysis of soil fertility parameters. *Precision Agriculture* 1: 5–14.

Campbell H.W. 1907. Campbell's soil culture manual. 3rd ed. Woodruff-Collins Press Printers and Binders, Lincoln, NE.

Campbell C.A., Selles F., Zentner R.P., De Jong R., Lemke R., & Hamel, C. 2006. Nitrate leaching in the semiarid prairie: effect of cropping frequency, crop type, and fertilizer after 37 years. *Canadian Journal of Soil Science* 86: 701-710.

Cao Q., Cui Z., Chen X., Khosla R., Dao T.H., & Miao Y. 2012. Quantifying spatial variability of indigenous nitrogen supply for precision nitrogen management in small scale farming. *Precision Agriculture* 13: 45–61.

Cassman K.G., Dobermann A., & Walters D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio* 31:132-140.

Cochran V., Danielson J., Kolberg R., & Miller P. 2006. Dryland cropping in the Canadian Prairies and the U.S. northern Great Plains. Pages 293-339 *in* Peterson, G.A., Unger, W., and Payne, W.A. eds. Dryland Agriculture. Agronomy Monograph No. 23, 2nd ed., ASA, Madison, WI.

Crews T.E. & Peoples M.B. 2004. Legume versus fertilizer sources of nitrogen: Ecological tradeoffs and human needs. *Agriculture Ecosystems & Environment* 102: 279-297. DOI: 10.1016/j.agee.2003.09.018.

Cutforth H. W., McConkey B. G., Woodvine R. J., Smith D. G., Jefferson P. G. &Akinremi O. O. 1999. Climate change in the semiarid prairie of southwestern Saskatchewan: Late winter–early spring. *Can. J. Plant Sci.* 79: 343–350.

Cutforth H. & Judiesch D. 2012. Temperature trends in the semiarid prairie of southwestern Saskatchewan revisited. *Can. J. Soil Sci.* 92: 803_806.

Dulière V., Zhang Y., & Salathé E.P. 2013. Changes in twentieth-century extreme temperature and precipitation over the western united states based on observations and regional climate model simulations. *Journal of Climate* 26: 8556–8575.

Folke C. 2006. Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change* 16: 253–267.

Franzen D.W. & Peck T.R. 1995. Site-specific management for agricultural systems. ASA-CSSA-SSSA publications.

GLO Records, n.d. Bureau of Land Management General Land Office. http://www.glorecords.blm.gov/ PatentSearch/

Hansen Z.K. & Libecap G.D. 2004. The allocation of property rights to land: US land policy and farm failure in the northern Great Plains. *Explorations in Economic History* 41:103–129.

Hansen N.C., Allen B.L., Baumhardt R.L., & Lyon D.J. 2012. Research achievements and adoption of no-till, dryland cropping in the semiarid US Great Plains. *Field Crops Research* 132: 196-203.

Hatfield J.L., Boote K.J., Kimball B.A., Ziska L.H., Izaurralde R.C., Ort D., Thomson A.M., & Wolfe D. 2011. Climate impacts on agriculture: implications for crop production. *Agronomy Journal* 103, 351–370.

Holling C.S. 1973. Resilience and stability of ecological systems. *Annual review of ecology and systematics* 4: 1–23.

Janzen H.H., Campbell C.A., Izaurralde R.C., Ellert B.H., Juma N., McGill W.B. & Zentner R.P. 1998. Management effects on soil C storage on the Canadian prairies. *Soil and Tillage Research* 47: 181-195.

Kantanantha N., Serban N., & Griffin P. 2010. Yield and Price Forecasting for Stochastic Crop Decision Planning. *Journal of Agricultural, Biological, and Environmental Statistics* 15: 362–380.

Keller M., Gutjahr C., Möhring J., Weis M., Sökefeld M., & Gerhards R. 2014. Estimating economic thresholds for site-specific weed control using manual weed counts and sensor technology: An example based on three winter wheat trials: Yield effect of weeds, herbicides and thresholds for site-specific weed control. *Pest Management Science* 70: 200–211.

Kerry R. & Oliver M.A. 2003. Variograms of ancillary data to aid sampling for soil surveys. *Precision Agriculture* 4: 261–278.

Khosla R., Inman D., Westfall D.G., Reich R.M., Frasier M., Mzuku M., Koch B., & Hornung A. 2008. A synthesis of multi-disciplinary research in precision agriculture: site-specific management zones in the semiarid western Great Plains of the USA. *Precision Agriculture* 9: 85–100.

King J.A., Dampney P.M.R., Lark R.M., Wheeler H.C., Bradley R.I., & Mayr T.R. 2005. Mapping potential crop management zones within fields: use of yield-map series and patterns of soil physical properties identified by electromagnetic induction sensing. *Precision Agriculture* 6: 167–181.

Kloppenburg J. 1991. Social theory and the de/reconstruction of agricultural science: local knowledge for an alternative agriculture. *Rural sociology* 56: 519–548.

Koch B., Khosla R., Frasier W.M., Westfall D.G., & Inman D. 2004. Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones. *Agronomy Journal* 96: 1572–1580.

Kunkel H.O. 1988. Issues of academic disciplines in agricultural research. *Agriculture and Human Values* 5: 16–25.

Lanning S.P., Kephart K., Carlson G.R., Eckhoff J.E., Stougaard R.N., Wichman D.M., Martin J.M., & Talbert L.E. 2010. Climatic Change and Agronomic Performance of Hard Red Spring Wheat from 1950 to 2007. *Crop Science* 50: 835.

Larney F.J., Lindwall C.W., Izaurralde R.C. & Moulin A.P. 1994. Tillage systems for soil and water conservation on the Canadian Prairie. P. 305-328. *In* Conservation tillage in temperate agroecosystems. CRC Press, Boca Raton.

Lindstrom M.J., Nelson W.W., & Schumacher, T.E. 1992. Quantifying tillage erosion rates due to moldboard plowing. *Soil and Tillage Research* 24: 243-255.

Long D.S., Whitmus J.D., Engel R.E., & Brester G.W. 2015. Net returns from terrain-based variable-rate nitrogen management on dryland spring wheat in northern montana. *Agronomy Journal* 107: 1055.

Long J.A., Lawrence R.L., Miller P.R., & Marshall L.A. 2014. Changes in field-level cropping sequences: Indicators of shifting agricultural practices. *Agriculture, Ecosystems & Environment* 189: 11–20.

Lorenz E.N. 1963. Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences* 20: 130–141.

Mallarino A.P. & Wittry D.J. 2004. Efficacy of grid and zone soil sampling approaches for site-specific assessment of phosphorus, potassium, pH, and organic matter. *Precision Agriculture* 5: 131–144.

Maxwell B.D. & Luschei E.C. 2005. Justification for site-specific weed management based on ecology and economics. *Weed Science* 53: 221–227.

May R.M. 1977. Thresholds and breakpoints in ecosystems with a multiplicity of stable states. *Nature* 269: 471–477.

McCormick S., Jordan C., & Bailey J.S. 2009. Within and between-field spatial variation in soil phosphorus in permanent grassland. *Precision Agriculture* 10: 262–276.

Meyer-Aurich A., Gandorfer M., Weersink A., & Wagner P. 2008. Economic analysis of site-specific wheat management with respect to grain quality and separation of the different quality fractions. *12th Congress of the European Association of Agricultural Economists*, Ghent, Belgium.

Miller P.R., Bekkerman A., Jones C.A., Burgess M.H., Holmes J.A. & Engel R.E. 2015. Pea in rotation with wheat reduced uncertainty of economic returns in Southwest Montana. *Agronomy Journal* 107: 541-550.

Mishra A.K. & El-Osta H.S. 2002. Managing risk in agriculture through hedging and crop insurance: what does a national survey reveal? *Agricultural Finance Review* 62: 135–148.

Mo K.C. 2010. Interdecadal Modulation of the Impact of ENSO on Precipitation and Temperature over the United States. Journal of Climate 23: 3639–3656.

Mortensen D.A. 1999. Site-specific Crop Management: Filling Critical Gaps. USDA Agricultural Outlook Forum.

Nielsen, D.C., Unger, P.W. & Miller, P.R., 2005. Efficient water use in dryland cropping systems in the Great Plains. *Agronomy Journal* 97: 364–372.

O'Dea J.K., Jones C.A., Zabinski C.A., Miller P.R., & Keren I.N. 2015. Legume, cropping intensity, and N-fertilization effects on soil attributes and processes from an eight-year-old semiarid wheat system. *Nutrient Cycling in Agroecosystems* 102: 179-194.

.

Odum E.P. 1989. Input management of production systems. *Science* 243, 177–182.

Padbury G., Waltman S., Caprio J., Coen G., McGinn S., Mortensen D., Nielsen G., & Sinclair R. 2002. Agroecosystems and land resources of the northern Great Plains. *Agronomy Journal* 94: 251–261.

Percival D.B. & Rothrock D.A. 2005. "Eyeballing" trends in climate time series: A cautionary note. *Journal of climate* 18: 886-890.

Popper K.R. 1959. The logic of scientific discovery. Hutchinson, London.

Power A.G. 2010. Ecosystem services and agriculture: tradeoffs and synergies. *Philosophical Transactions of the Royal Society B: Biological Sciences* 365: 2959–2971.

Robertson G.P. & Swinton S.M. 2005. Reconciling agricultural productivity and environmental integrity: a grand challenge for agriculture. *Frontiers in Ecology and the Environment* 3: 38–46.

Sadler E.J., Sudduth K.A., & Jones J.W. 2007. Separating spatial and temporal sources of variation for model testing in precision agriculture. *Precision Agriculture* 8: 297–310.

Salmon S.C., Mathews O.R., & Leukel R.W.. 1953. A half century of wheat improvement in the United States. *Adv. Agron.* 5: 1–151.

Schoennagel T., Veblen T.T., Romme W.H., Sibold J.S., & Cook E.R. 2005. ENSO and PDO variability affect drought-induced fire occurrence in Rocky Mountain subalpine forests. *Ecological Applications* 15: 2000–2014.

Shahandeh H., Wright A.L., & Hons F.M. 2011. Use of soil nitrogen parameters and texture for spatially-variable nitrogen fertilization. *Precision Agriculture* 12: 146–163.

Shahandeh H., Wright A.L., Hons F.M., & Lascano R.J. 2005. Spatial and temporal variation of soil nitrogen parameters related to soil texture and corn yield. *Agronomy Journal* 97: 772-782.

Shaner D.L., Khosla R., Brodahl M.K., Buchleiter G.W., & Farahani H.J. 2008. How well does zone sampling based on soil electrical conductivity maps represent soil variability? *Agronomy Journal* 100: 1472-1480.

Sheffield J., Barrett A.P., Colle B., Nelun Fernando D., Fu R., Geil K.L., Hu Q., Kinter J., Kumar S., Langenbrunner B., & others. 2013. North American Climate in CMIP5 Experiments. Part I: Evaluation of Historical Simulations of Continental and Regional Climatology. *Journal of Climate* 26: 9209–9245.

Simmons A.J. & Hollingsworth A. 2002. Some aspects of the improvement in skill of numerical weather prediction. Quarterly *Journal of the Royal Meteorological Society* 128: 647–677.

Strunz S. 2012. Is conceptual vagueness an asset? Arguments from philosophy of science applied to the concept of resilience. *Ecological Economics* 76: 112–118.

Suppe F. 1987. The limited applicability of agricultural research. *Agriculture and Human Values* 4: 4–14.

Tanaka D.L., Schillinger W.F., Papendick R.I., & McCool D.K. 2010. Soil and water conservation advances in the semiarid northern great plains. *Soil and Water Conservation Advances in the United States* p. 47–79.

Thrikawala S., Weersink A., Fox G., & Kachanoski G. 1999. Economic feasibility of variable-rate technology for nitrogen on corn. *American Journal of Agricultural Economics* 81: 914–927.

Tomek W.G. & Peterson H.H. 2001. Risk management in agricultural markets: a review. *Journal of Futures Markets* 21: 953–985.

USDA National Agricultural Statistics Service. 2015. Census of Agriculture 1964-2012. Retrieved from http://www.agcensus.usda.gov/Publications/

USDA National Agricultural Statistics Service Montana Office. State-wide Fertilizer Usage. 2011.

Velandia M., Rejesus R.M., Knight T.O., & Sherrick B.J. 2009. Factors affecting farmers' utilization of agricultural risk management tools: the case of crop insurance, forward contracting, and spreading sales. *Journal of Agricultural and Applied Economics* 41: 107–123.

Wiles L.J. 2008. Beyond patch spraying: site-specific weed management with several herbicides. *Precision Agriculture* 10: 277–290.

Wilson M.L. 1928. Dry farming in the north central Montana "Triangle." *Bulletin 66. Montana Agricultural Experiment Station*, Bozeman, MT.

Wisner R.N., Blue E.N., & Baldwin E.D. 1998. Preharvest Marketing Strategies Increase Net Returns for Corn and Soybean Growers. *Applied Economic Perspectives and Policy* 20: 288–307.

Yang W., Bryan B.A., MacDonald D.H., Ward J.R., Wells G., Crossman N.D., & Connor J.D. 2010. A conservation industry for sustaining natural capital and ecosystem services in agricultural landscapes. *Ecological Economics* 69: 680–689.

Zentner R.P., Lafond G.P., Derksen D.A., Nagy C.N., Wall D.D., & May W.P. 2004. Effects of tillage method and crop rotation on non-renewable energy use efficiency for a thin Black Chernozem in the Canadian Prairies. *Soil and Tillage Research* 77: 125–136.

CHAPTER THREE

A PROBABILISTIC BAYESIAN FRAMEWORK FOR PROGRESSIVELY UPDATING SITE-SPECIFIC RECOMMENDATIONS

Contribution of Authors and Co-Authors

Manuscript in Chapter 3

Author: Patrick G. Lawrence

Contributions: Conceived the study and methodology, synthesized the data set, analyzed results, and wrote the manuscript.

Co-Author: Bruce D. Maxwell

Contributions: Obtained funding, assisted with theoretical underpinnings, discussed the methodology and results, and edited the manuscript at all stages

Co-Author: Lisa J. Rew

Contributions: Assisted with research design, discussed the methodology and results, and edited the manuscript at all stages

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A probabilistic Bayesian framework for progressively updating site-specific recommendations

Patrick G. Lawrence · Lisa J. Rew · Bruce D. Maxwell

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Abstract The goal of this research was to create an agricultural adaptive management framework that enables the probabilistic optimization of N fertilizer to achieve maximized net returns under multiple uncertainties. These uncertainties come in the form of bioclimatic variables that drive crop yield, and economic variables that determine profitability. Taking advantage of variable rate application (VRA), spatial monitoring technologies, and historical datasets, we demonstrate a comprehensive spatiotemporal modeling approach that can achieve optimal efficiency for the producer under such uncertainties. The utility of VRA fertilizer research for producers is dependent upon a localized accurate understanding of crop responses under a range of possible climatic regimes. We propose an optimization framework that continuously updates by integrating annual on-site experiments, VRA prescriptions, crop prices received, input prices, and climatic conditions observed each year under a dryland spring wheat (*Triticum aestivum*) cropping system. The spatio-temporal Bayesian framework used to assimilate these data sources also enables calculation of the probabilities of economic returns and the risks associated with different VRA strategies. The results from our simulation experiments indicated that our framework can successfully arrive at optimum N management within 6–8 years using sequential Bayesian analysis, given complete uncertainty in water as a driver of crop yield. Once optimized, the spatial N management approach increased net returns by \$23–25 ha^{-1} over that of uniform N management. By identifying small-scale targeted treatments that can be merged with VRA prescriptions, our framework ensures continuous reductions in parameter uncertainty. Thus we have demonstrated a useful decision aid framework that can empower agricultural

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producers with site-specific management that fully accounts for the range of possible conditions farmers must face.

Keywords Site-specific experimentation · Bayesian statistics · Input optimization · Simulation experiment · Dryland agriculture · Spatial variation

Introduction

Variable rate application (VRA) research within the last 15 years has focused on finding the optimal spatial arrangement of fertilizer for maximizing net return and yield (Thrikawala et al. 1999; Mamo et al. 2003; Anselin et al. 2004; Liu et al. 2006; Biermacher et al. 2009; Meyer-Aurich et al. 2010). While these efforts have advanced understanding of the factors driving variation in crop productivity, the predominant outcome has been a fertilizer prescription map that is implied to be the best management strategy for an unspecified number of subsequent years (e.g. Anselin et al. 2004). However, given the short temporal scale of the datasets that produce these prescriptions, there remains substantial uncertainty in the expected crop responses. Such uncertainty, often caused by climatic variability (Mamo et al. 2003; Lambert et al. 2006; Florin et al. 2009), could be reduced by incorporating information from additional years of data. That is, if each year's prescription and response were assimilated into the data model and used to generate the following year's treatments, then predictions would continually improve, and a degree of adaptability would be built into the Precision Agriculture (PA) system.

Single-year prescriptions

Most VRA research to date has used some version of a randomized complete block strip experiment where fertilizer was applied at different rates to areas of the field that had been stratified based on some prior knowledge of crop response (Anselin et al. 2004; Liu et al. 2006; Shahandeh et al. 2010). These studies were typically based on 1 year of data, however there are isolated examples where additional years were incorporated (Shahandeh et al. 2005; Lambert et al. 2006). Using some form of linear or quadratic model that incorporates site-specific (for example soil texture), and occasionally year-specific variables, a regression on yield is then performed, which feeds into a net return function (Koch et al. 2004). This net return function is then maximized by finding the optimal value of fertilizer (usually nitrogen—N) to apply, and a prescription map is generated for each location in space or for management zones (Khosla et al. 2008).

A principal limitation of creating prescription maps based on 1 year of data is that it ignores the largest source of yield-limiting variability: climate (especially in dry climate systems). For example, if a prescription map based on an anomalous wet year were to be implemented during drier growing seasons, there would likely be a build-up of nitrogen in all but the most moist and responsive areas of the field. Furthermore, the ability of additional years of data to improve prescription performance is ignored, and the producer is left with a static recommendation that may offer no improvement over uniform application. Such condition-specific responses may at first glance suggest development of prescriptions for multiple precipitation scenarios, but until climate can be more accurately predicted, such approaches will not be fruitful. Maximizing the economic efficiency and minimizing pollution while accounting for spatiotemporal variation over multiple years would instead enable decision-making that is more robust to the full range of possible conditions.

Multi-year prescriptions: accounting for spatial and temporal variability

The primary hurdles for incorporating spatiotemporal variability and non-experimentally controlled fertilizer applications relate to technical difficulties and the availability of data. Despite the increasing ubiquity of PA equipment, many producers do not have a complete, organized, and consistent set of records that span multiple years. Without such temporally consistent data, it is impossible to begin accounting for climatic variation, and to assess trends over time. Yields and yield responses to N can vary drastically across years, particularly in dryland small grain systems, so incorporating multiple cropping cycles is extremely important for decreasing prediction error (Kravchenko et al. 2005; Sadler et al. 2007; Florin et al. 2009). Adding additional years of data could be accomplished by automating the process of annual data assimilation and model updating.

With multiple years of data that are spatially co-located, statistical dependencies arise between observations that are close in space and in time, increasing the difficulty of achieving unbiased estimates of model parameters. The primary approach to minimize the influence of spatial and temporal autocorrelation is through the use of within-group or between-group modeling structures, using either **G**-side (sometimes denoted as the matrix **D**) or **R**-side covariance matrices (Laird and Ware 1982; Robinson 1991). **G**-side covariance matrices are used in mixed models where each group is distributed as $N(0, \mathbf{G})$, independently of the other groups and the errors. **R**-side covariance matrices are used for repeated measures or spatial analysis where autocorrelation is a structural component of the errors, and are distributed as $N(0, \mathbf{R})$. Depending on the dataset and autocorrelation of the bioclimatic variables, either of these approaches may be appropriate to accomplish the goal of reducing bias in the parameters or response predictions.

The most obvious means of incorporating temporally dependent inter-annual climatic variation is to use model parameters that represent the prevailing meteorological conditions such as precipitation, temperature or solar radiation for each year of production. All yield observations within 1 year are likely to be temporally autocorrelated due to the unique climatic conditions that occur in one season, leading to a field-wide annual bias in yields. This autocorrelation can be addressed by inducing within-year correlation via mixed models (Thöle et al. 2013). If blocked experimental plots or strips were used in the experimental design, a crossed random-effects modeling structure (**G**-side) can account for the spatial autocorrelation in yield values caused by unobserved soil, topography or ecological factors, as long as the repetitions are sufficiently separated in space (within a field) to ensure independence. However, a crossed random-effects structure does not adequately deal with spatial autocorrelation of yields in situations where the treatments are continuous across a field, as would be expected in a real farm scenario where an N prescription map is being used (Fig. 1). In such a situation where each unit in the field (cell) is informing the statistical model, the block-specific random effects do not account for the spatial autocorrelation of nearby cells because those random effects themselves are assumed to be independent (not true in an **R**-side approach) regardless of the distance by which they are separated.

Although spatial variation often causes smaller differences in yield than temporal variation (Florin et al. 2009), it can be much more difficult to incorporate into a crop yield model. The complete characterization of variation in soil properties outside (even inside) strictly controlled experimental settings is nearly impossible, and it is very difficult to even

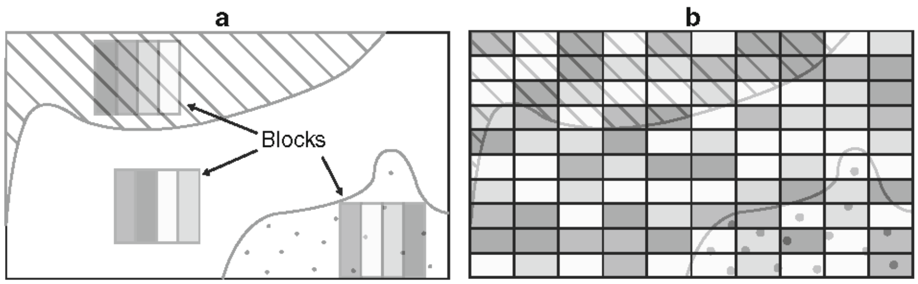

Fig. 1 The typical experimental layout of VRA (Bongiovanni et al. 2007), set against a background of edaphic spatial variation (*diagonal strikes* sandy, *dots* clayey, *empty* loam). In the randomized block design of **a**, there is correlation within blocks but not between, which can be easily dealt with using a random effect for each block (or fixed effects if the soil variation is of interest). In **b** the lack of discrete randomized blocks and the occurrence of cells on the transition zones between edaphic conditions makes the use of a mixed effects correlation structure inappropriate

know the scale of edaphic variation (Cambardella and Karlen 1999; Baxter et al. 2003; Kerry and Oliver 2003; Patzold et al. 2008). Measurements of apparent electrical conductivity (EC_a; mS m^{-1}) provide a potential way to efficiently collect continuous soils data, however the soil properties they measure (salinity, texture, and water content) are interrelated, making it difficult to interpret EC_a values (Corwin and Lesch 2003, 2005). Nevertheless, since these soil properties directly influence plant yield (Jung et al. 2005; King et al. 2005; Kühn et al. 2008), EC_a still may be adequate for characterizing edaphic variation if measured when soils are moist (Brevik et al. 2006). Other sources of spatial variation, such as topography and weed/pest pressure, can also be quantified, although biological organisms are difficult to measure in a spatially and temporally dense manner.

Another method to incorporate spatial variation, other than using random effects (**G**-side) for blocking factors, requires the use of a covariance matrix (**R**-side) that accounts for spatially autocorrelated errors (Lambert et al. 2006). By using an appropriate covariance matrix, the bias in the model parameters is reduced, although it can increase the difficulty of validating the fit and parameters chosen for the semivariogram. Inverse meta-modeling is another method that aims to use observed spatial variation in yield to inversely derive soil properties such as Available Water Capacity (AWC) (Florin et al. 2010), but if VRA has already been implemented on a field it may no longer be possible to separate inherent from management-induced variation.

A third method to deal with spatial autocorrelation of yield model residuals is Conditional Auto Regression (CAR) (Besag 1974; Jiang et al. 2009 for a PA example), which relies on the commonly derived lattice structure of aggregated PA data (Anselin et al. 2004). The advantage to working with the CAR model is that it is a computationally efficient way of managing fine-scale spatial statistical dependencies while allowing covariates to capture broader-scale trends (Lichstein et al. 2002). Using a simple linear regression, the baseline model for yield (Y) for each location i, omitting the CAR adjustment, is as follows:

$$Y_i \sim N\left(\mu, \sigma_e^2\right) \tag{1}$$

where every Y_i has the same variance, and the covariance between yield at location i and yield at another location j is modeled as zero (resulting in residual spatial autocorrelation if present). In contrast, the CAR model adds a spatial random effect ϕ to the model for the mean:

$$Y_i \sim \left(x_i^{'}\beta + \phi_i, \sigma_e^2\right) \tag{2}$$

where x_i' represents a vector of covariates, β is the associated parameter values, and σ_e^2 represents the independent and identically distributed (i.i.d.) errors. The set of conditional distributions used to account for spatial autocorrelation among yield responses (ϕ_i in Eq. 2) is specified by:

$$Y_i | Y_{j,j \neq i} \sim N\left(\sum\nolimits_j b_{ij} y_j, \tau^2\right) \tag{3}$$

where j represents the set of cells neighboring cell i. Y_i is thus characterized by a normal distribution function, with its mean conditional upon the average yield values y_j for neighboring cells. The b_{ij} are entries in the n x n symmetric matrix **B**, referred to as a spatial weights matrix, with all b_{ii} equal to 0, all b_{ij} adjacent to cell i equal to 1 (dependent observations), and all other b_{ij} equal to 0 (independent observations). Defined as such, this model for yield responses subsumes information from adjacent cells to arrive at parameter estimates for the focus cell in such a way that bias from spatial autocorrelation is reduced. If appropriate, the weights matrix may be modified to include more distant observations (second-order or higher). The variance–covariance matrix (not derived here) associated with the specification shown above is:

$$V = (\boldsymbol{I}_n - \boldsymbol{B})^{-1}\boldsymbol{M}$$

where $\boldsymbol{I}_n$ is the identity matrix, **B** is the aforementioned spatial weights matrix, and **M** is equal to $\sigma_e^2 I_n$. The complete specification for the CAR model also requires delineation of the prior distribution (prior distributions explained under the methods section) for ϕ_i, which is defined as follows:

$$\phi_i | \phi_{j \neq i} \sim N\left(\overline{\phi}_i, \frac{\tau_c^2}{m_i}\right), where\ \overline{\phi_i} = \frac{1}{m_i}\phi_j \sum\nolimits_{j \in \partial i} \phi_j \tag{5}$$

where ∂_i represents the set of neighbors surrounding cell i, and m_i is the number of these neighbors (Besag 1974; Besag et al. 1991). This implies that Y_i is conditioned both by the value of the explanatory variables but also by the adjacent yield values. As such, locations defined as neighbors have correlated random effects and non-neighboring locations have independent random effects.

Although alternate means of accounting for both spatial and temporal autocorrelation exist, none have been extensively promoted within the PA literature. Spatio-temporal CAR models (STCAR)s and dynamical spatio-temporal models (DSTM)s offer promising new approaches (Cressie and Wikle 2011), however they can be difficult to implement, require a larger set of temporal data than is likely to be available, and are computationally expensive. Despite this, they should be strongly considered as computational capacity increases and more extensive datasets become available.

Jiang et al. (2009) offered an advance in the PA research field that utilizes Bayesian statistics to implement a CAR model. The advantage to using Bayesian methods lies in the possibility of implementing hierarchical correlation structures and in achieving a concrete posterior probability rather than being forced to bootstrap parameter intervals obtained from frequentist statistics to obtain probability values. In addition, with Bayesian methods it is possible to separate the process from the data and parameter models, and to allow for continuous parameter updating as more data become available (Gelman et al. 2004). The example of Jiang et al. (2009) relied on precipitation and temperature covariates to account for temporal autocorrelation, but residual temporal autocorrelation was not quantified. Regardless, the spatial autocorrelation appeared to be adequately modeled, which led to the elimination of any spatial patterns in the regression residuals.

Multi-year prescriptions: an adaptive approach

We propose an adaptive system that extends the approach of Jiang et al. (2009), to accomplish the goal of generating continually updating probabilistic prescriptions that improve over time. In doing so, we illustrate spatio-temporal hierarchical Bayesian modeling with simulated results based on dryland spring wheat yield data from Montana. The demonstrated framework and model estimates yield as a function of nitrogen, precipitation, and apparent soil electrical conductivity (EC_a).

To ensure a reasonable level of accuracy in the model, we sought to realistically capture physiological crop responses by utilizing a non-linear yield equation (Archontoulis and Miguez 2013). This yield equation was then integrated into a net return function for profitability analysis. From there, the model parameters and optimization could be annually updated to achieve our objectives of progressively improved crop yield forecasts, prescription maps and visualizations of the unexplored parameter space. Each of these components is used to produce and provide new experimental treatments for the producer. Together, the advances achieved by these objectives lay the groundwork for a more accurate and responsive PA system that is able to incorporate the multiple forms of uncertainty that farmers face, increasing adaptive capacity for an uncertain future.

Methods

To achieve our goal we employed Bayesian statistical theory as it relates to the ability for models to self-update. Briefly, the standard formulation for a Bayesian posterior distribution is as follows:

$$p(\theta|D) = \frac{f(D|\theta)p(\theta)}{p(D)} \tag{6}$$

where θ is the parameter(s) of interest, D is the observed data, and f is the likelihood function. Therefore, the probability of the parameter given the observed data is equal to the product of the likelihood and the prior belief in the distribution of θ, divided by the marginal probability of the data (equivalently represented as $\int f(D|\theta)p(\theta)d\theta$ in a continuous context). This suggests that the posterior probability of the parameter is a weighted combination of the observed data and the prior certainty about the value of the parameter. Knowledge about the prior distribution is solely based on knowledge from previous research or intuition, but in practice is usually uninformative when no prior data are available (as is the case in this study for the first year of observations). This leaves the posterior entirely determined by the observed data. However, if the prior itself is based upon a probability distribution that requires additional parameters for specification (hyper-parameters λ), such as a Beta distribution that requires α and β parameters, then the posterior distribution is expanded as:

$$p(\theta|D) = \frac{p(D,\theta)}{p(D)} = \frac{f(D|\theta)p(\theta|\lambda)p(\lambda)}{p(D)} \frac{f(D|\theta)p(\theta|\lambda)p(\lambda)}{\iint f(D|\theta)p(\theta|\lambda)p(\lambda)d\theta d\lambda} \tag{7}$$

It is important to notice that the denominator in Eq. 7 is the marginal probability of the data when all of the parameters have been integrated over, and must equal one. In practice, this term is called the normalizing constant, and can be ignored if using computational (rather than analytical) methods to sample the posterior distribution.

Once 1 year of crop yield data has been collected, the resulting posterior can form the basis for a new prior distribution. In mathematical notation:

$$p(\theta|D', D) = \frac{f(D'|\theta)p(\theta|D)}{p(D')} \tag{8}$$

where D' is the current year's yield data, D is last year's yield data, and $p(D')$ is equivalent to $\int p(D\prime|\theta)p(\theta|D)d\theta$. The above equation simply demonstrates that during each time step, the old dataset can serve as the basis for the new prior, providing a platform for a continuously updating model that should become more precise after each time step, assuming that the process (yield) model is properly constructed.

To evaluate the posterior distribution, at any time step, it is possible to analytically derive the mathematical form of the posterior if the likelihood and prior functions are relatively simple and conjugate to each other. If this is not possible, then either Metropolis–Hastings or Gibbs (a more specific form of Metropolis–Hastings) sampling may be performed, whereby possible parameter values are proposed and either accepted or rejected in an iterative procedure. Over time, it can be mathematically shown that the parameter samples converge to the true joint posterior distribution (Gelman et al. 2004).

The non-linear bayesian car model

In the standard notation of linear regression, the yield model for cell i in year j (following the general logistic form in Archontoulis and Miguez 2013) used to address our objectives was as follows:

$$Yield_{ij} = \frac{\beta\max * precip_j}{1 + \exp\left(\beta_{shp} - \beta_1 * QuantN_{ij} - \beta_2 \times EC_{a,i} - \beta_3 * EC_{a,i} \times QuantN_{ij}\right)} + \phi_i + \varepsilon \tag{9}$$

where $\varepsilon \sim N\left(0, \sigma_e^2\right)$, and ϕ_i is the estimated spatial random effect associated with cell i, which is used to account for spatial autocorrelation (see Eq. 2). In this specification, the parameter β_{max} can be interpreted as the maximum amount of yield at the asymptote and β_{shp} can be interpreted as the shape parameter because it shifts the yield-N response curve to the left or right. EC_a represents the apparent electrical conductivity (mS m^{-1}) of the soil and serves as a proxy for soil properties that impact yield such as available water holding capacity. $QuantN_{ij}$ is the amount of nitrogen applied to cell i in year j in the form of urea (kg ha^{-1}). Details on the spatial random effect, the variance–covariance matrix, and the spatial weighting scheme are identical to the CAR model described in the introduction.

Although some potentially relevant factors such as temperature and soil N are omitted, this model sufficiently allows for the examination of the Bayesian framework as influenced by edaphic ($EC_{a,i}$; changes over space but not across years) and management ($QuantN_{ij}$) variables, plus an annually changing (precipitation) variable. The nonlinear term represents an asymptotic (logistic) response of yield to N application, which more closely resembles the actual biological response function than a linear model (Archontoulis and Miguez 2013) except at very high toxic N rates, which a farmer is unlikely to ever apply. If this model was being used for the purpose of hypothesis testing, then it would be appropriate to transform the N variable to comply with the assumptions of linear regression. However, since the aim is simulation, for which unrealistic values such as negative numbers or infinitely increasing yields would skew optimizations, the more physiologically accurate non-linear approach is more appropriate.

From a Bayesian CAR perspective, the model was formulated as follows:

$$p\left(\beta_{\max}, \beta_{shp}, \beta_{1-3}, \sigma_e^2, \tau_c^2 | yield\right) = \frac{f\left(Yield|\beta_{\max}, \beta_{shap}, \beta_{1-5}, \sigma, \tau_c\right) p\left(\beta_{\max}, \beta_{shap}, \beta_{1-3}, \sigma_e^2, \tau_c^2\right)}{\iint d\beta_{\max} d\beta_{shp} d\beta_{1-3} d\sigma_e d\tau_{c^*} f\left(Yield|\beta_{\max}, \beta_{shp}, \beta_{1-3}, \sigma_e^2, \tau_c^2\right) \times p\left(\beta_{\max}, \beta_{shp}, \beta_{1-3}, \sigma_e^2, \tau_c^2\right)} \tag{10}$$

where the likelihood is modeled by a normal distribution, with $Y_{ij} \sim N\left(\mu, \sigma_e^2\right)$, and μ equal to nonlinear function (9) + ϕ_i, with a common spatial variance of τ_c^2 for the random effects. In our model (Fig. 2), we also specified a set of hyper-parameters on the β_1, β_2, β_3, β_{max}, β_{shp}, σ_e^2 and τ_c^2 parameters, which reflected our uncertainty in their prior distributions (Gelman et al. 2004; Jiang et al. 2009).

Integration into the net return-maximizing function

To enable economic analysis, the posterior distributions for the parameters of interest (β_{max}, β_{shp}, $\beta_{1\ 3}$) and for the nuisance parameter (ϕ_i) from the crop yield model were integrated into a net return function. In all years of the simulation, the precipitation amount changed and the crop price to be received at harvest was unknown. Therefore, uncertainty in both of these values was incorporated into the net return function following the approach of Anselin et al. (2004).

$$\begin{aligned} NetReturn_{ij} = {} & Price_{crop,j} \\ & * E\left[\frac{\beta\max * precip_j}{1 + \exp\left(\beta_{shp} - \beta_1 * QuantN_{ij} - \beta_2 * EC_{a,i} - \beta_3 * EC_{a,i} * QuantN_{ij}\right)} + \phi_i\right] \\ & - PriceN_j * QuantN_{ij} - FC \end{aligned} \tag{11}$$

where E[] is the expected value of the yield function and ϕ_i the spatial random effect in cell i (conditional on the neighboring cell random effects), $PriceN_j$ is the price of N (dollars/kg) in the current year, $QuantN_{ij}$ is the quantity of N applied (kg/ha), and FC is other average fixed costs associated with crop management ($605.44/ha) (USDA 2012a). The difference between the previous formulation (Anselin et al. 2004) and our construction is that instead of using a fixed value for the crop price and expected values for the parameters, we used distributions:

$$\begin{aligned} Net\,return_{ij} = {} & p\left(price_{crop,j}|Histprice_{crop}\right) * p\left(Yield_{ij}|param\right) * p(param) \\ & - p\left(priceN_j|Hist\,\Pr iceN\right) * QuantN_{ij} - FC. \end{aligned} \tag{12}$$

Where net return is in $/ha, $p(Price_{crop,j}|HistPrice_{crop})$ is the posterior probability distribution of crop prices from an autoregressive time series model for a historical dataset of prices ($/kg), $p(Yld_{ij}|param)*p(param)$ is the posterior probability of yield values given the

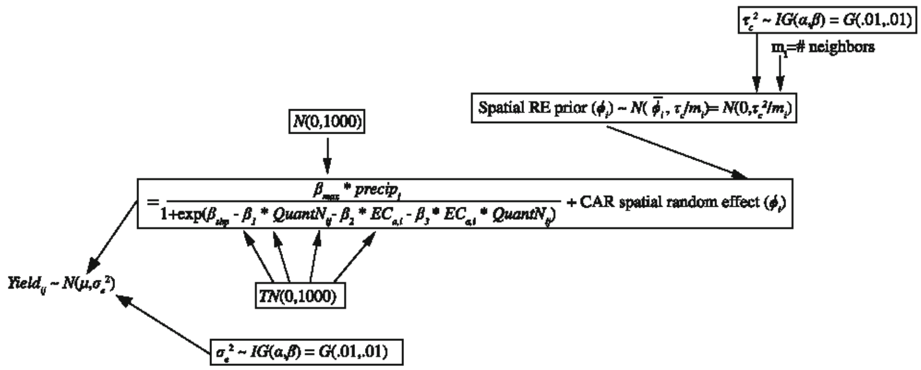

Fig. 2 Diagrammatic flow of the Bayesian CAR model with all distributions for the parameters and hyper-parameters specified

uncertainty in the parameter values, the amount of applied N, and the cell-specific random intercepts, $p(priceN_j|HistPriceN)$ is the probability of current N prices given the historical distribution of nitrogen prices, $QuantN_{ij}$ is the quantity of N applied to cell i in year j, and FC represents the fixed costs.

Since the output of this function is a distribution on net return from which $QuantN_{ij}$ cannot be optimized, we instead performed Monte-Carlo simulations on the input distributions to obtain unique net return realizations. This was accomplished by drawing one set of possible parameters from the posterior parameter distributions, adjusting up or down to reflect the spatial effect of cell i and the unexplained variance, then optimizing N to obtain the maximum net return for cell i. This was performed 1,000 times in order to derive a distribution of the optimal values of N rate to apply to each cell. For a producer, the final parameter of interest would be the mean of the optimal N values for each cell, which integrated all of the uncertainty in the parameters including precipitation and the commodity price received (Fig. 3).

Annual updating

The net return-maximizing optimization process culminated in a site (cell)-specific N rate prescription map. The following year, the updating process began, inserting the posterior μ and σ values for each parameter as the new priors, and using new observations for the data. For each subsequent year, it was expected that the variance of each parameter would sequentially converge to the true variance, increasing certainty in the optimization prescriptions.

Fully exploring the parameter spaces

If a producer were to use the raw prescription map each year without modification, it is highly possible that some areas would receive exclusively large, or small, amounts of N. While this may be optimal based on the derived spatial crop responses to N, it could prevent the exploration of parameter combinations that might increase the net returns. For example, if only wet years (in an arid location where extra moisture is nearly always beneficial) had been observed, it might be assumed that under clayey soils the crop would

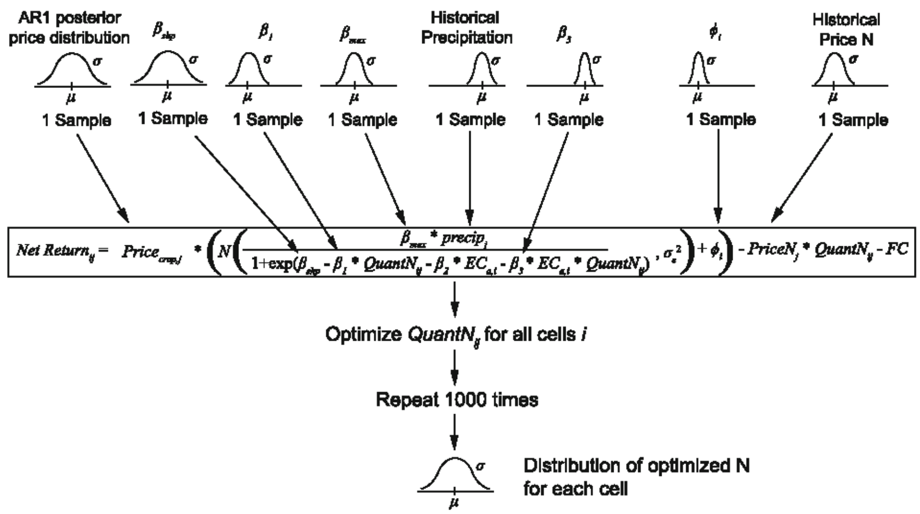

Fig. 3 The process by which crop yield parameter posterior distributions are sampled, N rate applied was optimized, and a distribution of optimized N was derived for each cell

respond favorably to high levels of N. However, that relationship might not hold true under dry years. This illustrates the importance of exploring the parameter space completely, at least during the initial years of PA implementation, in order to determine the crop responses under a full range of possible conditions. This exploration must be continued until enough years have been sampled to have high certainty in the distribution of conditions. Our framework accomplished this exploration through the use of annual N rate experiments on top of the optimized N prescriptions, and through visualizations of the N-EC-precipitation parameter space.

Simulation model implementation

The model as described above was implemented (Table 1) on a simulated 30-row by 30-column grid, with each grid cell representing a theoretical hectare. In practice, most fields are divided into smaller cell sizes that fit the size of the VRA fertilizing equipment (albeit with a similar number of total cells), however the use of one hectare cells provided easy interpretability for this example and was ideal for visualizing results. Mean values and variances for the input variables were chosen to be similar to those observed within multiple ~50 ha fields (111.49°W, 47.68°N) growing non-irrigated spring wheat, located near Great Falls, Montana. We chose to use simulated rather than real data for the EC_a and ϕ_i variables in order to have complete knowledge of the structure of spatial variation. The spatially correlated EC_a Gaussian random field grid (Fig. 4) was generated within the R package RandomFields (R Core Team 2012; Schlather 2012) and was characterized by an exponential isotropic spatial covariance structure ($\sigma^2 = 640$, $\mu = 50$, range = 50, nugget = 0, scale = 1). Realized precipitation values for each year of the simulation were based on historical precipitation data (site: Sun River 4s) (National Climatic Data Center 2013), with the distribution centered at 26 cm and a standard deviation of 6.4 cm. Crop price received was based on a posterior distribution from a simple time series autoregressive lag 1 (AR1) model for first-differenced price data (1998–2012) obtained from the

Montana Wheat and Barley Committee (MWBC) (Montana Wheat and Barley Committee 2013) for current data; historical data obtained directly from the MWBC. The price uncertainty experienced by a farmer was approximated by obtaining the forecasted distribution 1 year (365 days) into the future. Fertilizer cost data are generally proprietary, therefore a normal distribution was used to approximate its uncertainty $N(\mu, \sigma) = N(\$0.55/\text{kg}, \$0.055\text{kg})$, and was based on annual fertilizer cost data available from the USDA (USDA 2012a). Finally, fixed costs for the producer were obtained from the USDA (USDA 2012b), and were \$605.44/ha omitting fertilizer costs, which were included in the model.

Initial conditions for the simulated updating process assumed that a farmer beginning to use PA technology would start with at least 1 year of yield monitor data under a uniform fertilizer application (140 kg/ha) before attempting to implement VRA. Following the first year of observing spatially variable yields, the field was stratified into three different yield classes with equal frequency (high, medium, low), within which different N rate treatments were applied. N rate treatments were selected to minimize influence on profitability (i.e. occupied small areas). These treatments as designed were three cells long within the direction of travel, which helped to ensure that the fertilizer spreader had adequate time to turn on, definitively spread the fertilizer, and turn off within the designated treatment area. The average farmer is unlikely to implement such a spatial experimental design themselves without substantial assistance, thus the implementation was automated as much as possible.

To calculate yields in the initial year and in subsequent iterations, Eq. (9) was applied using the parameter coefficients (Table 2). The β_{shp} parameter was fixed in order to eliminate its tendency to co-vary with the other exponential parameters (all parameters shifting up or down together, resulting in non-differentiable curves). It was based on generalized yield responses to N in Montana, where substantial yield gains from N additions typically occur between 0 and 80 kg/ha (Jackson 1998). Further variation was added to the yield for realism by drawing random values from a normal distribution (centered at zero and with a standard deviation of 270 kg/ha) then adding those values to each cell in each year. The value of the additional variance was based on observed residual variation from the aforementioned study site near Great Falls. The mean parameter values were taken as the "true" parameter values, which would later be estimated using the Bayesian MCMC process (Gelman et al. 2004).

The value for ϕ_i, the spatial random effect, was calculated from a multivariate normal distribution with a mean of zero and covariance matrix with σ's of 75 kg/ha (5,625 kg/ha σ^2) for neighboring cells, and 0 kg/ha for non-neighboring cells. These values were based on observed spatial autocorrelation from the previously mentioned field experiment (Fig. 4). Markov Chain Monte-Carlo (MCMC) simulations for the posterior distributions of the parameters were performed using the python programming language and the free python package pymc (Fonnesbeck et al. 2012). Previous implementations of CAR models have primarily been implemented with the software WinBUGS ("Windows version of Bayesian Updating using Gibbs Sampler", http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml), however WinBUGS has not been updated since 2007, and we deemed it valuable to build our framework in an open source software package that was continuing to be developed and improved.

Prior distributions (as explained in the introduction) used for the coefficient parameters followed either normal or truncated normal distributions (Table 3) (Jiang et al. 2009). The truncated normal distributions were used in order to prevent the non-linear parameters from moving into unrealistic values in our system. The variances were set to be extremely large ($1e^{-12}$) in the first year in order to make the priors non-informative for both the normal and truncated normal distributions. If expert knowledge was available that could

Table 1 Iterative process for refining parameter estimates and optimizations

Year 0	1. Generate EC_a surface from exponential spatial correlation structure (Fig. 4) 2. Generate yield autocorrelation structure ϕ_i 3. Generate initial precipitation value $\sim N(\mu = 26.2$ cm, $\sigma = 6.4$ cm) 4. Apply N at uniform rate of 140 kg/ha = input N 5. Calculate initial yield surface with Eq. 9 (from input N, EC_a, precip, ϕ_i and additional random variation N(0,270 kg/ha))
Year 1	1. Stratify year 0 yield into 3 equal sized classes (high, medium, low) 2. Apply randomized block treatments within each class (0,60,120,180 kg/ha), uniform N elsewhere (140 kg/ha) = input N 3. Simulate a new precipitation value $\sim N(\mu = 26.2$ cm, $\sigma = 6.4$ cm) 4. Calculate year 1 yield with Eq. 9 (from input N, EC_a, precip, ϕ_i and additional random variation N(0,270 kg/ha)) 5. Run Bayesian CAR and extract posterior distributions 6. Optimize N for the next year based on samples from parameter posterior distributions
Years 2–6	1. Stratify year $t - 1$ yield into 3 equal sized classes (high, medium, low) 2. Apply randomized block treatments within each class (0,60,120,180 kg/ha) 3. Merge optimized N prescription and randomized treatment layers = input N 4. Simulate a new precipitation value $\sim N(\mu = 26.2$ cm, $\sigma = 6.4$ cm) 5. Calculate year t yield with Eq. 9 (from input N, EC_a, precip, ϕ_i and additional random variation N(0,270 kg/ha)) 6. Run Bayesian CAR with posteriors from year $t - 1$ as the year t priors and extract posterior distributions 7. Optimize N for the next year based on samples from parameter posterior distributions

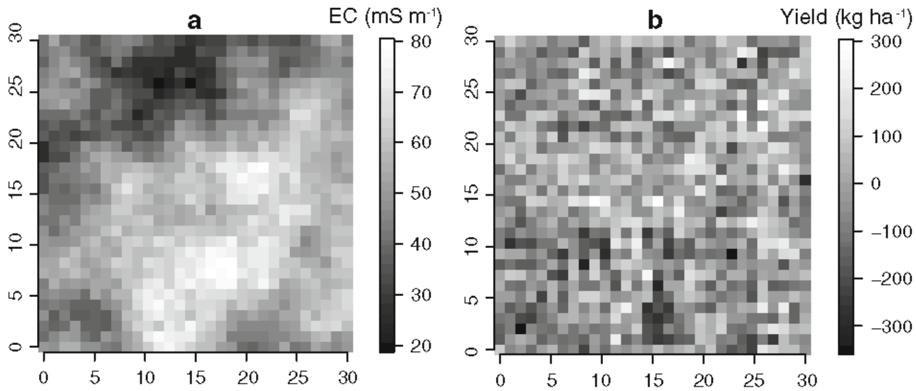

Fig. 4 EC_a surface with an exponential spatial autocorrelation structure (**a**), and surface of yield values (k/ha; ϕ_i) used to induce spatial autocorrelation in the response values (**b**)

Table 2 "True" parameters used to calculate yield within Eq. (9)

Parameter	β_{max}	β_{shp}	β_1	β_2	β_3	$\sigma_e = 1/\sqrt{\tau^2}$	$\sigma_s = \sqrt{\tau_c^2}/\sqrt{8}$
Value	137.8	4.8	0.02	.03	.0015	270	75

σ_e and σ_s are shown rather than τ^2 and τ_c^2 to enable the parameters to be interpreted on meaningful scales. Equivalent values for τ^2 and τ_c^2 -are .0000137 and 45 000 (parameterized as an inverse in python package pymc (Fonnesbeck et al. 2012) as .000022 (1/45 000))

direct the priors to be informative, then such knowledge could be incorporated initially, and would improve the convergence of the posterior distributions.

The prior distributions in the first year for the total model variance, σ_e^2 and the spatial variance (τ_c^2) were set to follow inverse-gamma distributions $(\sim IG(a,b))$ (Jiang et al. 2009), which were again specified to be non-informative (Gelman et al. 2004). In subsequent years, the priors were determined by the previous years' posterior distributions. During each year, the model was run for 100 000 iterations, using a burn-in period of 40 000 (wherein initial samples are discarded due to high autocorrelation) samples and a thinning rate of 20 in order to improve convergence and reduce autocorrelation between the samples. Convergence was confirmed through visual assessment of the parameter trace plots and autocorrelation plots.

Results and discussion

Convergence

Bayesian model validity depends on how well the specified model represents reality and the degree to which the posterior parameter distributions have converged. For this simulation model, distributions of the primary parameters of interest converged after 6 years of the simulation (excluding year zero), and the primary variance parameter σ_e required 8 years to converge (Fig. 5). The spatial variance parameter σ_s had not converged after 8 years, however it was trending towards its true value. Its lack of convergence was reasonable given all the other sources of confounding spatial variability, though it is

Table 3 Prior distributions for the coefficients (β), total variance (σ_e^2) and spatial variance (parameters τ_c^2) *TN* designates a truncated normal distribution

Parameter	Prior distribution with hyper-parameters	Hyper-parameter values	Prior distribution specification in pymc	Pymc hyper-parameter values
QuantN (β_1)	$TN(0,\sigma^2,a_N,b_N)$	*TN*(0.1, 1 E12, 0, 0.3)	*TN*(0.1, 1/σ^2, a, b)	*TN*(0.1, 1 E-12, 0, 0.3)
EC_a (β_2)	$TN(0,\sigma^2,a_{EC},b_{EC})$	*TN*(0.1, 1 E12, 0, 0.5)	*TN*(0.1, 1/σ^2, a, b)	*TN*(0.1, 1 E-12, 0, 0.5)
*QuantN**EC_a (β_3)	$TN(0,\sigma^2,a_{NEC},b_{NEC})$	*TN*(0.1, 1 E12, 0, 0.5)	*TN*(0.1, 1/σ^2, a, b)	*TN*(0.1, 1 E-12, 0, 0.5)
β_{shp}	$TN(0,\sigma^2,a_{shp},b_{shp})$	*TN*(0.1, 1 E12, 2, 10)	*TN*(0.1, 1/σ^2, a, b)	*TN*(0.1, 1 E-12, 2, 10)
Precip (β_{max})	$N(0,\sigma^2)$	*N*(0.0, 1 E12)	*N*(0.1, 1/σ^2)	*N*(0.0, 1 E-12)
σ_e^2	$IG(\alpha_e, \beta_e)$	*IG*(0.01, 100)	$Gamma(a_e, 1/b_e)$	*Gamma*(0.01, 0.01)
τ_c^2	$IG(\alpha_\tau, \beta_\tau)$	*IG*(0.01, 100)	$Gamma(a_\tau, 1/b_\tau)$	*Gamma*(0.01, 0.01)

possible that with an expanded CAR neighborhood size the parameter could be more accurately and quickly estimated. Additional simulations (not shown) using unique randomly drawn values of precipitation converged after 6–10 years, indicating that convergence can be achieved under different precipitation scenarios. In either case, multiple years of precipitation observations were required, reinforcing the need to collect and utilize multi-year data, and create N rate experiments over time.

Spatiotemporal variation

Residuals following year 6 of the simulations show minimal spatial pattern (Fig. 6), indicating that spatial autocorrelation was sufficiently accounted for (Moran's I $= 0.01$, p value for significant spatial autocorrelation $= 0.48$). Since temporal variation in yields was simulated using only one variable (precipitation), and that variable was included in the CAR model, temporal autocorrelation for each cell and for the field as a whole became insignificant once the model converged. This could be deduced from the lack of field-wide residual trends between years (after convergence), even under different precipitation conditions (Figs. 6, 7). If a longer set of years was observed, quantitative metrics rather than visual assessment could be used to assess the temporal autocorrelation. In a real world scenario with many possible drivers of temporal variation rather than only precipitation, it would be essential to assess residual temporal autocorrelation, which would give insight into the ability of temporal covariates to explain inter-annual variation. If the temporal covariates did not perform adequately, more climatic variables should be considered in the analysis.

The parameter space plots (Fig. 8) suggest that in addition to multiple years of precipitation observations, the experimental treatments applied in each year were crucial for achieving convergence. Within each year, the optimizations are visible as obvious clusters of points, whereas the fertilization treatments can be discerned by their correspondence to levels of 0, 60, 120 and 180 kg/ha of N. In the first 5 years of the simulation before convergence was achieved (years 5 and 6 omitted for clarity), the optimization chose N values that were near 0 kg/ha, whereas after convergence the optimization selected values clustered between 70 and 130 kg/ha. If only optimized N values were applied in each year (i.e. not applying rate experiments to explore the parameter space), convergence would be far less efficient or even impossible, especially for non-linear functions. The strategy of applying small experimental strip treatments, comprised of a range of N values in different yielding areas, helped speed convergence while eliminating the need for a farmer to devote their entire field to potentially non-profitable experimentation.

Small differences between the true parameters and the estimated parameters had negligible effects on the relationship between yield and N after year 6 (Fig. 9). With the exception of the spatial intercept, these parameters were identical for all areas in the field in each year. We chose to fix the value of the shape parameter due to its interdependence with β_1, β_2, and β_3, however given a sufficiently comprehensive dataset, it may be possible for the shape parameter to be estimated within the model. Furthermore, depending upon the purpose of the model, it may not matter whether the exponential parameters are interdependent if the realized Yield-N relationship remains unaffected. This behavior was observed during previous model runs when β_{shp} was not fixed.

Optimization

Maximizing net return and reducing the amount of unnecessary fertilizer applied requires knowledge of the underlying N-yield relationship and the response of net return to the full

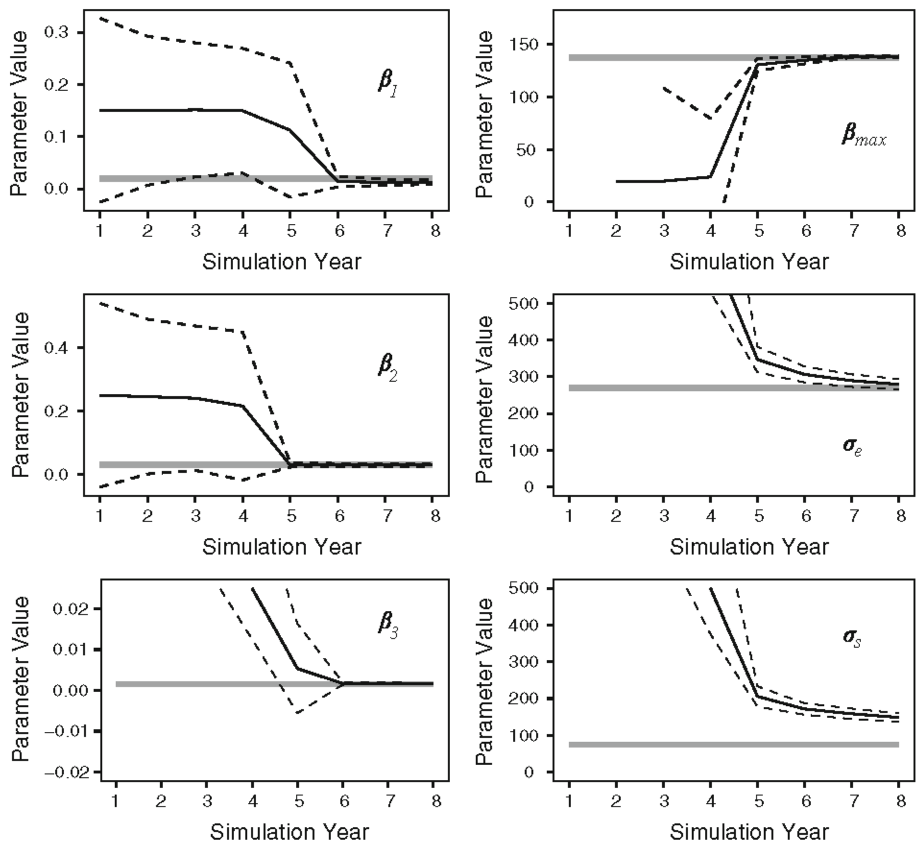

Fig. 5 Convergence of the posterior distributions in successive simulation years. *Solid lines* represent the posterior means, and *dotted lines* represent the ±2 standard deviations. The *gray lines* represent the true values of the parameters. β_1 = nitrogen, β_2 = EC_a, β_3 = nitrogen*EC_a, β_{max} = precipitation

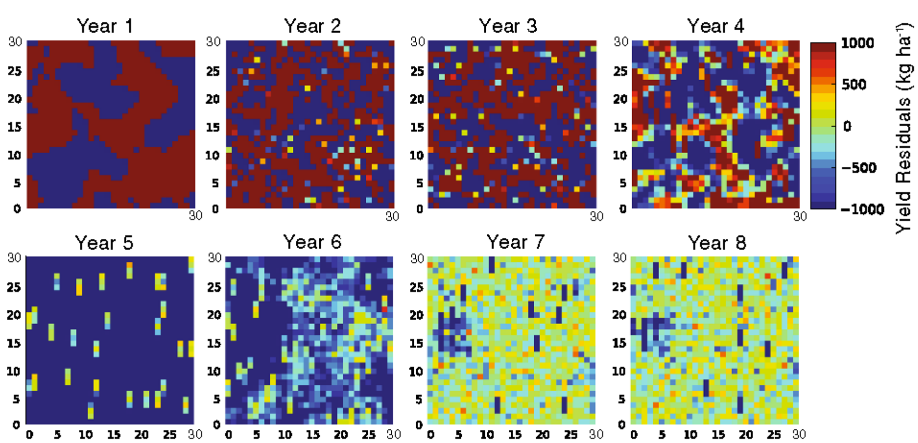

Fig. 6 Yield residuals for years 1–8 for the entire field, with convergence in year 6

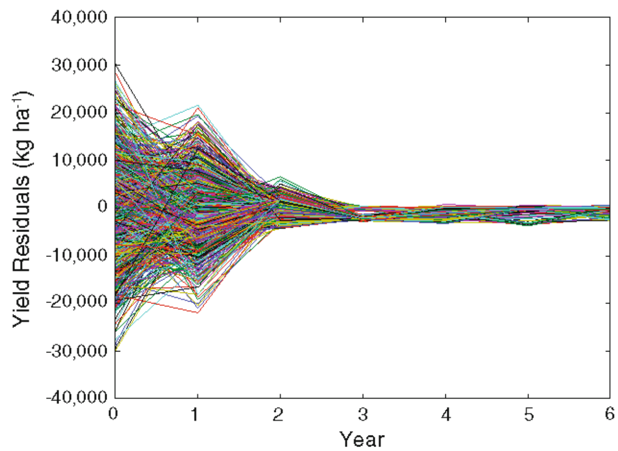

Fig. 7 Yield residuals for years 1–6 for each individual cell in the 900-cell field

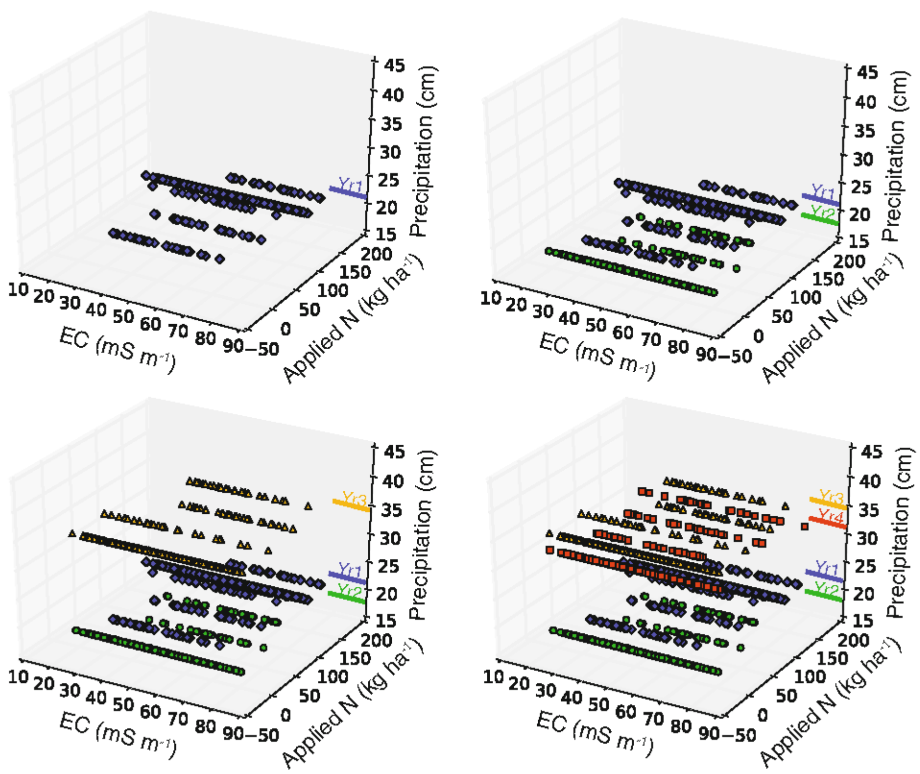

Fig. 8 Exploration of the first 4 years (year 0 with uniform N at 120 kg/ha and the next 3 years) of the precipitation-N-EC parameter space. *Blue diamonds* = year 1, *green circles* = year 2, *orange triangles* = year 3, *red squares* = year 4

range of bioclimatic and economic variability. Therefore, as a wider range of conditions are observed, the underlying crop parameters are better understood and the optimization is more efficient at maximizing net returns. Predictably, the optimizations for years 1–5 resulted in

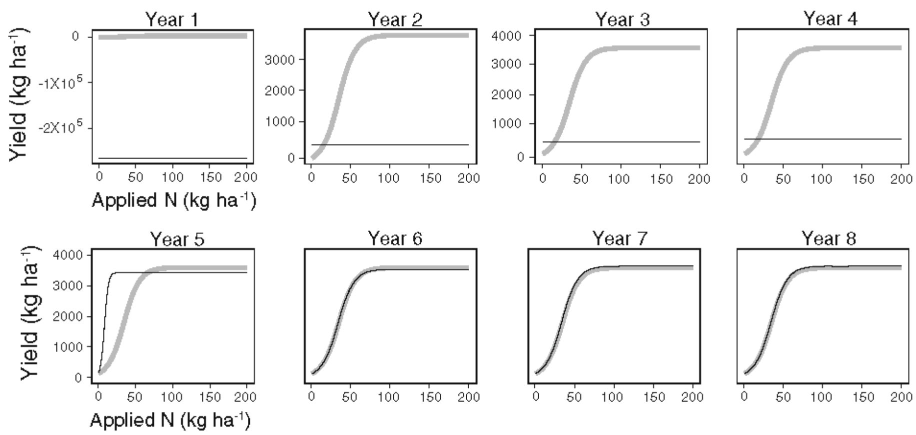

Fig. 9 Comparison of the calculated aggregate yields over the entire field for a range of N values using the true parameter values (*gray lines*), and the parameter posterior distribution means (*black lines*)

low net return realizations due to the lack of parameter convergence (Fig. 10, fourth row and bottom panel). In a real-world scenario it may be advisable for a producer to maintain uniform fertilization except in experimental strips, until a sufficient range of precipitation conditions have been observed (Fig. 10, second panel from the bottom) and some nominal level of convergence is achieved. However, after year 5, the optimizations successfully maximized net returns within the constraint of unknown random precipitation, generating a \$23–25 ha^{-1} advantage over uniform fertilization (Fig. 10, bottom panel). Over time (up to convergence at ~6–10 years) the VRA prescriptions and treatments continually improved, refining knowledge of the driving parameters and increasing profitable returns.

Once the parameters converged (~6 years), the optimization map was largely spatially and temporally static. Different levels of yield were observed, but those levels were driven by the temporal variation of precipitation in our dryland system. If additional information was available on the amount of expected precipitation just prior to fertilization, then the optimization could incorporate that updated information and choose different levels of N. Advance predictions of available water from statistical or process-based models would further increase the accuracy of the optimization and would reduce the risk of over-fertilization especially for such dryland agricultural systems.

Additional variables for future inclusion

The model used for this simulation employs only a few variables for simplicity, however additional driving variables could foreseeably be incorporated into the non-linear function. Whenever explanatory variables are available that help describe the variation in crop yield and reduce spatiotemporal autocorrelation, their use would increase accuracy and further understanding of the system driving factors. For example, if soil water availability was known prior to N fertilizer application, it would likely be more predictive than precipitation in dryland systems with arid moisture regimes. Equally important, if some measure of soil N was available prior to fertilization, then the effects of applied versus intrinsic N could be disentangled, resulting in increased model accuracy. In addition, ecological factors such as weed density and an indicator variable for the previous crop could be included, which would help identify the degree to which the yield-nitrogen relationship depends on plant competition or previous crop nutrient use.

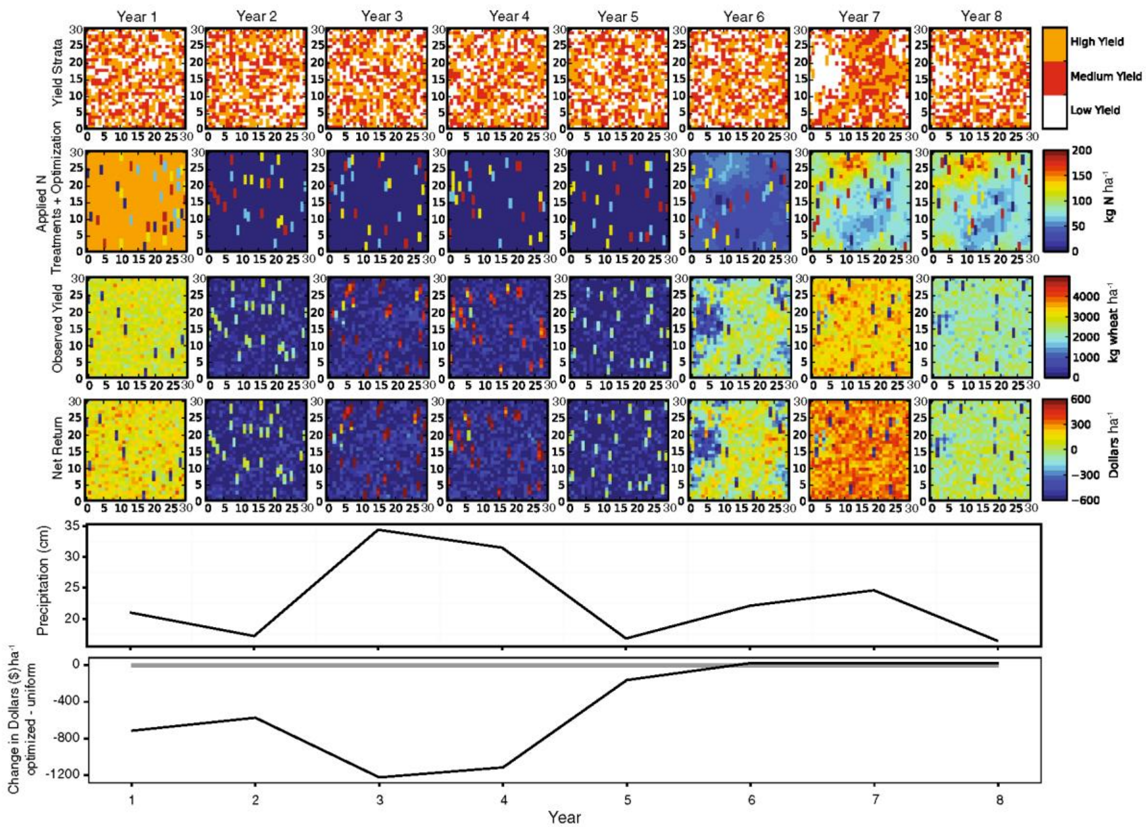

Fig. 10 Simulation of recommended applied N with successive annual model refinement on a theoretical 900 ha field where each 1 ha cell received a prescribed N rate. Details of the sequential process, displayed in columns from left to right, is provided in Table 1. Annual precipitation is included for reference, in addition to the change in dollars/hectare between the optimized and uniform fertilization (140 kg ha^{-1}). Colored blocks in row two represent experimental treatment areas used to reduce time to parameter optimization. Fully optimized maps displayed in the second row, under years 7 and 8

The drawback to including more variables is a possible increase in the number of years of data that would be needed to achieve convergence. Furthermore, with additional variables, more creative parameter space visualizations would be required such as using colors for a fourth dimension. However, the advantage of including key driving variables may offset any drawbacks of additional data requirements, especially if the variables explained large variations in yield.

Conclusion

Our goal was to create an agricultural adaptive management framework that employs VRA and spatial monitoring technologies and explicitly includes the uncertainties of principal factors driving crop yield and quality. While the resulting framework for understanding agricultural management-response relationships has yet to be tested on field-collected data, our results indicate that it has strong potential as a decision aid (with the statistical details hidden) for farmers to progressively manage their nutrient inputs toward an optimization based on maximized net returns. In such a scenario, farmers would generate the data to parameterize the models (experimental designs automatically implemented with VRA), but would then have the ability to modify simulated variables such as precipitation to predict impacts on profitability. Most importantly, this methodology does not require farmers to sacrifice their entire fields to experimentation, as they could simply apply experimental strips until sufficient time had passed to render the data necessary for model convergence.

Another key aspect is that the model incorporates climatic variation, without which prescriptions would be inaccurate, especially in dry-land farming systems. By utilizing a more biologically-appropriate non-linear function instead of the typical linear or linear-quadratic response function (Anselin et al. 2004), the model also moves one step closer towards generating field-based ecological understanding by placing increased emphasis on the local variance rather than the mean crop response to inputs. Furthermore, it simultaneously accounts for spatiotemporal dependence, which will always be a source of bias for regular regression models when farmers are unable to implement the carefully designed experiments commonly used in scientific settings.

In addition to providing an improved model, the entire framework benefits from the inclusion of historical precipitation, input cost and price uncertainties. When farmers make management decisions, they must incorporate all of these uncertainties into their choices if they impact profitability. Therefore, it is only appropriate to quantitatively include uncertainty in the optimizations to provide probabilistic projections of net returns.

In summary, this approach advances precision agriculture towards a probability-based, self-updating system that is consistent with the needs of farmers. It provides adaptability and encourages continual experimentation, leading to an end result of increased profitability, resilience and site-specific understanding of the agricultural system.

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References

Anselin, L., Bongiovanni, R., & Lowenberg-DeBoer, J. (2004). A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *American Journal of Agricultural Economics, 86*(3), 675–687.

Archontoulis, S. V., & Miguez, F. E. (2013). Nonlinear regression models and applications in agricultural research. *Agronomy Journal*. doi:10.2134/agronj2012.0506 .

Baxter, S. J., Oliver, M. A., & Gaunt, J. (2003). A geostatistical analysis of the spatial variation of soil mineral nitrogen and potentially available nitrogen within an arable field. *Precision Agriculture, 4*(2), 213–226.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society. Series B (Methodological)*. 36(2), 192-236.

Besag, J., York, J., & Mollie, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics, 43*(1), 1–59.

Biermacher, J. T., Brorsen, B. W., Epplin, F. M., Solie, J. B., & Raun, W. R. (2009). The economic potential of precision nitrogen application with wheat based on plant sensing. *Agricultural Economics, 40*(4), 397–407. doi:10.1111/j.1574-0862.2009.00387.x.

Bongiovanni, R. G., Robledo, C. W., & Lambert, D. M. (2007). Economics of site-specific nitrogen management for protein content in wheat. *Computers and Electronics in Agriculture, 58*(1), 13–24. doi:10.1016/j.compag.2007.01.018.

Brevik, E. C., Fenton, T. E., & Lazari, A. (2006). Soil electrical conductivity as a function of soil water content and implications for soil mapping. *Precision Agriculture, 7*(6), 393–404. doi:10.1007/s11119-006-9021-x.

Cambardella, C. A., & Karlen, D. L. (1999). Spatial analysis of soil fertility parameters. *Precision Agriculture, 1*(1), 5–14.

Corwin, D. L., & Lesch, S. M. (2003). Application of soil electrical conductivity to precision agriculture. *Agronomy Journal, 95*(3), 455–471.

Corwin, D. L., & Lesch, S. M. (2005). Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture, 46*(1–3), 11–43. doi:10.1016/j.compag.2004.10.005.

Cressie, N., & Wikle, C. K. (2011). *Statistics for Spatio-Temporal Data*. Hoboken: John Wiley & Sons Inc.

Florin, M. J., McBratney, A. B., & Whelan, B. M. (2009). Quantification and comparison of wheat yield variation across space and time. *European Journal of Agronomy, 30*(3), 212–219. doi:10.1016/j.eja.2008.10.003.

Florin, M. J., McBratney, A. B., Whelan, B. M., & Minasny, B. (2010). Inverse meta-modelling to estimate soil available water capacity at high spatial resolution across a farm. *Precision Agriculture, 12*(3), 421–438. doi:10.1007/s11119-010-9184-3.

Fonnesbeck, C., Patil, A., Huard, D., & Salvatier, J. (2012). *PyMC*. Retrieved June 6, 2013, from http://github.com/pymc-devs/pymc.

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2004). *Bayesian Data Analysis* (2nd ed). New York, NY: Chapman & Hall/CRC.

Jackson, G. (1998). Predicting Spring Wheat Yield and Protein Response to Nitrogen. *MSU Fertilizer Facts*, no. 17. Retrieved August 10, 2013 from http://www.sarc.montana.edu/php/Research/ffacts/?id=17

Jiang, P., He, Z., Kitchen, N. R., & Sudduth, K. A. (2009). Bayesian analysis of within-field variability of corn yield using a spatial hierarchical model. *Precision Agriculture, 10*(2), 111–127. doi:10.1007/s11119-008-9070-4.

Jung, W. K., Kitchen, N. R., Sudduth, K. A., Kremer, R. J., & Motavalli, P. P. (2005). Relationship of apparent soil electrical conductivity to claypan soil properties. *Soil Science Society of America Journal, 69*(3), 883–892.

Kerry, R., & Oliver, M. A. (2003). Variograms of ancillary data to aid sampling for soil surveys. *Precision Agriculture, 4*(3), 261–278.

Khosla, R., Inman, D., Westfall, D. G., Reich, R. M., Frasier, M., Mzuku, M., Koch.B. and Hornung.A. (2008). A synthesis of multi-disciplinary research in precision agriculture: site-specific management zones in the semi-arid western Great Plains of the USA. *Precision Agriculture, 9*(1–2), 85–100. doi:10.1007/s11119-008-9057-1.

King, J. A., Dampney, P. M. R., Lark, R. M., Wheeler, H. C., Bradley, R. I., & Mayr, T. R. (2005). Mapping potential crop management zones within fields: use of yield-map series and patterns of soil physical properties identified by electromagnetic induction sensing. *Precision Agriculture, 6*(2), 167–181.

Koch, B., Khosla, R., Frasier, W. M., Westfall, D. G., & Inman, D. (2004). Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones. *Agronomy Journal, 96*(6), 1572–1580.

Kravchenko, A. N., Robertson, G. P., Thelen, K. D., & Harwood, R. R. (2005). Management, topographical, and weather effects on spatial variability of crop grain yields. *Agronomy Journal, 97*(2), 514–523.

Kühn, J., Brenning, A., Wehrhan, M., Koszinski, S., & Sommer, M. (2008). Interpretation of electrical conductivity patterns by soil properties and geological maps for precision agriculture. *Precision Agriculture, 10*(6), 490–507. doi:10.1007/s11119-008-9103-z.

Laird, N. M., & Ware, J. H. (1982). Random effects models for longitudinal data. *Biometrics, 38*, 963–974.

Lambert, D. M., Lowenberg-DeBoer, J., & Malzer, G. L. (2006). Economic analysis of spatial-temporal patterns in corn and soybean response to nitrogen and phosphorus. *Agronomy Journal, 98*(1), 43. doi:10.2134/agronj2005.0005.

Lichstein, J. W., Simons, T. R., Shriner, S. A., & Franzreb, K. E. (2002). Spatial autocorrelation and autoregressive models in ecology. *Ecological Monographs, 72*(3), 445–463.

Liu, Y., Swinton, S. M., & Miller, N. R. (2006). Is site-specific yield response consistent over time? Does it pay? *American Journal of Agricultural Economics, 88*(2), 471–483.

Mamo, M., Malzer, G. L., Mulla, D. J., Huggins, D. R., & Strock, J. (2003). Spatial and temporal variation in economically optimum nitrogen rate for corn. *Agronomy Journal, 95*(4), 958–964.

Meyer-Aurich, A., Weersink, A., Gandorfer, M., & Wagner, P. (2010). Optimal site-specific fertilization and harvesting strategies with respect to crop yield and quality response to nitrogen. *Agricultural Systems, 103*(7), 478–485. doi:10.1016/j.agsy.2010.05.001.

Montana Wheat and Barley Committee. (2013). Pricing: Montana Wheat & Barley Committee. Retrieved April 4, 2013, from http://wbc.agr.mt.gov/wbc/Producers/Pricing/local/2013_GreatFalls.xls.

National Climatic Data Center. (2013). NCDC: Precipitation Data. Retrieved March 3, 2013, from http://gis.ncdc.noaa.gov/map/viewer/#app=cdo&cfg=cdo&theme=precip&layers=000111.

Patzold, S., Mertens, F. M., Bornemann, L., Koleczek, B., Franke, J., Feilhauer, H., et al. (2008). Soil heterogeneity at the field scale: a challenge for precision crop protection. *Precision Agriculture, 9*(6), 367–390. doi:10.1007/s11119-008-9077-x.

R Core Team. (2012). *R*: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/.

Robinson, G. K. (1991). That BLUP is a good thing: the estimation of random effects. *Statistical Science, 6*(1), 15–32.

Sadler, E. J., Sudduth, K. A., & Jones, J. W. (2007). Separating spatial and temporal sources of variation for model testing in precision agriculture. *Precision Agriculture, 8*(6), 297–310. doi:10.1007/s11119-007-9046-9.

Schlather, M. (2012). RandomFields: Simulation and Analysis of Random Fields. Retrieved November 6, 2012, from http://CRAN.R-project.org/package=RandomFields.

Shahandeh, H., Wright, A. L., & Hons, F. M. (2010). Use of soil nitrogen parameters and texture for spatially-variable nitrogen fertilization. *Precision Agriculture, 12*(1), 146–163. doi:10.1007/s11119-010-9163-8.

Shahandeh, H., Wright, A. L., Hons, F. M., & Lascano, R. J. (2005). Spatial and temporal variation of soil nitrogen parameters related to soil texture and corn yield. *Agronomy Journal, 97*(3), 772. doi:10.2134/agronj2004.0287.

Thöle, H., Richter, C., & Ehlert, D. (2013). Strategy of statistical model selection for precision farming on-farm experiments. *Precision Agriculture*. doi:10.1007/s11119-013-9306-9.

Thrikawala, S., Weersink, A., Fox, G., & Kachanoski, G. (1999). Economic feasibility of variable-rate technology for nitrogen on corn. *American Journal of Agricultural Economics, 81*(4), 914–927.

USDA ERS. (2012). Commodity Costs and Returns. Retrieved April 7, 2013, from http://www.ers.usda.gov/datafiles/Commodity_Costs_and_Returns/Data/Current_Costs_and_Returns_All_commodities/cwhea.xls.

USDA ERS. (2012). Fertilizer Price Indexes, 1960-2012. Retrieved April 7, 2013, from http://www.ers.usda.gov/datafiles/Fertilizer_Use_and_Price/Fertilizer_Prices/table7.xls.

CHAPTER FOUR

MANAGING UNCERTAINTY IN SEMIARID DRYLAND AGRICULTURE: A DATA-DRIVEN APPROACH TO OPTIMIZE INPUTS AND CROP ROTATIONS BASED ON FARMER RISK PREFERENCES

Contribution of Authors and Co-Authors

Manuscript in Chapter Four

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Contributions: Assisted with study design, analysis, and manuscript preparation at all stages.

Co-Author: Lisa J. Rew

Contributions: Provided guidance on data analysis and assisted with manuscript editing.

Co-Author: Anton Bekkerman

Contributions: Conceived integration of utility function into the analysis, provided counsel on economic sections, and assisted with manuscript editing.

Co-Author: Clain Jones

Contributions: Provided guidance on soil data analysis, assisted with nutrient interpretations and helped with overall manuscript preparation.

Co-Author: Perry Miller

Contributions: Assisted with interpretation of crop rotation experimental data and manuscript editing.

Manuscript Information Page

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Abstract

Managing dryland agricultural systems for economic and environmental sustainability is challenging given the compounding uncertainty of major production and economic variables. This complexity often leads to agronomic choices based on recommendations extrapolated from disparate small-plot studies, which are subsequently modified by farmers' inherent levels of risk aversion. Ideally, management prescriptions would be sensitive to the unique site-specific relationships determined on each farm, and to farmers' risk preferences.

This paper assesses profit-maximizing site-specific nitrogen application and crop rotation strategies for dryland wheat farmers with a range of hypothetical risk preferences. The analysis accounted for spatiotemporal uncertainty in soils, the crop production function, precipitation, and prices.

An eight-year precision agriculture dataset of environmental variables and inputs linked with wheat yield responses from a dryland small-grains farm in Montana under wheat-fallow (W-F), continuous wheat (C-W), and wheat-pea (W-P) management was paired with historical economic and weather data. Data were analyzed with a decision-making framework that prescribed unique spatial optimizations of nitrogen fertilization inputs and crop rotation choices. The optimal rotation in this system was wheat-pea and only minimal levels of fertilization were prescribed, except when the farmer was extremely risk averse. As the risk aversion of the farmer decreased, the differences in expected utility between alternative fertilization strategies became negligible. While this study's results provide a specific strategy for the farm fields under study, the framework

for deriving field-specific optimal management under uncertainty and alternative risk preferences is applicable to dryland agricultural systems in general.

Introduction

Farmers' management strategies for large-scale dryland agricultural systems are often influenced by a combination of scientific knowledge, social factors or influences, and intuition. Society increasingly demands that this *ad-hoc* method of management provide for intensified production (Godfray *et al.* 2010) while maintaining environmental quality (Diaz and Rosenberg 2008), all within a spatially heterogeneous farm landscape. As climate change increases the frequency of extreme weather conditions, this management status quo will increasingly struggle to provide consistent yields (Battisti and Naylor 2009) and net returns, especially if adverse economic and climate conditions are simultaneously encountered. Therefore a more structured method of management is required to integrate the multiple uncertainties of climate, prices, and environmental variation, providing results that are farm-specific, crop-specific, field-specific, and sensitive to the risk tolerance of farmers (Antle 1983).

In this paper, we assess optimal site-specific nitrogen management and crop rotation strategies on a semiarid dryland small-grains farm, while accounting for multiple uncertainties. Relative to irrigated systems, the success of dryland agricultural systems is considerably more constrained by multiple production and market uncertainties. Dryland systems rely on sporadic precipitation that may have non-linear impacts on crop yields. Moreover, precipitation levels have high spatial variability (Mock 1996; Guirguis and

Avissar 2008) making it difficult to make broad recommendations that are applicable across fields and farms. In the United States, spatially and temporally accurate seasonal predictions for precipitation are often unreliable (Dulière *et al.* 2013), and increasingly accurate predictions will become more important to manage for drought or wet periods at individual farm locations.

In addition to vulnerability due to precipitation uncertainty, dryland systems are also susceptible to economic fluctuations. Net revenues per unit area are often more uncertain and profit margins are potentially lower. Furthermore, in the NGP, farmers earn additional price premiums or receive penalties depending on the protein content of the wheat. Thus fluctuations in crop prices, protein levels and premiums, and input prices can jeopardize dryland farms' economic sustainability.

Farmers manage risk associated with variability in precipitation and prices using a range of strategies. These strategies seek to maximize farmers' expected utility, which characterizes a farmer’s valuation of economic and production outputs such as profits, yields, crop quality, and other aspects of the production environment (Antle 1983). Farmer attitudes toward risk also influence their expected utility by placing different weights on their perceived valuation of yield or profit maximization. Risk aversion under uncertainty can impact choices of nitrogen fertilization (Monjardino *et al.* 2015) and crop rotation (Maynard *et al.* 1997).

Due to the high level of inherent variability and potentially smaller profit margins in dryland systems, managing uncertainty is likely to be an ideal test-case for assessing quantitative optimization methods to maximize utility under these uncertainties. The increasing volume and fidelity of spatially explicit precision agricultural data available on individual farm fields will help make this optimization attainable. To harness these data sources and determine optima frameworks and methods for integrating the major driving variables in dryland agricultural systems are needed. This will result in decision-making tools that allow farmers to estimate the future probabilistic impacts of current or alternative management decisions.

Attempts to optimize inputs and management based on site-specific data generally optimize single input factors and take place within a relatively well-controlled experimental setting (in contrast to farm settings that are not managed for experimental rigor). Furthermore, the resulting prescriptions are often tuned to only a few years of data and to single fields (Anselin *et al.* 2004; Liu *et al.* 2006; Shahandeh *et al.* 2011). Several studies have considered multiple fields, but either only individual fields were empirically assessed before synthesis (Long *et al.* 2015), or only subsets of the entire spatial dataset were used (Whelan *et al.* 2012). Until a sufficiently high resolution spatiotemporal dataset is available for each field, it is necessary to combine data from multiple fields to understand the influence of interacting climate and edaphic factors on management decisions. Unfortunately, even with data aggregation, the sheer amount of information required to parameterize spatially-explicit process-based models of crop yield (e.g. Jones *et al.* 2003) is prohibitive. As site-specific data become more accurate and more common, a gradual shift towards process-based models will likely occur. Until then, empirical modeling approaches that are constrained to a relatively small number of variables (though limited by the computational power required to estimate spatial or spatiotemporal autocorrelative statistical structures) are necessary.

In this study, we integrate uncertainties from multiple fields and years within a dryland production system with the purpose of identifying the optimal spatial nitrogen fertilization and crop rotation strategies for each field to maximize farmer profits. Evidence suggests that, in dryland systems, wheat-pea rotations may be more profitable than wheat-fallow rotations (Chen *et al.* 2012; Miller *et al.* 2015). However, these advantages have not been tested within the greater context of on-farm uncertainty. We perform these tests and extend previous work to understand how the risk preferences of individual farmers could influence agronomic optimization. The analysis used is a modification of the spatial nitrogen optimization framework of Lawrence et al. (2015) that extends analysis of wheat-fallow rotations to legume-wheat and continuous wheat crop rotations, and is applied to eight years of data from an operational farm in Montana.

Methods

General Approach

We use an approach that accounts for as many yield-influencing factors as was practical in an empirical model, without using process-based components. The biophysical model estimates yield as a function of growing season precipitation, fertilizer nitrogen, spatial variation in soil properties, and spatial water accumulation. The model for yield is nested within a model for farmer net returns, which is then used to estimate an economic utility function to represent farmers' alternative risk preferences.

<u>Data Sources</u>

Yield and nitrogen fertilizer input data are from a dryland farm located 30 km northwest of Great Falls, Montana for 2006 – 2013. Four farm fields were selected based on data availability and spatial coverage during this time period (Figure 4.1, Table 4.1) and for relative consistency in cropping cycles. Fields B and C were adjacent but were treated separately because of a 50 ft wide strip of gravel road that separated the fields. Each field was divided into 18.3 by 18.3 m cells (60 ft on a side), which corresponded to the operational width of the fertilizer spreading truck (the largest piece of farm equipment) and was therefore the default scale of management. Winter wheat was continuously cropped or alternated with fallow or dry pea (except in 2011 when spring wheat was planted in fields A, B and C due to the impacts of excessive moisture on the winter wheat crop). The mean and variance of the spring wheat crop yields were very similar to the winter wheat crop observed in other studies (Miller and Holmes 2005) and we deemed it more valuable to include yield data corresponding with weather conditions in 2011 than to discard the data due to crop ecophysiological differences. The focus of this analysis was on optimization within the winter wheat crop; however, estimates for the net returns from fallow or pea rotations were incorporated to account for the full impact of cropping rotation choice (Bekkerman, unpublished data 2015).

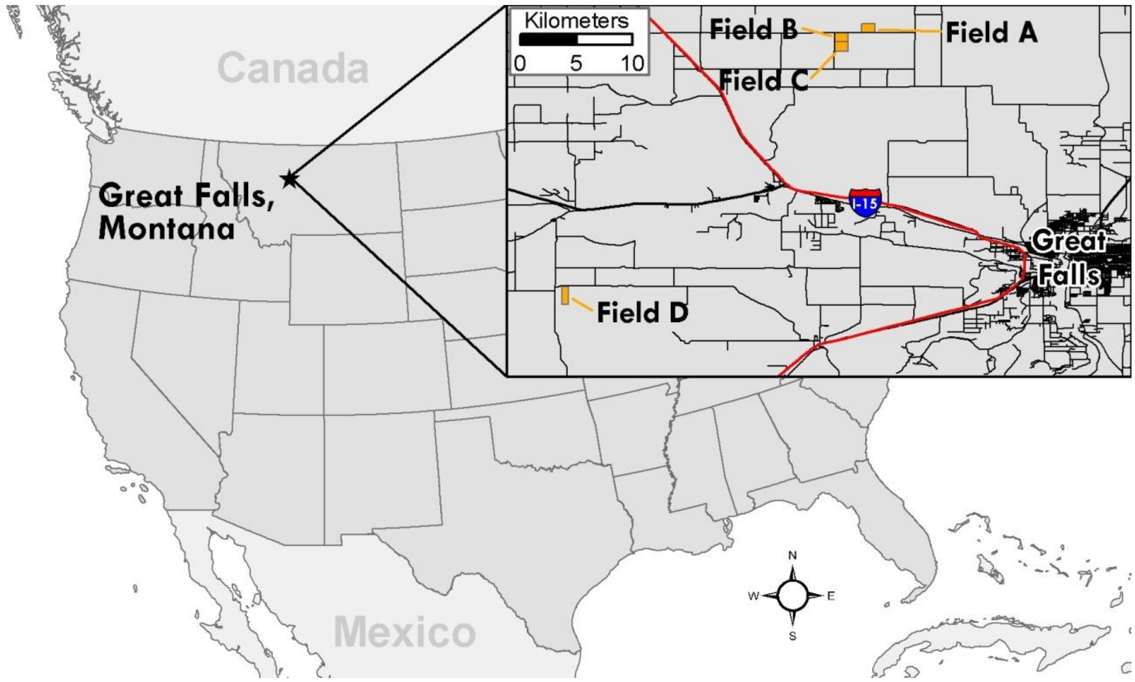

Figure 4.1. Map of field locations near Great Falls, Montana, USA.

Table 4.1. Data availability and planted crops[a] for field locations near Great Falls, Montana, USA.

Field	2006	2007	2008	2009	2010	2011	2012	2013
A	WW	F	WW	F	WW	SW	WW	F
B	WW	F	WW	F	WW	SW/P	WW	F
C	WW	F	WW	F	WW	SW/P	WW	F
D	F	WW	P	WW	WW*/P	WW*	Peas	WW

[a] WW, winter wheat; F, Fallow; P, Pea; SW, spring wheat; *data not available

Yield monitor data were collected using an RDS Ceres 8000i yield monitor calibrated according to manufacturer protocol. Fertilizer ‘as-applied’ data were collected during the same time period, with the form of fertilizer being predominately urea granules (with the exception of liquid urea-ammonium nitrate used in 2012 due to dry conditions). Every year when wheat was planted, the farmer applied variable rates of fertilizer throughout each field, with the quantities recorded and georeferenced as individual points. During 2006-2010, the rates of fertilizer were determined by the farmer, as would be encountered in a production environment. Starting in the 2011 cropping season, experimental nitrogen fertilizer rate treatments of 0, 40, 80, and 120 kg ha^{-1} were spatially distributed in each field in order to correspond to areas with divergent prior yields(i.e. high, medium, and low previous yields) and replicated four times (Figure 4.2). Treatment distribution facilitated exploration of the nitrogen-soil apparent Electrical Conductivity (EC_a)-precipitation parameter space (Whelan *et al.* 2012; Lawrence *et al.* 2015). Exploring the parameter space enables the impacts of most combinations of input variables to be known. For example, if the experimental nitrogen treatments were only applied in one area of the field, then it would be impossible to determine the interactive effects of nitrogen rate and EC_a (which may be relatively uniform in that area of the field) on yields. Similarly, if the experimental treatments were applied across the field but not across years, then the effects of different levels of precipitation would be unknown. Farmer-prescribed site-specific nitrogen levels were applied in between the experimental treatment areas.

In addition to fertilizer, soil properties also have a large influence on yield, although it is difficult to quantify many of these properties with sufficient spatial resolution. Therefore, to partially account for their influence, soil apparent electrical conductivity (EC_a) was measured, which may serve as a proxy for soil water holding capacity (Corwin and Lesch 2003). Electrical conductivity was measured in each field in 2006 using a Veris Soil EC 3100 sensor when each field was moist but drivable (May). Resolution of the EC_a measurements was 7 m (within-pass) by 15 m (between passes);

the resulting data were averaged to produce one EC_a measurement for each cell. The EC_a measurements are sensitive to soil moisture but were all taken within the span of one week, thus significantly minimizing potential temporal variability errors at the sub-field level. However, because EC_a combines multiple soil properties, such as texture, aggregation, among others, and has no detectable relation to *in situ* nutrient concentrations (Heiniger *et al.* 2003), it was important to understand which soil factors not captured by EC might be influencing yields. Therefore, to estimate the potential impact of these unobserved variables and residual levels of soil nitrate, 72 soil cores (each composited from three cores in a 0.5-m^2 area), spatially distributed across experimental treatment strips, were collected in fields B and C in early June 2012 with a truck-mounted probe, and were analyzed for available nitrogen (nitrate-N plus exchangeable ammonium), Olsen phosphorus, exchangeable potassium, exchangeable calcium, exchangeable magnesium, exchangeable sodium, sulfur, soluble salts, organic carbon, depth to rock (measured by the maximum penetration of the soil probe before hitting rock), pH and texture at 0 – 15 (all variables), 15-60 (nitrate-N only), and 60 – 90 cm (nitrate-N only), unless restricted by rock. These soil measurements were too sparse spatially and temporally to be included in the statistical model, but were useful for exploring residual variation.

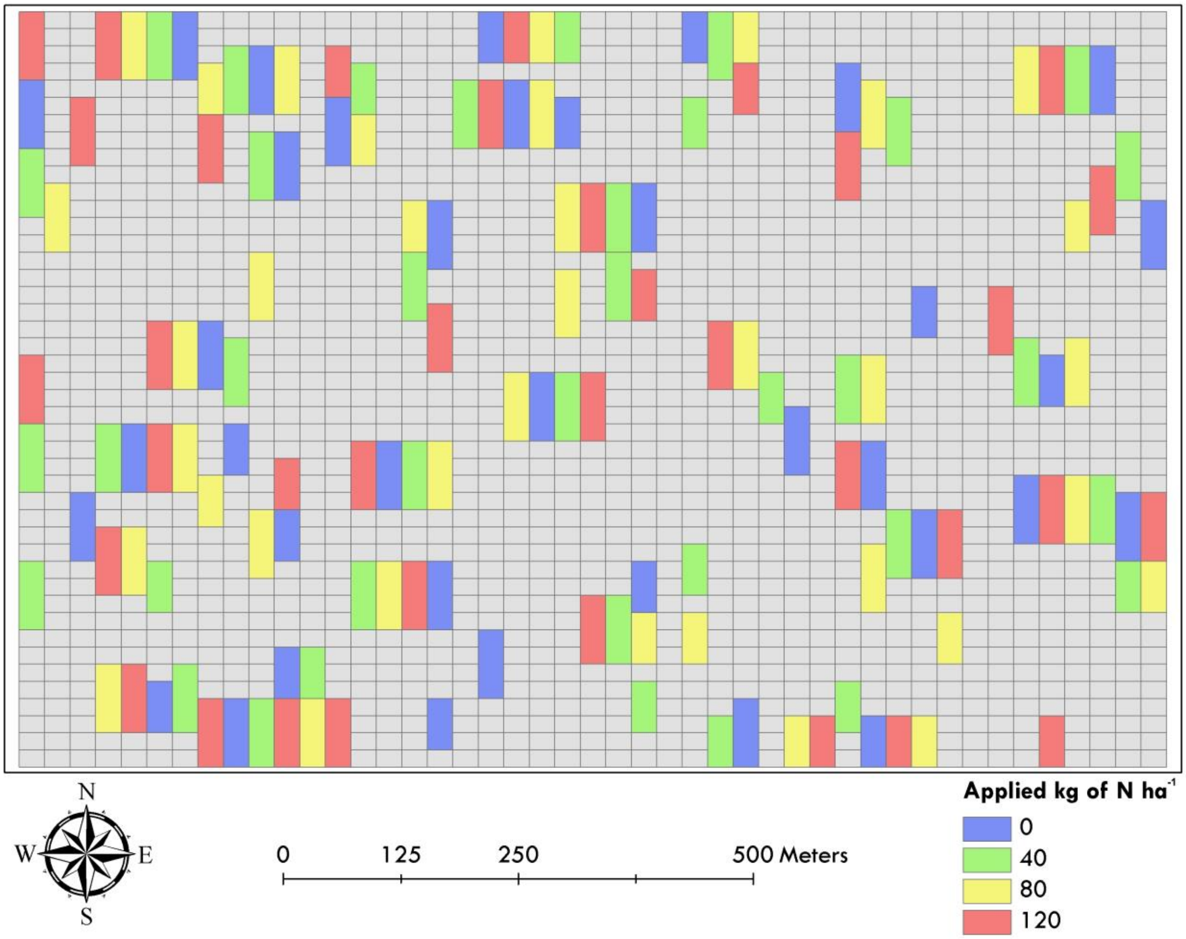

Figure 4.2. Nitrogen fertilizer treatment map in field A, 2011, where treatments were stratified by previous crop year yield outcome (high, medium, low).

Further complicating the influence of soils on yields, the topography of the landscape can alter the amount of accumulated water available for plant use. Therefore, a topographic water index (TWI) was calculated using real-time kinematic (RTK) elevation data from the combine, from which erroneous outlying observations had been removed using a low-pass filter (Macmillan *et al.* 2000). The topographic water index represents the relative amount of water that accumulates in each location of the field, considering the upslope area, slope, and other factors (Beven and Kirkby 1979).

Historical weather data were obtained from a weather station (POWER: USC00246700) 12 km west of fields A-C, and another station located 2 km west of field D (SUN RIVER 4E: USC00248021), maintained by the Global Historical Climate Network database (NCDC). Precipitation data from each station were aggregated into annual growing season precipitation values (Apr-May-Jun; Figure 4.3). Historical regional grain prices were obtained from the Montana Wheat and Barley Committee (MWBC), and annual fertilizer price data were obtained from the USDA Economic Research Service (USDA NASS 2015).

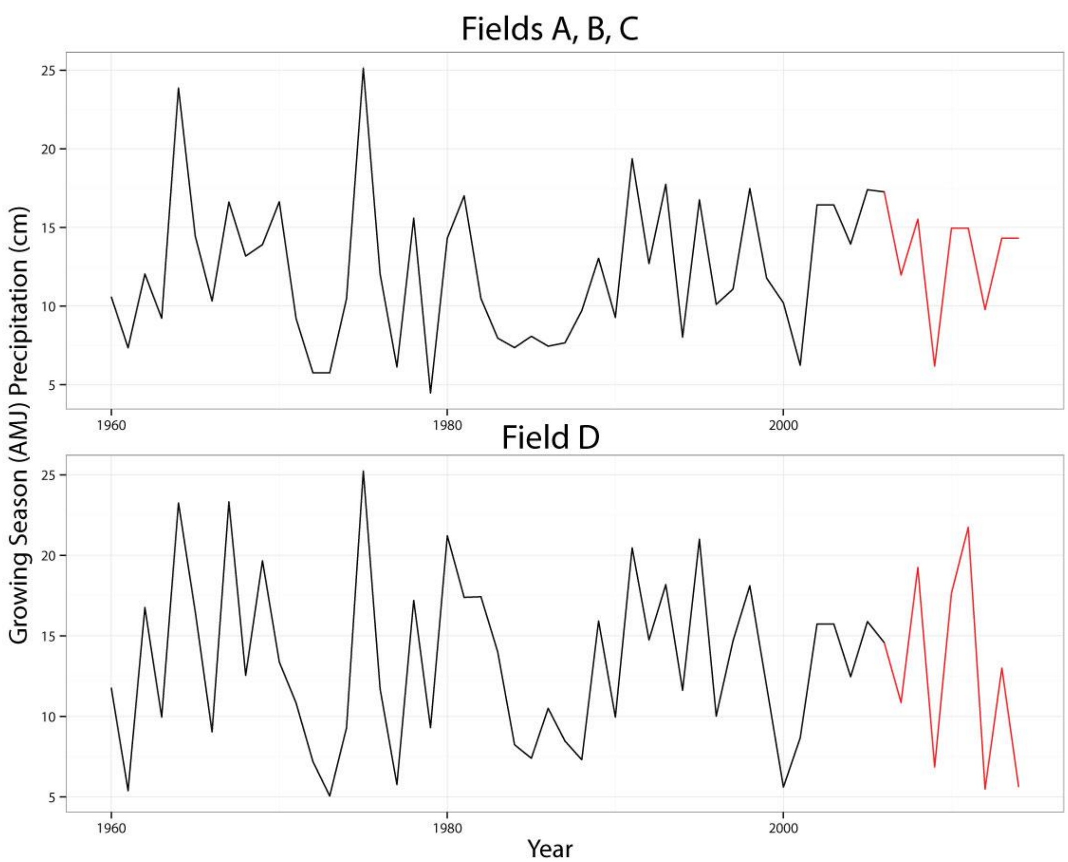

Figure 4.3. Mean monthly growing season precipitation (April-May-June) for 1960-2014 for both field locations. The precipitation values corresponding with the years evaluated in this analysis are colored red.

Data Cleaning and Storage

Each set of annual yield data were cleaned in accordance with the methods established by Sudduth *et al.* (2007); however, new processing scripts were created to re-implement these methods to accommodate the alternative format of the cooperating producer's yield data (Appendix A). In addition to lag correction and filtering, outliers within each cell of the field were investigated and removed if they were anomalously low compared to other values within the cell. Data from the outer two rows and columns of each field were removed to eliminate statistical noise caused by higher levels of equipment traffic and the effects of turning around in the headlands.

Following cleaning, an explicit database (PostGIS: http://PostGIS.net) was used to relate each individual yield and as-applied fertilizer datapoint to a cell in the field (a one-to-many relationship) for easy extraction and querying. The data points collected for the independent variables and yields were not spatially co-located at exact locations, requiring procedures (Appendix A) to synthesize a dataset that could be used for statistical analysis.

Modeling Strategy – Autocorrelation.

The spatiotemporal structure of the dataset forced careful consideration of the spatial and temporal dependence in the modeling process. Within each year, weather conditions would be expected to be relatively similar across fields, implying correlation across fields and cells (Figure 4.4). Across years, observations within each field would also be expected to be dependent. Furthermore, nested within those field-level correlations, each sub-field cell would likely be spatially autocorrelated with neighboring cells, as neighboring observations tend to be more similar than distant observations. Thus there was a hierarchical, crossed correlation structure to the dataset, which has the potential to reduce model efficiency, increase standard errors, and reduce the effective sample size (degrees of freedom).

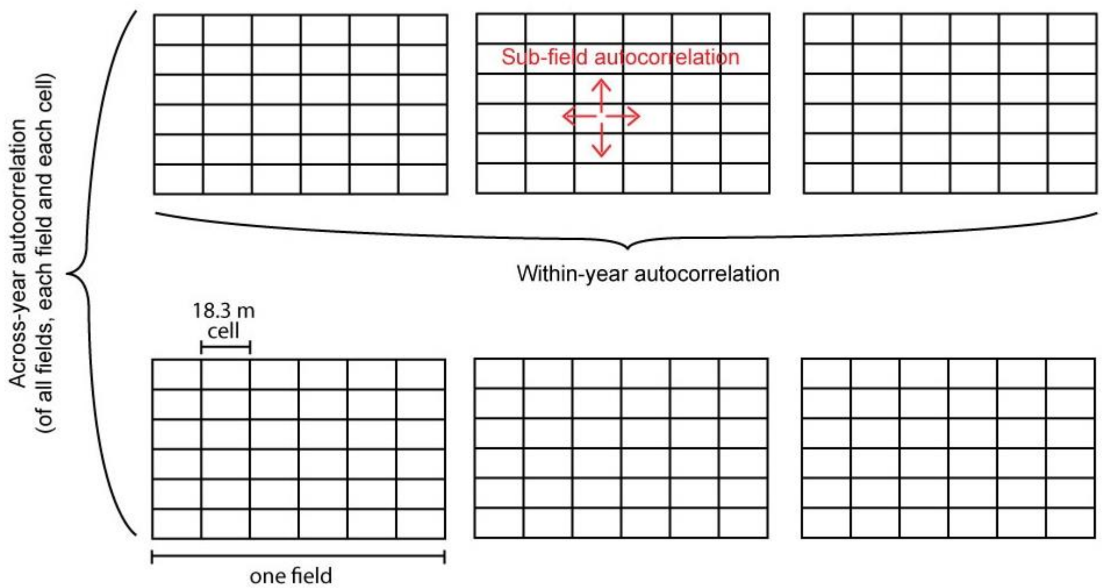

Figure 4.4. Autocorrelation structure of the cell lattices.

Many methods exist to account for the spatiotemporal dependencies within single fields. In the simulation study informing this paper (Lawrence *et al.* 2015), a Conditional-Autoregressive (CAR) structure (Besag 1974) was used for the simulation model when only one field was under consideration. For such scenarios, spatial regression approaches utilizing variograms may also be appropriate (Cressie 1991, Long *et al.* 2015). However, no statistical tools are currently available for estimating nested spatial lag or other autocorrelative models when including multiple fields, each with spatial autocorrelation of sub-field cells. Thus the approach taken here was to use a crossed random-effects correlative structure to account for within-field and within-year spatial autocorrelation that seeks to mimic a more explicit spatiotemporal model structure by capturing unobserved correlation implicit in field- and year-level variables. Following estimation, the spatial autocorrelation in the residuals for each field year was assessed with the Moran's I statistic (Moran 1950; Cliff and Ord 1981; discussed in the results), and by visually examining spatial plots of the residuals for each field-year.

In every field-year, spatial autocorrelation persisted despite the year and field random effects included in the models (p-value <.0001 from Moran's I). The spatial distribution of normalized residuals indicated that the scale of those residuals was small despite the high significance level of spatial autocorrelation. In general, spatial autocorrelation would be expected to increase the estimated variance of the predictors, although given the quantity of data analyzed it would be unlikely to result in large p-values (less likely to produce type I errors). Unfortunately, given the previously mentioned limitations, it was not possible to quantify those impacts with our data structure.

Functional Model Structure and Selection

To derive the model that best estimated yield, regressions were run on multiple models using all possible combinations of input variables. Although linear models tend to converge more consistently and have the advantage of computational speed when estimating many possible combinations of parameters, non-linear models are more likely to accurately represent the response of a crop to changing soil and nutrient conditions (Archontoulis and Miguez 2013). Therefore only non-linear models of yield were assessed for this analysis. Among non-linear models, sigmoidal models are ideal for representing biological processes (Birch 1999; Sepaskhah *et al.* 2011). At low levels of the driving independent variables (e.g. nutrients), sufficient quantities are not available to generate an observable growth response. As the levels increase, the biological response exponentially increases up to an inflection point, after which there are reductions in marginal responses to further increases. Although these models' parameter values may be more difficult to estimate, they provide improved predictions outside the range of observed data ensuring realistic optimization.

The major driving variable in the system, precipitation, controlled the upper level of the asymptote in the non-linear model (Equation 1). Thus, one basic form of the model for yield in cell *i*, year *j*, and field *k* was as follows:

$$Yield_{ij} = \frac{\beta max * precip_j}{1+\exp(-\beta_1 * QuantN_{ij} - \beta_2 * EC_{a,i} - \beta_3 * EC_{a,i} * QuantN_{ij})} + \beta_4 * Fallow_{j-1} + \beta_5 * Pea_{j-1} + field_k + year_j + \varepsilon \qquad (1)$$

where ε ~ $N(0,\sigma_e^2)$. In this specification, the parameter β_{max} can be interpreted as the maximum amount of yield at the asymptote. $EC_{a,i}$ represents the apparent electrical conductivity (dS m^{-1}) of the soil in one cell and serves as a proxy for soil properties that impact yield such as available water holding capacity. $QuantN_{ij}$ is the amount of nitrogen applied to cell *i* in year *j* in kg ha^{-1}. $Fallow_{j-1}$ and Pea_{j-1} represent whether the field was under fallow management or was cropped with pea in the previous growing season. If neither of these previous cropping conditions applied, it is implied that a wheat crop was grown in the previous season. Summerfallow management is a common moisture-conservation strategy used in the NGP, and pea is the most common legume used in place of fallow, which can improve economic returns (Chen *et al.* 2012) and provides for crop-rotational benefits due to biological nitrogen fixation and breaking of pest cycles. $Field_k$ and $Year_i$ represent the year and field-specific random effects.

Within the denominator of the non-linear model, TWI and its interaction with nitrogen were also considered for inclusion, as greater water availability could either provide greater mass flow of nitrate to plant roots or could potentially promote leaching. Interactions between EC and TWI could also be possible, as more finely textured soils could foreseeably amplify the accumulation of water.

All models were evaluated using Bayesian and frequentist statistical methods; the top model was selected using k-fold cross-validation (James *et al.* 2013; Appendix B). Cross-validation was used as the metric of comparison because it is relevant across non-linear models and because it selects for models that are superior at prediction beyond observed data.

Residual Soil Core Analysis

With the empirical approach taken here, it was expected that some spatial variables impacting yield would be difficult to measure with sufficient spatial resolution, thus they were not included in the full 8-year statistical model. As described in the section on data cleaning and storage, soil characteristics not subsumed by EC_a are such an example, but were expected to provide some explanation for gaps between estimated and actual yields. Therefore, data from the soil cores in 2012 in fields B and C were regressed against the residuals from the top model that corresponded with the spatial location of the soil cores. The temporally invariant soil properties of texture, organic matter, and depth to rock were regressed against residuals from all years. Nutrient levels measured in the soil cores were only regressed against the residuals from 2012, as nutrients are subject to much more rapid temporal variation than physical soil properties. The regressions with and without nutrients from the soil samples were performed separately. Due to the large number of possible models, with nine possible explanatory variables and five field-year dependent yield datasets, a stepwise Akaike Information Criterion (AIC) procedure was implemented for variable selection. For the regressions omitting nutrients, the frequency with which each variable was retained was counted across all field-years, with the most commonly occurring variables serving as the most likely explanations for unexplained yield patterns. For the regressions containing nutrients, the regression output is presented for the model with the lowest AIC value.

Net Return Integration

Following the soil core residual assessments, posterior distributions for the top model were collated. These posterior estimates were then used in combination with crop prices and nitrogen prices to calculate a net return (NR) for each cell (Equation 2).

$$Net\ Return_{ij} = Price_{crop,j} * Yield_{ij} - PriceN_j * QuantN_{ij} - FC \qquad (2)$$

where $Price_{crop,j}$ is the price of the crop (\$ kg^{-1}) in the current year at an assumed 12% protein level, $PriceN_j$ is the price of N (\$ kg^{-1}) in the current year, $QuantN_{ij}$ is the quantity of N applied (kg ha^{-1}), and FC is other average fixed costs associated with crop management, including weed control during the wheat cropping year (\$422 ha^{-1}; Bekkerman, unpublished data 2015). The net returns from each crop rotation were adjusted to be two-year net returns based on estimated returns from the alternating cropping cycle. Protein premiums or discounts were assumed to be neutral (0$ for an assumed 12.0 % protein) .For fallow rotations, there was a cost of \$65 ha^{-1}associated with weed control, for pea there was a gain of \$85 ha^{-1} from the additional crop revenue (MT Dept of Ag 2015), and for continuous wheat the one-year returns from the model output were doubled. Uncertainty in crop prices was represented by drawing randomly from the 5-year distribution of April-May crop prices (MT Dept. of Ag 2015). Due to the low temporal frequency of available fertilizer price data, the historical 5-year distribution of fertilizer prices was also used (USDA NASS 2015).

To represent the uncertainty in net return, we applied a sequence of Monte-Carlo simulation steps (detailed in Appendix C) with draws to integrate randomly drawn values from all of the supporting data sources. The result was a unique distribution of net returns for the three previous crops, for all cells (n = 7283), and for multiple nitrogen values. Before calculating utilities from the distribution of net returns, probabilities of discrete NR ranges were required (e.g. 10% probability of achieving a net return between \$30 and \$40). Therefore a kernel density estimator was constructed for the NR values, which enforced propriety (integration to one) and enabled such calculations.

Utility Calculation

Attitudes toward risk are heterogeneous among farmers and can lead to divergent management strategies to maximize perceived benefits such as profits or yields. Farmers who are less risk averse (more risk loving) are more willing to accept the potential for receiving a higher net return in exchange for taking on a higher chance that they may experience no or negative returns. Conversely, risk-averse farmers value a more certain positive net return, even if it is lower. Risk-tolerant farmers thus gain more 'utility' from higher net returns, where utility is defined as the subjective benefit derived by individual farmers for a specific level of net return. Accounting for these different risk preferences can lead to different management strategies for maximizing farmers' expected utility. To account for the alternative risk preferences, the Constant Relative Risk Aversion (CRRA) utility function was used (Pratt 1964, Arrow 1965, Equation 3, 4).

Constant Relative Risk Aversion utility function:

$U(NR) = NR^{(1-r)}/(1-r)$ for $r \neq 1$

$U(NR) = \log_e(NR)$ for $r = 1$ (4)

where NR is the net return and r is the risk aversion coefficient. When the risk aversion parameter, *r*, is less than zero, the CRRA function is concave. This represents a non-linear increase in utility as the NR increases. When r is zero, then each unit increase in NR results in a linear increase in utility, and when r is positive there are diminishing returns to the farmer for greater NRs (risk aversion). Due to the large amount of variability in the variables driving the net returns and low yields, there were a significant number of instances where NR was less than zero, which is not allowed under the CRRA function. In such instances, we assumed that the negative NR values were synonymous with disutility for the farmer. Therefore, disutility was calculated as the absolute value of NR, after which the sign of the utility was altered to be negative.

To optimize the nitrogen level for each previous cropping choice, each cell, and each risk preference, the nitrogen value that resulted in the highest utility was selected for each of these combinations. This produced spatial maps of optimal fertilization values for specific risk preferences and cropping choices that accounted for the range of uncertainties impacting the model.

Results

Model Selection

Incorporating the uncertainty of the major driving variables on dryland farms to calculate optimum site-specific input levels is a challenging task. Large spatiotemporal datasets can help overcome the limitations of high dimensionality and variability, yet there are still multiple models that may be appropriate for analyzing each dataset. We analyzed the top two frequentist and Bayesian models to understand the impact of model choice on final results (Appendix D), however only the results from the best model (model 4 which was Bayesian) are presented here. The form of the model with the lowest (best) consistent cross-validation score was:

$$Yield_{ij} = \frac{\beta max * precip_j}{1 + \exp(-\beta_1 * QuantN_{ij} - \beta_2 * TWI_{a,i})} + Fallow_{j-1} + Peas_{j-1} + field_k + year_j$$

For this model, a 100 kg ha^{-1} increase in nitrogen, from 50 to 150 kg ha^{-1} was associated with a negligible (mean 0.1 kg ha^{-1}; Bayesian credible interval overlaps with zero) increase in yield when growing season precipitation (Apr-May-Jun) was 14.8 cm (mean at this location). Crops grown after a previous wheat crop performed the worst, and had much higher yields when grown after pea and fallow, although there were significant differences across models (Table 7.1, Appendix C). For the best-performing model, the wheat-pea rotation consistently produced higher net returns.

Soil Core Analysis

Although the focus of the analysis was on optimization using variables with high spatial resolution that were readily obtainable by farmers, the soil core data collected in 2012 was useful for understanding future methods for improving prediction accuracy. Regressions of the soil core data against the residuals from all years (omitting nutrients) indicated that the texture (jointly as percentage of clay and silt), depth to rock and soluble salts consistently accounted for the largest amount of residual variation (Figure 4.5). This suggests that the EC_a measurements, while useful for improving yield predictions, did not adequately account for the spatial variation in soil texture or actual levels of soluble salts, and possibly by extension the water holding capacity of the soil (Corwin and Lesch 2003).

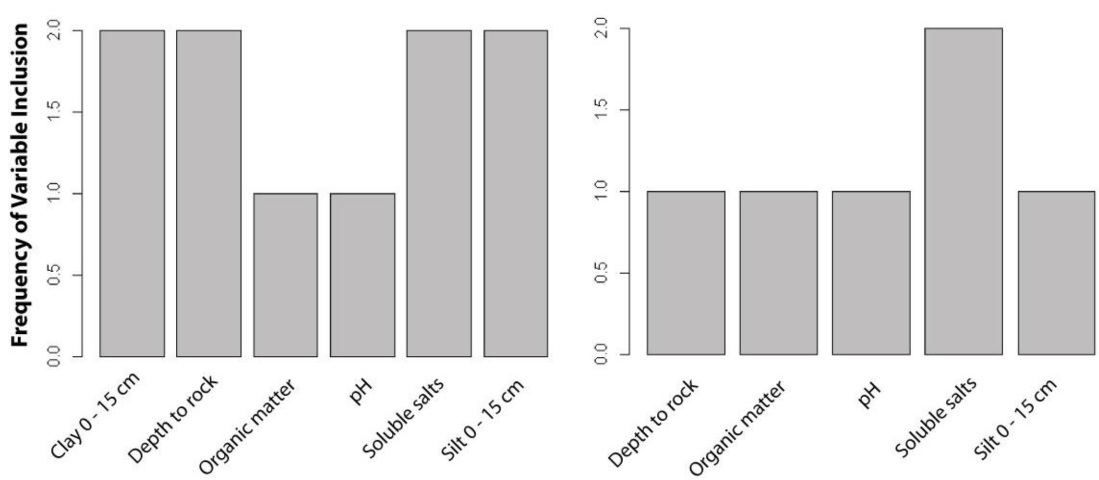

Figure 4.5. Frequency with which predictor variables were retained in equations to predict the residual variation, as selected by the lowest AIC scores (left). Frequency with which predictor variables in the final equations had p-values < 0.05 (right).

For the year (2012) in which nutrients were assessed, organic matter, soluble salts, and ammonium (0-15 cm) were strongly associated with the unexplained residual variation in yields (Table 4.2). For every one percent increase in organic matter, there was an associated 286 kg ha^{-1} increase in residual yields (residuals from nonlinear model), and for every 1 kg ha^{-1} increase in available nitrogen (over fertilizer nitrogen) there was an associated 3.2 kg ha^{-1} increase in the residual yields. Conversely, for every 0.1 mmhos/cm increase in soluble salts, there was an associated 54.2 kg ha^{-1} decrease, and for every 1 mg kg^{-1} increase in phosphorus there was an associated 10.5 kg ha^{-1} decrease in residual yields.

Table 4.2. Results from the regression of residuals from the non-linear model (dependent variable; kg ha^{-1}) against soil core properties (including nutrients; independent variables), selected based on the lowest AIC value. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Adjusted $R^2 = 0.37$.

Coefficient	**β**	**SE**
Intercept	-713	320
Organic Matter	286**	95
Soluble Salts	-54.2***	95
Available Nitrogen	3.2***	0.9
Olsen Phosphorus	-10.5**	3.9

These results suggest that, if feasible, a higher frequency and resolution of soil sampling could improve yield predictions.

<u>Utilities and Optimization</u>

Due to the low yields and net returns observed in the fields under study (Figure 4.6, top panel), the utilities to the farmer were generally either low or negative. Minimal responses to nitrogen fertilization resulted in low levels of prescribed nitrogen, except when farmers were very risk averse (*r* > 1; Figure 4.6, bottom panel). For risk-averse farmers, high levels of optimized nitrogen were prescribed when *r* was near one, and those levels diminished as the risk aversion continued to increase above one. For farmers who were slightly risk averse to risk tolerant, only a small number of cells in the field warranted levels of nitrogen greater than 0 kg ha^{-1}.

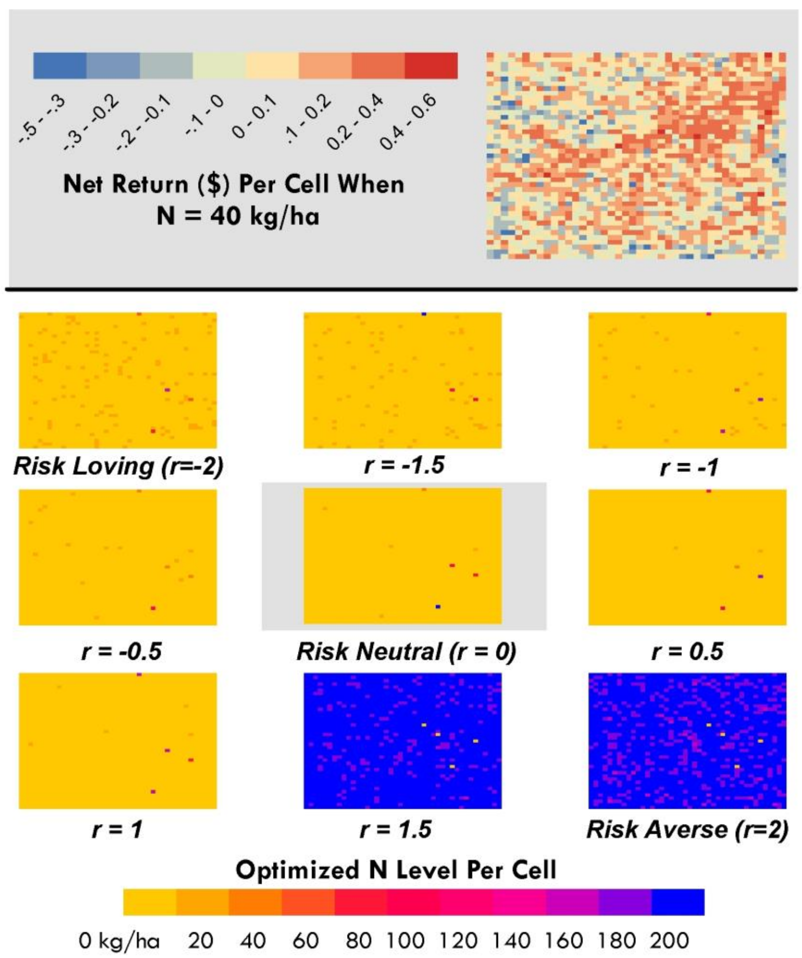

Figure 4.6. Net returns at 40 kg ha^{-1} of nitrogen (top row) for one draw of parameter values from the wheat-pea rotation (top panel, steps 3-7 in Appendix C). Optimized levels of N under alternative risk preferences in Field B, over all draws of parameter values (lower maps, for alternative levels of risk aversion; *r* = -2 to *r* = 2). Other fields displayed nearly identical optimized N patterns.

Across all cells and nitrogen levels, two-year utilities associated with peas as the previous crop were the highest, and utilities associated with continuous cropping were always the lowest, except for at very high levels of risk aversion (Figure 4.7). Both wheat-fallow and continuous wheat consistently produced negative net returns and negative utilities, suggesting that the farmer would have achieved higher utilities by not producing crops on the observed fields. It should be noted that these utilities were only calculated for two-year rotations, and long-term studies show increasing returns with wheat-pea rotations (Miller *et al.* 2015).

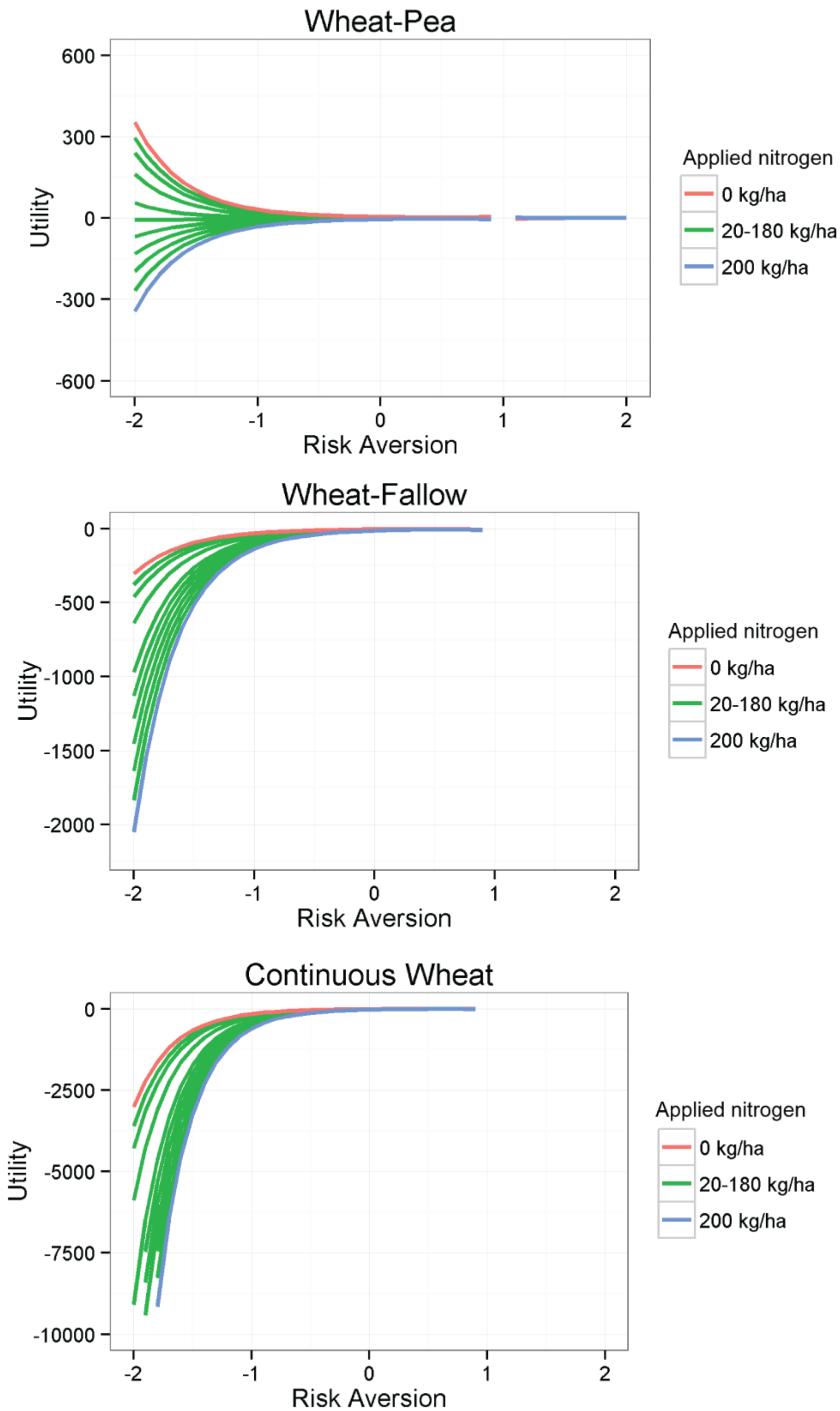

Figure 4.7. Aggregated utilities (+/- 1 sd, shaded) across all cells, under alternative cropping regimes (individual graphs) and fertilization levels (colors). For each graph, the mean net return was calculated for each cell under levels of fertilization from 0 kg ha^{-1} to 200 kg ha^{-1}. The net returns were then modified by farmers' alternative risk preferences via the CRRA function, from risk tolerance (*r* = -2) to risk aversion (*r* = 2).

As farmers became more risk tolerant (r<0), the utilities tended to become more exaggerated. Simultaneously, the optimal fertilization strategy of 0 kg ha^{-1} became more highly preferred (resulted in higher utilities). At such low levels of *r*, the reduction in costs from applying 0 kg ha^{-1} (rather than a rate greater than zero) of nitrogen had a bigger impact on utility than the potential decrease in revenue from a low level of fertilization.

In contrast, as the risk preference moved towards risk aversion, the difference in utilities between the alternative fertilization strategies converged. The utilities associated with the different fertilization levels became increasingly similar as *r* increased, suggesting that the optimal fertilization strategy was less certain.

As the risk preference approached 1, the form of the CRRA function started to heavily influence the utilities, culminating in an asymptote (gap) at 1. This threshold was artificial, and in reality the gradual shift towards risk aversion would likely result in a smooth curve between 0.5 and 1.5. Regardless, the preferred fertilization strategies would still shift from 0 kg ha^{-1} when $r < 1$ to 200 kg ha^{-1} when $r > 1$, as seen in the figures. This indicates that as farmers become more risk averse, there is a point at which they gain more utility from applying high levels of nitrogen rather than reducing costs by not applying nitrogen.

Discussion

IVa. Yield-Nitrogen Responses

The extremely low increases in yield associated with higher levels of fertilization suggest either that the majority of the fertilizer was lost before uptake by the crop, the relationship between nitrogen and yield was concealed by the high level of spatial or measurement variation, the level of soil nitrogen was already high before fertilization, obscuring any response to additional nitrogen, or the yield was limited by factors other than the level of nitrogen, in part due to high levels of soil nitrate-N. The median level of available nitrogen within the soil cores collected in 2012 was 103 kg ha^{-1} (including nitrate-N at 0-90 cm and ammonium at 0-15 cm), which, in Montana, is sufficient to attain a yield of 2.38 Mg ha^{-1} if no other growth factors are limiting yield (Dinkins and Jones 2013), although there was substantial variation about the mean. The average yields for the observed field years were only 2.04 Mg ha^{-1}, suggesting that, at least in fields B and C where soil core measurements were taken, yields were limited by factors other than the level of available nitrogen or that there was more heterogeneity in available N than indicated by the soil cores. This high level of residual soil nitrogen is likely responsible for the lack of an observable yield response to even the highest levels of nitrogen application.

Despite the high overall levels, there were still a significant number of soil core locations with lower levels of available nitrogen. Farmers typically collect a small number (e.g. 1 – 5) of soil cores per field to inform their fertilization strategy, thus it is possible that for any given field they could select a set of cores that were not representative of the average. However, the expense of collecting additional soil cores, plus the high density required (Schabenburger and Gotway 2005) to accurately characterize spatial variation are prohibitive for production applications. This discrepancy between the density of soil information required for research applications or taking advantage of spatial variation, and the density of soil information that can feasibly be collected, highlights the importance of developing new technologies for reducing the cost and time of soil sampling.

Optimization

Site-specific analyses and optimizations are powerful tools for improving farm management under multiple uncertainties. The outcomes displayed here are suggestive of a regional functional relationship between inputs and revenues, yet they have the greatest relevance at the site of data collection. At different farms in the region, crop responses will be unique. It is tempting to extend results from single or multiple locations to a larger area, yet such extrapolations must necessarily be tentative and provisional. For example, the optimizations at 0 kg ha^{-1} of nitrogen derived here may not be applicable to other locations due to the high levels of residual soil nitrogen that minimized the yield response to fertilizer nitrogen. However, even using a more realistic response function, the optimizations still arrived at 0 kg ha^{-1}, suggesting that other factors such as precipitation were limiting the economic benefits from applying additional nitrogen, especially within the current form of non-linear function where the impact of nitrogen was limited by the amount of precipitation in the numerator.

The unusual results found in this analysis, specifically with flat yield-nitrogen responses, often-negative utilities, and low overall yields, are indicative of the high levels of residual nitrogen (possibly from years of over-fertilization) and the low production capacity of the land used for this study. For locations in the region with a limited yield potential, a choice of wheat-pea rotations would be optimal disregarding farmer behavior relative to risk. If wheat-fallow or continuous wheat rotations are chosen, then there would be a high likelihood of low net returns. The selection of wheat-pea rotations for maximizing net returns is consistent with other studies (Burgess *et* al. 2012; Chen *et al*. 2012, Miller *et al.* 2015). Furthermore, it parallels the long-term increase in adoption of pulses in the NGP, both for economic, agronomic, and pest management reasons (Miller *et al.* 2015).

The optimal choice of fertilization strategy for the farmer is less clear, and depends on their risk preference. For most farmers in similar locations who are somewhat risk averse, the differences in expected utility between 0 and 200 kg ha^{-1} choices is small, so any level of fertilization would produce a similar outcome. However, applying fertilizer at 0 kg ha^{-1} over multiple years may deplete the soil profile of nutrients, so this strategy would not be advised over time. The lack of a yield-nitrogen response was likely related to already high levels of residual soil nitrate from long periods of over-fertilization, however it must be emphasized that the dominant driver of yields in this region is available soil water, and that large percentages of applied urea may be lost through volatilization (Engel et al. 2011) or other unknown pathways (such as leaching). Therefore, any relationship between levels of applied nitrogen and yield may still be obscured, even if residual soil nitrogen is taken into account.

In other fields in the region, or in agricultural systems with more productive soils, these yield-response relationships may be different. However, the *process* of analyzing dryland agricultural systems presented here could easily be extended to other locations. Ideally, rather than combining data across fields and managing the computational and spatial autocorrelation difficulties, six or more years of data would be available from individual fields (potentially fewer years in locations with more consistent climates), with nitrogen rate experimentation performed in each year. The result would be a patchwork of optimal crop rotation and fertilization strategies that were tailored to the unique soil and climatological conditions on each farm field, and the risk preferences of each individual farmer.

IVc. Uncertainty and Spatial Patterns

As demonstrated in Figure 4.7, uncertainty is a dominate feature of semiarid dryland agricultural systems in the Northern Great Plains. Even with a relatively high-resolution and long-term dataset, the expected outcomes from using optimal fertilization levels were not substantially different from the outcomes when using alternative fertilization levels. Considering the lack of spatial patterning to the optimal fertilization levels (Figure 4.6), it might be concluded that adopting a spatial nitrogen management strategy was economically disadvantageous, as found in several studies (Liu *et al.* 2006; Long *et al. 2015*) that accounted for the costs of technology acquisition. We did not take the costs of VRA technology into consideration, but note that this equipment is increasingly available regardless of whether it is used in practice. Furthermore, the lack of a spatial pattern is likely to be highly dependent on the slope of the nitrogen response curve when precipitation is limiting and on variable interactions in the regression model, the first of which was not found in this setting due to the high levels of residual soil nitrogen. As the spatial patterns in crop responses become more pronounced, VRA technology is more likely to produce higher net returns.

Uncertainty in precipitation and prices were also significant drivers in the optimizations. If only one or two years of data had been used to derive the optimal crop rotations and nitrogen fertilization strategies, there is a high probability that both of those years would have had similar levels of precipitation or similar prices. In such a case, prescriptions would be tuned to only one set of historical conditions and would mislead farmers seeking management strategies resilient to a wide range of conditions. Incorporating historical variability, simulation, and measures of economic risk into a comprehensive modeling framework, modified by farmer risk preferences, is therefore crucial for holistic analysis of semiarid dryland agricultural systems (Monjardino *et al*. 2015).

Conclusion

Semiarid dryland agricultural systems pose difficult management challenges due to the high amount of uncertainty in the driving biophysical variables. This uncertainty challenges the default management strategy of uniform agronomic prescriptions across years and across fields. As a result, methods to understand and take advantage of the variability have a high likelihood of producing benefits, especially if they are site-specifically calibrated with respect to the total uncertainty (climate, prices, costs) impacting the agricultural system, and the risk preferences of individual farmers.

In this paper we have applied a data analysis framework to accomplish these goals, which resulted in prescriptions of low nitrogen fertilization rates and a wheat-pea rotation for most farmer risk preferences. As site-specific sensors and statistical techniques evolve, the uncertainty in predicted outcomes will decrease and management recommendations will improve. Over time, the wide gap between experimental and production agriculture will continue to shrink, resulting in a more unified understanding of dryland agricultural systems under a multitude of bioeconomic conditions. The end product will be a suite of management alternatives that are optimized for the location, the market, the farmer, and ultimately, social benefits.

Acknowledgments

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References

Anselin L., Bongiovanni R., & Lowenberg-DeBoer J. 2004. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *American Journal of Agricultural Economics* 86: 675–687.

Antle J.M.1983. Incorporating risk in production analysis. *American Journal of Agricultural Economics* 65: 1099–1106.

Archontoulis S.V. & Miguez F.E. 2013. Nonlinear regression models and applications in agricultural research. *Agronomy Journal* 105: 1-13.

Arrow K. 1965, *Aspects of the Theory of Risk-Bearing*. Helsinki: Yrjö Jahnssonin Säätiö Foundation.

Bates D., Maechler M., & Walker S. 2015. *lme4: Linear mixed-effects models using Eigen and S4.*

Battisti B. & Naylor R.L. 2009. Historical warnings of future food insecurity with unprecedented seasonal heat. *Science* 323: 240–244.

Bekkerman A. 2015. Costs and Revenue for several crop rotations in Montana. *Unpublished data*.

Besag J. 1974. Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society. Series B (Methodological)*: 192–236.

Beven K.J. & Kirkby M.J. 1979. A physically based, variable contributing area model of basin hydrology / Un modèle à base physique de zone d’appel variable de l’hydrologie du bassin versant. *Hydrological Sciences Bulletin* 24: 43–69.

Birch C.P. 1999. A new generalized logistic sigmoid growth equation compared with the Richards growth equation. *Annals of Botany* 83: 713–723.

Burgess M**.**, Miller P., & Jones C.A.. 2012. Pulse crops improve energy intensity and productivity of cereal production in Montana, U.S.A. *Journal of Sustainable Agriculture* 36: 699-718.

Chen C., Neill K., Burgess M., & Bekkerman A. 2012. Agronomic benefit and economic potential of introducing fall-seeded pea and lentil into conventional wheat-based crop rotations. *Agronomy Journal* 104: 215-224.

Cliff A.D & Ord J.K. 1981. *Spatial Processes*. London: Pion.

Corwin D.L. & Lesch S.M. 2003. Application of soil electrical conductivity to precision agriculture. *Agronomy Journal*, 95, 455–471.

Cressie N. 1993. *Statistics for spatial data*. Canada: Wiley.

Diaz R.J. & Rosenberg R. 2008. Spreading dead zones and consequences for marine ecosystems. *Science* 321: 926–929.

Dinkins C.P. and Jones C. 2013. Developing fertilizer recommendations for agriculture. MontGuide 200703AG. Montana State University Extension Publications.

Dulière V., Zhang Y., & Salathé E.P. 2013. Changes in twentieth-century extreme temperature and precipitation over the western united states based on observations and regional climate model simulations. *Journal of Climate* 26: 8556–8575.

Engel R., Jones C., & Wallander R.. 2011. Ammonia volatilization from urea and mitigation by NBPT following surface application to cold soils. *Soil Sci Soc Am J.* 75: 2348-2357.

Godfray H.C.J., Beddington J.R., Crute I.R., Haddad L., Lawrence D., Muir J.F., Pretty J., Robinson S., Thomas S.M., & Toulmin C. 2010. Food security: the challenge of feeding 9 billion people. *Science* 327: 812–818.

Grant G.D. Spring wheat yield response to nitrogen, 1993-2006. *Unpublished data.*

Guirguis K.J. & Avissar R. 2008. An analysis of precipitation variability, persistence, and observational data uncertainty in the Western United States. *Journal of Hydrometeorology* 9: 843–865.

Heiniger R.W., McBride R.G., & Clay D.E. 2003. Using soil electrical conductivity to improve nutrient management. *Agronomy Journal* 95: 508–519.

Jones J.W., Hoogenboom G., Porter C.H., Boote K.J., Batchelor W.D., Hunt L.A., Wilkens P.W., Singh U., Gijsman A.J., & Ritchie J.T. 2003. The DSSAT cropping system model. *European journal of agronomy* 18: 235–265.

Lawrence P.G., Rew L.J., & Maxwell B.D. 2015. A probabilistic Bayesian framework for progressively updating site-specific recommendations. *Precision Agriculture* 16: 275–296.

Liu Y., Swinton S.M., & Miller N.R. 2006. Is site-specific yield response consistent over time? Does it pay? *American Journal of Agricultural Economics* 88: 471–483.

Long D.S., Whitmus J.D., Engel R.E., & Brester G.W. 2015. Net returns from terrain-based variable-rate nitrogen management on dryland spring wheat in northern montana. *Agronomy Journal* 107: 1055-1067.

Macmillan R.A., Pettapiece W.W., Nolan S.C., & Goddard T.W. 2000. A generic procedure for automatically segmenting landforms into landform elements using DEMs, heuristic rules and fuzzy logic. *Fuzzy Sets and Systems* 113: 81–109.

Maynard L.J., Harper J.K., Hoffman L.D., & others. 1997. Impact of risk preferences on crop rotation choice. *Agricultural and Resource Economics Review* 26: 106–114.

Miller P.R. & Holmes J.A. 2005. Cropping sequence effects of four broadleaf crops on four cereal crops in the northern Great Plains. *Agronomy journal* 97: 189–200.

Mock C.J. 1996. Climatic controls and spatial variations of precipitation in the Western United States. *Journal of Climate* 9: 1111–1125.

Monjardino M., McBeath T., Ouzman J., Llewellyn R., & Jones B. 2015. Farmer risk-aversion limits closure of yield and profit gaps: A study of nitrogen management in the southern Australian wheatbelt. *Agricultural Systems* 137: 108–118.

Montana Department of Agriculture. 2015. Wheat Prices. Available at: http://wbc.agr.mt.gov/wbc/Producers/Pricing.html.

Moran P.A. 1950. Notes on continuous stochastic phenomena. *Biometrika* 37: 178-81.

O'Dea J.K., Jones C.A., Zabinski C.A., Miller P.R., & Keren I.N. 2015. Legume, cropping intensity, and N-fertilization effects on soil attributes and processes from an eight-year-old semiarid wheat system. *Nutrient Cycling in Agroecosystems* 102: 179–194.

Pratt J.W. 1964. Risk Aversion in the Small and in the Large. *Econometrica* 32: 122-136.

Schabenberger O. & Gotway C.A. 2004. *Statistical Methods for Data Analysis*. Boca Raton: Chapman & Hall/CRC Press.

Sepaskhah A.R., Fahandezh-Saadi S., & Zand-Parsa S. 2011. Logistic model application for prediction of maize yield under water and nitrogen management. *Agricultural Water Management* 99: 51–57.

Shahandeh H., Wright A.L., & Hons F.M. 2011. Use of soil nitrogen parameters and texture for spatially-variable nitrogen fertilization. *Precision Agriculture* 12: 146–163.

USDA National Agricultural Statistics Service. 2015. Agricultural Prices [Data File]. Retrieved from http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx

Whelan B.M., Taylor J.A., & McBratney A.B. 2012. A "small strip" approach to empirically determining management class yield response functions and calculating the potential financial "net wastage" associated with whole-field uniform-rate fertiliser application. *Field Crops Research* 139: 47–56.

CHAPTER FIVE

VULNERABILITY OF DRYLAND AGRICULTURAL REGIMES TO ECONOMIC AND CLIMATIC CHANGE

Contribution of Authors and Co-Authors

Manuscript in Chapter 5

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Contributions: Assisted with study design, interpretation of survey data, and manuscript editing.

Co-Author: Lisa J. Rew

Contributions: Assisted with interview planning, survey design, fieldwork, interpretation and manuscript writing.

Co-Author: Colter Ellis

Contributions: Contributed to analysis and interpretation of interview and survey data. Also assisted with manuscript drafting.

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Contributions: Helped conceive the methods for analyzing survey data, provided feedback on analysis, assisted with manuscript editing.

Manuscript Information Page

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Abstract

Large-scale agricultural systems are central to food production in much of North America, but their ubiquity could be threatened by vulnerability to economic and climatic stressors during the 21st century. Research has focused on understanding the influence of climatic changes on physiological processes in these systems and has increasingly recognized that other factors such as social, economic, and ecological variation may affect overall impacts. Our research assesses the vulnerability of large-scale agricultural systems to variation in multiple stressors and investigates alternative strategies to adapt to novel conditions. We examine semiarid dryland farms in the northern Great Plains (NGP) of Montana, which represent agricultural systems that are likely to be the first to be affected by climate change. Farmers in the NGP have experienced three distinct periods of elevated economic and drought related variability since the 1970s, primarily driven by uncertainty in soil moisture, but at times amplified by uncertainty in nitrogen and wheat prices. This study seeks to better understand how farmers evaluate and respond to these conditions. The results indicate that although farmers perceived few alternative agronomic options for adapting to drought, strategies for adapting to high input prices were more plentiful. Furthermore, we find increasing the overall resilience of dryland agricultural systems to economic and climatic changes requires intrinsic valuation of crop rotations and use of on-farm experimentation to parameterize crop response to input functions.

Introduction

Crop production in North America is overwhelmingly represented by large-scale monoculture or biculture commodity farms. With increasing recognition of the potential impacts of climate change on agricultural production (e.g. Lobell *et al.* 2008), there is elevated concern over the vulnerability of existing crops and commodity farming systems to changes in temperature and precipitation (Hatfield *et al.* 2011). Simultaneously, increased variability in commodity and input prices over the last decade has increased the role of economic uncertainty as a challenge in making farm management decisions. Together, these stressors have the potential to threaten large numbers of commodity-reliant farms, but individual farm impacts will be determined by the magnitude and variability of the stressors, the tools that farmers have to mitigate impacts, and the ability of farmers to assimilate new practices that are better adapted to novel climate (Berkes *et al.* 2007, Tarleton and Ramsey 2008).

In the United States, climate change has been predicted to be manifest in a number of outcomes. In general, temperatures are expected to increase and precipitation levels will be more uncertain (Karl 2009). These two factors have an important effect on crop production that is particularly pronounced through their combined impact on evapotranspiration. Unfortunately, sub-regional predictions for these variables are still in their infancy and are often unreliable (Dulière *et al.* 2013).

The locations where the impacts of changing precipitation, temperature, and evapotranspiration would be most immediately observable are where they are already near an upper threshold, beyond which crop production would be unlikely; that is, nearly too dry or too hot (Delgado *et al.* 2011). If farmers cannot mitigate the effects of these two components through altered production practices or increased irrigation, they would necessarily be more vulnerable and at risk of ecological and economic failure. Consequently, arid and semiarid dryland agroecosystems could be considered early warning locations for observing the impacts of climate change on farm sustainability.

Within dryland systems, spring and winter wheat (*Triticum aestivum*) are two of the major crops produced due to their tolerance for low moisture levels. While a variety of production practices exist to further enhance the water use efficiency of wheat, further gains may be difficult to attain, and will require improvements such as greater quantities of crop residues, careful crop cultivar selection, flexible rotations, and improvements in the timing of cultural operations (Nielsen *et al.* 2005).

Due to the reliance of dryland systems in the NGP on wheat, fluctuations in the commodity price of wheat have a significant impact on farmer revenues in the region. Hedging strategies, such as selling futures contracts in advance of the harvest date, are effective measures for mitigating the risk of price fluctuations, yet they require the capacity to store large quantities of grain for long periods of time, and are not used by a majority of farmers (Mishra and El-Osta 2002, Velandia *et al.* 2009). High levels of fertilizer use, which have become more commonplace in the USA since 1980, further expose farmers to the uncertainties of global energy prices, as fertilizer is the largest energetic input into the system (Piringer and Steinberg 2006). This dependence on fertilizer has only increased as the sources of nitrogen used prior to 1950, such as legume green manures or animal manure, are either difficult to use on large scales (for conventional farmers), or carry an economic penalty associated with non-cash producing crops (i.e. green manure crops). Together, exposure of farm budgets to commodity markets for revenue, and energy markets for costs, creates a financial vice that tightens and loosens in response to the volatility of global financial markets, and is clearly out of the control of the farm manager.

The ability of farmers to resist the economic vice, while under pressure from climate change, depends on the tools that are available for mitigation (Howden *et al.* 2007), and on the adaptability of farmers (individually and collectively) to novel conditions (Berkes *et al.* 2007). Historical events (McLeman 2008), farmer perceptions of risk and uncertainty (Sunding and Zilberman 2000), and pathways of social agricultural learning (Roling and Jiggins 1998) all lend insight into this adaptation process. Furthermore, qualitative understanding of the relationship between information sharing, learning, adaptive capacity and resilience can create a window into the adaptability of farmers and how it may be enhanced to endure climate change and fluctuating prices (Tarnoczi 2011).

To explore the vulnerability of dryland agroecosystems, we chose to focus on a geographical region that is already strongly influenced by climate change and economic fluctuations. The northern Great Plains (NGP) is an agricultural region that primarily produces dryland wheat, has a semiarid climate (<400 mm per year), and is dominated by large farms (e.g. greater than 800 ha). Previous studies have examined the adaptation process in neighboring regions (Bradshaw 2004, Tarnoczi 2011), the adoption of sustainable agricultural processes in the NGP (Saltiel *et al.* 1987), and quantitative methods for explaining farm-scale vulnerability within the context of climate (Antle *et al.* 2004). Our research adopted a hybrid methodological approach by exploring the link between the quantitative reality of economic and climatic stress (manifested as the risk of bankruptcy) and qualitative farmer perceptions of adaptability. Specifically, we sought to understand how the historical and current uncertainty of these stressors influences farmer vulnerability and adaptability.

To study this question, we first reviewed the current economic vulnerability of NGP farmers within a historical context. It was expected that since the date when reliable farm census and survey data became available (1970), farmers have become more reliant on external inputs. Therefore, fluctuations in the price of inputs and the price of wheat could have significant impacts when unmatched by parallel increases in yields. Conditions of drought could further exacerbate these economic pressures by reducing yields and net returns disastrously. Second, the research explored the number and quality of options that farmers have to mitigate the impacts of these stressors. We sought to understand how the uncertainty and complex interactions of the stressors structure farmers' strategies for staying economically solvent. Together, the physical reality and responses to uncertainty have important implications for the resilience of dryland agricultural systems.

Methods

To gain an understanding of the dynamics of the physical stressors and how farmers manage for their uncertainty, a mixed methods research approach was used in which quantitative data on prices and drought stress were compared to qualitative data of farmer perceptions.

Historical Analysis – Economic and Drought Variability

To assess farmers' perception toward economic uncertainty, we focus on two factors that farmers believe to be the primary determinants (other than yield) of profitability: the cost of nitrogen and the price of wheat. The Palmer Drought Z-index (PZI), averaged over the growing season months from April until August, was used as a quantitative indicator of moisture stress, and has been shown to be the moisture index most highly correlated with yields in the NGP (Quiring 2003). To assess the uncertainty in these variables as experienced by the farmer, the Coefficient of Variation (CV) was calculated for each measure on a 5-yr rolling basis extending from 1965 through 2014. The Coefficient of Variation is a unit-less measure that allows variables measured on different scales to be compared. High CV values indicate periods with elevated variability, suggesting amplified uncertainty for the farmer in the previous 5-yr period.

In addition to calculating the CV measures on each individual metric, the CVs from all metrics were additively combined into an aggregate measure of total variability.

Prices for nitrogen and wheat were obtained for the period 1960 – 2013 (USDA NASS 2015a,b). Wheat prices were adjusted to reflect the annual proportion of winter wheat and spring wheat hectares planted in Montana (USDA NASS 2015c). Nitrogen fertilizer prices were weighted by the proportion of each fertilizer type used in each year (USDA NASS MT 2011). Both fertilizer and wheat prices were converted to real prices using Consumer Price Index data (Bureau of Labor Statistics 2015), with 1980 as the baseline year. PZI data for climate district 3 in Montana were obtained from the National Climatic Data Center (2015).

Farmer Perceptions of
Uncertainty and Adaptation

We used a multi-stage inquiry procedure to understand the options available to NGP farmers and to learn about their adaptations to uncertainty. First, we extensively interviewed three farmers to generate initial knowledge on adaptability options and beliefs. Specifically, open-ended questions were asked about five potentially impactful forms of uncertainty: drought, weeds/pests, input prices, crop prices, and uncertainty in spatially varying crop responses and nutrient levels. The respondents were also asked to discuss other forms of uncertainty they deemed important. Thus, while we adopted a 'top-down' approach where the set of conditions potentially causing vulnerability was assumed (Cutter 1996), we also allowed for more flexible responses that did not fit with our preconceptions (Pittman 2011). Seventeen additional interviews were conducted with other producers to validate and provide detail to the impactful forms of uncertainty. Interviews were conducted both in-person and by phone to capture farmers' reaction to observed conditions (in fields, in the combine, at the machine shop, etc.) throughout the growing season. All interviews were digitally recorded, transcribed, and hand-coded to derive initial themes used to inform the next stage of inquiry (Miles and Huberman 1994). Each farmer was purposefully sampled to capture a relevant range of methods and geographies (Maxwell 2013).

Qualitative interviews conducted in the first research stage were used to develop a theoretically grounded survey instrument (Dillman 2000). Using in-person and web-based surveys, several drought and price scenarios were sketched, with respondents requested to detail the specific agronomic actions they would take to respond, and where they would seek additional information needed for adaptation. Questions covering the same subject matter were posed with several alternative wordings to validate the responses of each farmer using a combination of open-ended wordings and multiple choice options. Basic background information was collected about age, length of experience with farming, irrigation status (irrigated or dryland), and scale of operation; the primary stressors outlined in the case study interviews were also validated. The data were only used if the respondents fit the criteria of having farming as their primary occupation, that they primarily grew wheat or other small grains, and their farm was larger than 500 acres. All of the respondents were men, eliminating the possibility to make generalizations to women. A total number of 54 surveys were returned out of 718 (37 in paper form and 17 electronically). The surveys were administered to farmers associated with the Montana Grain Growers Association (MGGA) and farmers attending workshops on herbicides and precision agriculture facilitated by Montana State University Extension Specialists.

Results

Historical Patterns Of Economic and Climatic Vulnerability

Two of the key drivers of economic vulnerability in dryland agriculture are instability in prices and uncertainty in available moisture. These factors have the potential to negatively impact farms by inhibiting long-term operational and agronomic planning; each can affect a farm individually or multiple factors can have additive or multiplicative effects. This section documents the historic variability in fertilizer costs and wheat prices, and the variability in moisture stress for crops in the NGP. Trends in variability are set against the backdrop of agronomic change in this region.

From 1970 onwards, the amount of fertilizer used per hectare consistently increased (Figure 5.1), even though the specific forms of nitrogen fertilizer changed from predominantly anhydrous ammonia to urea (USDA NASS MT 2011). During this same period, the real prices of nitrogen fertilizer and wheat declined from an absolute maximum in 1972-1975 to an absolute minimum in 1998, then climbed to a local maximum in 2008 (Figure 5.2). Therefore, although the prices experienced by farmers in 2008 were likely the highest seen during many of their lifetimes, they were still lower than the price spikes associated with the oil and geopolitical crises of the 1970s.

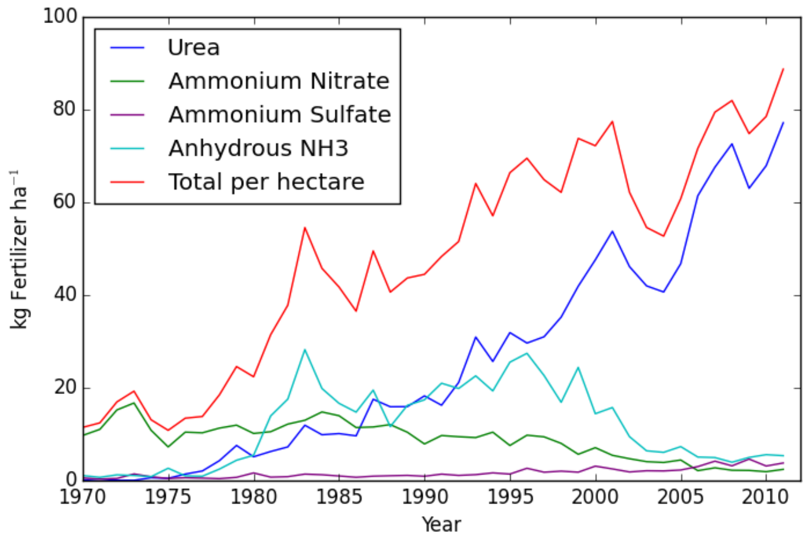

Figure 5.1. Kilograms of fertilizer used on a per-hectare basis in Montana, 1970-2011.

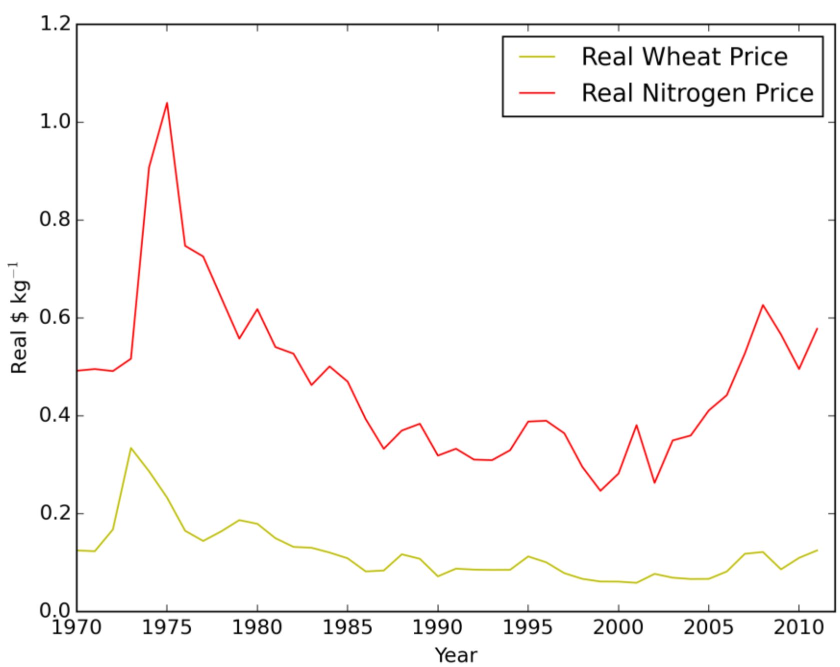

Figure 5.2. Trends in real (inflation-adjusted) nitrogen and wheat prices from 1970 – 2012

The spread between the real nitrogen and fertilizer prices fluctuated during this same time period, which would have impacted farmer net returns. Notably, the spread has widened since 2002, with increases in nitrogen prices outstripping the associated increases in wheat prices. However, productivity per unit area also increased during the whole time period from 1970 (Figure 5.3) and the total mix of variable and fixed costs changed for farmers, so the comprehensive impact on net returns is ambiguous.

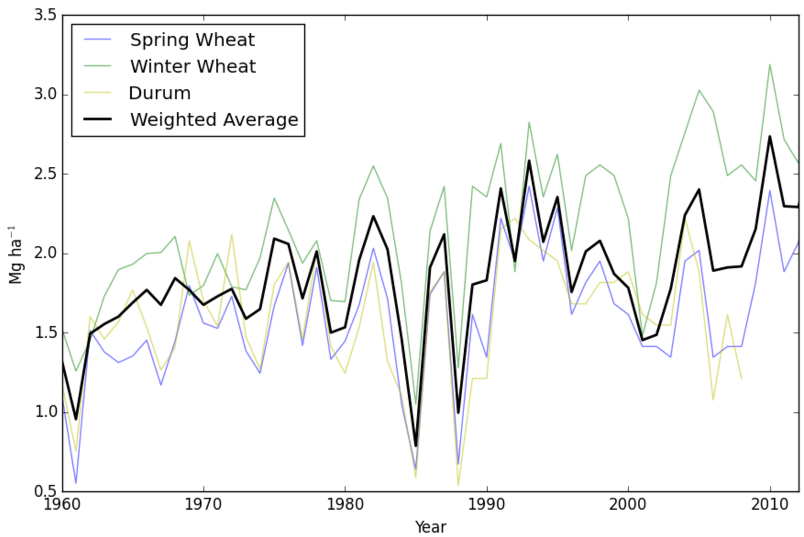

Figure 5.3. Productivity trends for wheat varieties in Montana, 1960 - 2014

The PZI was more variable during this time period, with elevated periods of moisture stress (negative values represent greater stress) during the early and late 1980s, and during the early-mid 2000s (Figure 5.4).

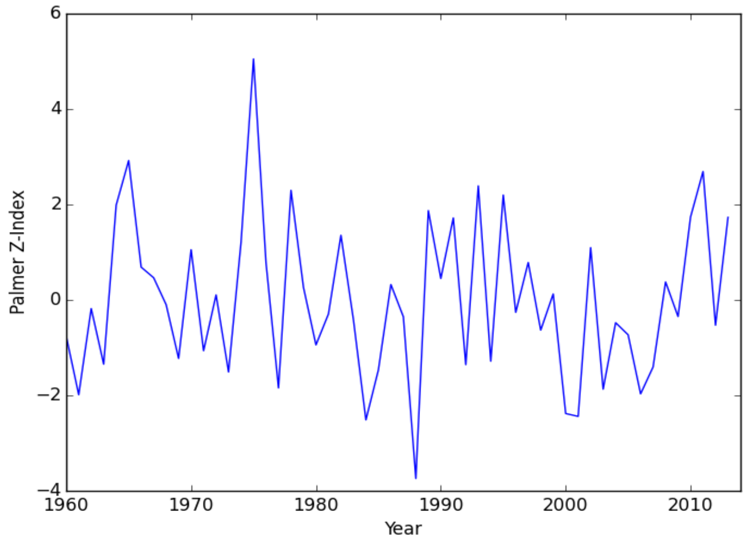

Figure 5.4. Fluctuations in the Palmer Z-Index for the years 1960-2012. Lower values are associated with low levels of available soil moisture.

Despite the fluctuations in the actual values of the prices and PZI during this time period, the degree of variability in these factors may have an even greater impact by creating uncertainty for the farmer. Three notable peaks were observed in the 5-year CV indicator of total variability: in the mid-late 1970s, in the late 1980s, and throughout the 2000s (Figure 5.5). The first peak was the only period of uncertainty driven by all three input factors (nitrogen price, wheat price, *and* PZI), whereas the second was driven by the PZI alone, and the third by prices and the PZI during alternate time periods. The peak in the late 1980s corresponded with the previous 5 years of serious drought that was associated with many farmer exits (Figure 5.6).

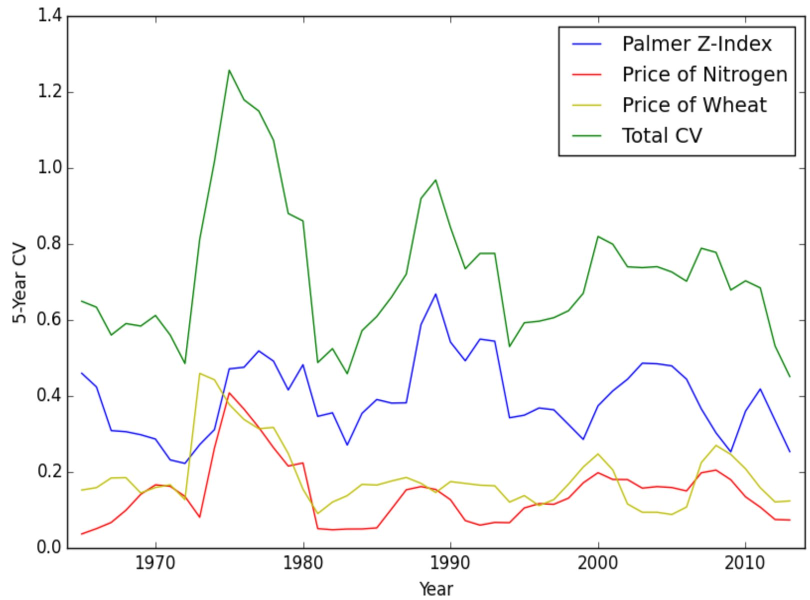

Figure 5.5. Coefficients of Variation (CV) for preceding 5-year periods, 1965-2012.

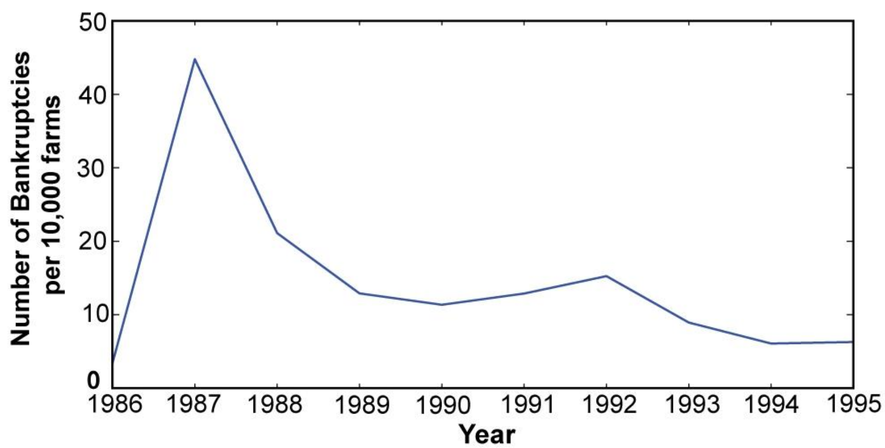

Figure 5.6. Farmer bankruptcies in the Northern Great Plains, 1986 – 1995.

Depending on the age and experience of individual farmers, the high levels of variability in the late 1980s and the 2000s is likely to be remembered by farmers and reflected in their past and current strategies of stress adaptation. In general, increased stress and variability creates a more difficult situation for agricultural management and increases vulnerability. However, the reactions of farmers strongly influence the impacts of the stressors and their longer-term consequences.

Number and Quality of
Options for Mitigating Stressors

There were distinct periods during the last 45 years when farmers experienced acute stress from drought, prices, or both. The reactions of farmers to the stressors, and their relative desire to minimize the associated risks has the potential to structure their agronomic decisions and future vulnerability.

Drought. Almost universally, the farmers questioned perceived drought as a major limiting factor in their ability to make agronomic changes. The most common analogy mentioned by the interviewees was having their 'hands tied.' As one farmer explained, "You just tighten the belt, you don't buy new stuff, … you just get by. I'd say more just cut back the costs, try to be conservative." Other farmers described the process of cutting back as one of re-using old equipment and 'putting patches on patches'. The specter of drought was frustrating for many of them largely because it removed their perceptions of control over their own farming systems:

> Well the biggest change I've had to, and still am responding to, is drought! You know, nothing works anymore because we don't get any rain. It's really frustrating because all you do should be successful, and when it doesn't rain it doesn't work. That's pretty much out of our hands as to what we can do.

With that lack of control, there was a feeling that the only available option was to revert to agricultural practices that they had been using for generations. These practices were not necessarily viewed as ideal, but farmers felt that they were the only available option. One farmer noted,

> ... in Montana, we are always just a week away from a drought. We live in a very sparse rainfall environment … I think we're doing about as good a job as we can with managing the moisture that we get …. There's room to allow for less moisture by changing our rotation some. But winter wheat is probably the most efficient water user that we have …. So we'd probably peel back to fewer spring wheat acres, fewer pea acres, which is painful to say. Or maybe we'd just quit re-cropping. We'd go from 2/3rds cropped every year to 50-50 or maybe even less…. But summerfallow is not very efficient.

Thus the semiarid nature of the NGP along with its climatic heterogeneity may impact farmers' perceptions that their only available option is a rotation of winter wheat-fallow, which has been used since agriculture was first applied by Euro-American settlers in the region. Farmers perceived rotations as preferable in terms of pest management and nitrogen fixation, yet these benefits were contrasted with the perceived superior water-use efficiency of winter wheat. When pushed to the brink, their instincts suggested that the trade-off favored the time-tested and conservative crop, thus they would inevitably end up planting wheat. Farmers did recognize, however, that this was a choice intended to increase short-term survival, but may not improve the agronomic and environmental sustainability of their cropping systems in the longer term.

Although drought was perceived to be a common occurrence, its high unpredictability, even within one growing season, meant that farmers were reluctant to plan for years when moisture was more plentiful. This unpredictability made it difficult to plant crops that would have a longer-term benefit when it was uncertain whether the moisture would be available to realize those benefits. However, there were several outlying farmers who tried to make long-term plans for drought despite the prospect of short-term consequences. Other studies have confirmed the rarity of this perspective amongst ‘conventional’ farmers (Tarnoczi 2011), and a relatively higher prevalence among organic farmers (Knutson 2011). As one of the outlying farmers stated:

> My opinion is, is that, dealing with drought issues… I want to say a long-term crop management system, so that what you do builds your soil so that you can withstand drought. So, as a result, on our farm, we fairly consistently raise spring wheat, winter wheat, durum, peas, lentils and either canola, soybeans, …. So we’re pretty diversified. Our soil organic matter is increasing……..each 1 percent stores another inch of water. In a drought situation that one inch is the difference between failure and just average.

In contrast, to respond to the drought of the early 2000s, one farmer explained that he couldn’t try any new crops because he didn’t have the financial resources to do so. During the more serious and prolonged drought of the 1980s, another farmer had to resort to alternative means of making money, “Oh I opened a garage and started mechanicing. And that’s the only thing that saved me. Because seriously in the ten years since – I started in 1980 – all those ten years, I never averaged double digit yields.” Simultaneously, this farmer started using no-till management, but still consistently stuck with wheat as the conservative crop.

The overwhelming sentiment of using wheat as a conservative crop vocalized during the interviews was consistent with these final comments. With the arrival of a new period of drought, especially under economic distress, the majority of farms in the NGP would likely revert to wheat-fallow at the expense of long-term agronomic sustainability. To confirm the lack of options under a drought scenario, the disseminated survey asked several questions regarding how producers would respond. The data obtained were consistent with the tendency to prefer conservative options under drought, albeit with a substantial level of variability (wide tails on the distribution of responses). Concretely, when asked about how they would respond to drought, a majority of farmers indicated that they would only sow one alternative crop (31%), with fewer farmers suggesting they would sow two (28%), three (11%), four (6%), and six (1 respondent) alternative crops. The specific crops mentioned were highly variable (Table 5.1), with the largest numbers of farmers suggesting wheat, which is already the dominant crop, or that they were unsure or needed more information.

Table 5.1. Summary of the types of alternative crops farmers stated they would use in response to extended drought (each respondent could list more than one).

Crop	**Respondents (*n* = *45*)**
Wheat	20%
Peas/lentils	18%
Safflower	13%
forage/grass	9%
corn	7%
no change necessary	7%
cover crops	4%
fallow	4%
canola	4%
miscellaneous other crops	16%
Total number of farmers considering alternative crop(s)	71%
not sure/need info	20%

Management practices that the farmers had at their disposal to manage the impact of drought (Table 5.2) were very limited, with many of the practices, such as no-till, being already used. Other responses reflected this lack of readily accessible options, including reducing expenses, lowering yield goals to reduce the amount of fertilizer used, changing planting dates, and utilizing crop rotations to increase moisture retention.

Table 5.2. Summary of the management practices farmers stated they would use in response to extended drought (each respondent could list more than one).

Management Practice	**Respondents (*n=46*)**
lower yield goals/fertilization rate	10.9%
less continuous cropping/recropping	8.7%
fallowing	8.7%
no-till	8.7%
change seeding dates	6.5%
stripper header	6.5%
reduce costs	4.3%
cover crops	4.3%
water efficient crops	4.3%
not sure/no change	15.2%

With wheat as the primary crop used to respond to drought, and various common cost and moisture-reduction strategies as the primary management responses, it appears that future periods of drought are likely to produce a predictable response. However, under favorable economic conditions, producers may have more leeway to experiment with alternative crops that could also create long-term agronomic benefits. This depends on the ability of farmers to reduce costs and plant crops that may, at least in part, supplant some of the benefits of fertilization (Miller *et al.* 2015).

High Nitrogen Prices. Similar to the responses to drought, the most common reaction of farmers to high nitrogen prices was to reduce fertilizer applications, which was considered to be the conservative approach. In contrast to drought, most farmers had more recent memories of dealing with high nitrogen prices, which in 2008 were the highest experienced since 1975 (Figure 5.2). In response to a survey question regarding whether they had experienced high fertilizer prices more frequently, less frequently, or with no change in frequency in recent years, 86% responded "more frequently."

Most farmers regard nitrogen fertilizer as the largest variable expense on their farm, "My highest input is fertilizer. I'm doing my own soil determinations [using soil tests to determine appropriate level of fertilizer], I'm deciding whether it's to my advantage to cut that back. They [grain buyers] haven't been paying for protein premiums lately." Reducing fertilizer applications was therefore perceived to hold the promise of reducing costs, but with a concomitant penalty in yield and revenue. Depending on the additional price premium given to wheat with a higher protein content (perceived as requiring higher nitrogen levels), the reduction in fertilizer could further reduce revenue by incurring a low-protein discount in addition to lower yields. However, the reduced revenues are by no means assured given the uncertainty in precipitation (which affects yield *and* protein) and, consequently, prices.

Although it was not definitively established, this unclear relationship between reduced nitrogen applications and revenues may have prompted a minority of farmers to arrive at contradictory views. One farmer reasoned that the price of fertilizer inputs would have little impact simply due to supply and demand,

> "Well, it would hit me hard, but you know I've jokingly said I just love the hell out of high fertilizer prices, cause in retrospect, going back, every time we've had high fertilizer prices we've had high commodity prices… I firmly believe that … the chemical or the petroleum businesses – they'll bring their prices down. They want to sell their products."

Another farmer suggested that the price was only minimally related to revenues, "… the optimal rate of nitrogen, which is our biggest fertilizer component, is, whether it's 500 bucks a ton or 800 bucks a ton, doesn't really significantly impact how much you put on. I mean, … it has a bearing, but to maximize your profit, it's not as huge a factor as you would think."

Another subset of farmers expressed resignation to the price of nitrogen, noting that, "…the input cost isn't such a concern, … it is what it is……and we don't change our rotation based on inputs too much." Combined with the aforementioned responses, the general consensus that emerged was that high nitrogen prices generally prompted farmers to reduce fertilizer inputs, but that this modal response was by no means uniform.

Regardless of their sensitivity and opinions about the impact of high nitrogen prices, all farmers mentioned the use of pulse crops as a common solution for reducing nitrogen inputs. Most acknowledged that the 'nitrogen credit' associated with using nitrogen-fixing pulse crops was small, however they still perceived that benefit as being worthwhile. Several even mentioned adaptively using pulse crops in response to higher input prices, "We're going to start rotating alfalfa into our rotation and leaving it for a couple years to put [i.e. increase] nitrogen in the ground and cut down our fertilizer costs. So anything we do on the rotation is generally with the goal of keeping input costs low."

As stated by another farmer when asked about his response to the drought in the early 2000s, "We did plant more peas at that time. We actually did because then we didn't have to use the fertilizer. Didn't have to use as much Roundup on the fallow. … right there helps, just being diversified. Not being all in wheat so you got to have Roundup, and you gotta have nitrogen. Peas have nitrogen…"

However, the farmers who used pulses adaptively in response to high input prices were in the minority, with most choosing pulses for the generalized "rotational benefits" of pest and weed suppression. Reductions in fertilizer nitrogen applications were commonly regarded as an auxiliary benefit that may have some impact, although that impact was limited and uncertain.

In summary, although farmers perceived themselves to have more options for dealing with high fertilizer prices than drought, the options were still limited and primarily consisted in cutting back on a short-term basis, doing nothing, or in a few cases adopting leguminous rotation crops. Every farmer perceived the nitrogen requirements of wheat to be fairly static, yet none of the interviewees mentioned the low global average nitrogen use efficiency of less than 50% (Cassman *et al* 2002) which casts doubt on the efficacy of fertilizer, or the prospects of increasing frequency of leguminous rotations as a means to reduce nitrogen applications.

Pathways Of Adaptation And Mitigation

As described in the previous sections, the sequence of reactions to drought or adverse economic conditions results in a cascade of compounding uncertainty. At the first level of the sequence, fluctuating precipitation and variable prices impact farms in a spatially and temporally heterogeneous manner. At the second level of the sequence, the variable initial conditions are further scattered by non-uniform responses of the crop and subsequent revenues. Finally, farmers respond to all of these factors by perceiving and reacting in unique ways to each of the possible scenarios depending on their experiences and personalities. Given the immense array of possible final outcomes, it is worth considering whether there are any consistencies to the adaptations that may suggest how farmers may react to future periods of drought or economic stress.

Our data suggested that there are some common patterns to farmer adaptations to novel conditions as would be experienced under climate change or economic stress. Generally, their patterns of choosing agronomic options were consistent with the broader sociological literature on adoption (Rogers and Beal 1958, Mason 1964, Ruttan 1996, Marra 2003), which characterizes the process using the general stages of Awareness, Interest, Evaluation, Trial, and Adoption. Minor variations on these stages were observed, but rather than focusing on consistencies between our data and previous work, we briefly outlined the ways that farmers gathered information, then focused on the adaptation process as it was influenced by the two major stressors.

Prior to experiencing any form of stress, the interviewed farmers were exposed to a large number of information sources. From these sources, the farmers tended to rely most heavily on personal experience, but information from neighbors was also highly important as a means to learn of new adaptation options (Figure 5.7). Despite choosing one or two sources as their *primary* outlets for information, most farmers acknowledged their tendency to consult a variety of information sources. As mentioned by one farmer, "That's just the way it is now …. you have to collect information from different people and from different information tracks." To elaborate, the farmer explained, "Well, when I was growing up, which was a long time ago, the county agent was the knower of all things. We had a great county agent, and I think that that model is maybe not a good model right now, because there's just so much more to know, and you can't be an expert in all things."

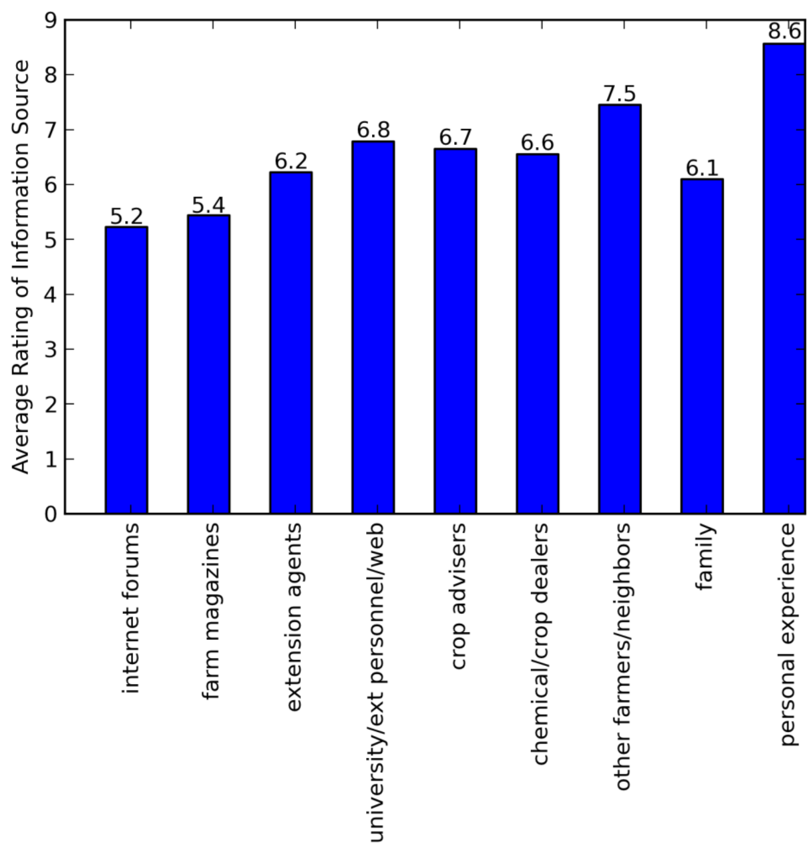

Figure 5.7. Information sources used by farmers. Responses were reported on a Likert scale from 1 – 10.

Thus farmers acknowledged their need to gather information from many different information sources. They generally perceived a decline in the quality of information provided by some of the previously comprehensive technical sources (possibly due to breadth of information now required), which may help explain why the majority of them most heavily rely on personal experience for day-to-day decisions. The survey data supported this observation, with farmers citing a diversity of sources including internet forums, extension publications, university personnel, chemical dealers, and personal experience for their sources of agronomic information.

The diversity of information sources available to farmers was further modulated by the personal background and history of each farmer. Many farmers placed a high value on the information learned from their family mentors, "I've been pretty fortunate that they've given me lots of rope. …We planted 7 different crops and we implemented no-till farming. Things have really changed in the last ten or fifteen years and I guess I think that's a testimony to the older generation because they've given me the opportunity to do it and by doing it I've kind of proven to them that it works and it's sustainable and it's better for the bottom line." Other farmers, while recognizing family influences, placed more importance on the ideals learned from contemporary peers.

Whether from the internet, extension agents, or another source, farmers were thus exposed to new practices that they had not already employed. This took various forms, including chemical/seed dealers proposing a new herbicide, or farm magazines promoting a new crop. However, when farmers were stressed, they unanimously cut back on trials of new practices, operating *reactively* instead of *proactively*.

Regardless of their exposure to information sources, the reflex was one of reducing costs and conservatism. As one farmer stated, "I think we get more conservative. We have to". This is consistent with the respondents' reactions under the stress of drought or high input prices – cutting back. In response to the extended period of drought during the 1980s, one farmer said, "We didn't spend anything – you held everything you could, you fixed stuff [equipment] rather than bought new stuff…. You sat tight because you didn't have any money to change anything up." During periods of drought or unfavorable prices (or both), adaptation and adoption of new practices was severely restricted. The general process of information acquisition, interest, and evaluation no longer functioned as normal, and any adaptations that required even a modest level of risk were ruled out.

Adaptation to climate or economic stressors may be less likely to occur during periods of significant stress or variability, as farmers' core instinct for economic preservation overrides the desire to adopt new, potentially risky practices, even if these practices could potentially relieve stress. Outside of those periods of stress, the patterns of adaptation were dictated by a consistent set of criteria expressed by the farmers. The most important criterion for evaluating a new practice was its economic viability, which meant that it either lowered costs for the farmer, enhanced yields, or tapped into a lucrative market (for a new crop). For example, many farmers were considering planting dryland corn due to relatively high current corn prices. One interviewee justified his interest in using corn as a new crop, but was holding back due to the initial investment requirements, "I do think corn has a good fit here because of the local market. It's the equipment barrier there – buying a 80,000 dollar planter, and then a 70,000 dollar corn header for 200 acres is all I would be jumping into, so, … it doesn't pay."

Behind economic opportunity, the second prominent consideration for farmers was rotation. Every farmer interviewed emphasized a belief in the value of rotating crops, both for reducing weed and pest issues, but also for reducing nitrogen costs and for increasing the intensity of cropping (rather than having years of fallow). One farmer explained this by saying, “The thing of it is with new crops you want to try it on a small scale and not try to get too much money invested in it. But you’re always trying to find better ways to be stewards of the land by trying these rotations so maybe you won’t have to use as much fertilizer - using peas or lentils for fixing nitrogen in the ground.”

Logistics and the time required to implement new practice was the third most frequently cited constraint for adoption by the interviewees. Most NGP farmers work long hours during the growing season by themselves or with a limited number of other family members or employees, thus the difficulty of dealing with new equipment, covering more ground with the herbicide sprayer, or expending other precious time was a significant consideration.

During periods of low stress and when the economic, rotational, and logistical requirements for the new practice were met, farmers would then proceed through the next stages of the adoption process. However, at all points during the process they were highly sensitive to observations or comments by their peers validating or rejecting the proposed practice. These observations and or social learning sometimes irreversibly convinced farmers to abandon their exploration of the new practice. Social observations (farmers watching neighbor farmers), in particular, were very strong motivations or deterrents, and held substantial weight, “I think we just try to see what each other is doing and share those results. A lot of times through those results are actually obvious. A windshield tour will give you an idea of what's going on." Another mentioned considering a new practices, "as long as it [ideas from other farmers] works for them. If it doesn't work for them, I don't mess with it." In contrast, if superior results were observed either visually or through cues of wealth indicating a successful farm, then the interest of the observing farmers would be elevated.

Finally, during periods of low stress and if the previous requirements were met, farmers would stage a trial of the new practice. Without exception, every farmer surveyed mentioned that during periods without stress, they would regularly try new practices in sub-fields or even new fields. These trials ranged from 40-360 acres, with an average of 200 acres used. Their motivations for trying new crops or techniques were often driven by a perception of farmer-to-farmer competition, "The thing that's big is just the competitiveness of it all. It's just like anything else, I mean, when you're self-employed and if your neighbors are getting big deals and big crops, your goal is to get a bigger crop than any of them, but it's from a friendly, competitive standpoint. A lot of stuff is learned from your neighbors or your friends." The pressure to excel and stand out among peers, and to be viewed as 'progressive', drove them towards experimenting more aggressively, "…if you sit around and wait for your neighbors to do it then you're kind of behind. The first one around, I guess, to try new farming practices – that's what I mean by progressive."

Discussion

Total Stress

We have illustrated three distinct periods of total input variability experienced by farmers since 1965. These periods of uncertainty have been largely driven by drought, which, as the most limiting production factor in the NGP, was expected. However, fluctuations in prices amplified total variability in the 1970s and extended the period of uncertainty in the 2000s. As farmers used higher quantities of fertilizer throughout this time period, the effects of fluctuations in the price of nitrogen fertilizer may have been perceived to have larger impacts, despite associated increases in yields.

The explanations for increased fertilizer use are complex, however they may be partially explained by the concept that farmers "fertilize for the good years" (Babcock 1992), with the assumption that increased profits under favorable weather conditions offset the costs of over-fertilizing during bad years. This assumption depends on the rate of increase of the marginal productivity of nitrogen as precipitation increases, and the marginal increase in net returns from increased yields. In dryland scenarios with a non-linear yield response and extended periods of drought, this strategy of over-fertilization may be detrimental to net returns and therefore may increase total stress. Farmer adaptation to these stressors parallels their temporal predictability, which, as discussed later, suggests specific approaches for increasing adaptability.

Drought Adaptations

Given the paucity of crops and management practices cited by farmers for managing drought, farmers could face serious consequences if a severe drought were to develop in the NGP. Such droughts are not uncommon, with the most severe of the 20th century occurring during the dust bowl of the 1930s and the drought of the mid to late 1980s. During such conditions, most farmers stated that they would choose to exclusively plant wheat and fallow their fields more frequently, which they perceived to be economically rational decisions over short time periods. This contrasts the general trend of reduced acres under summerfallow in the US and in adjacent areas of Canada, even during years of drought (Tanaka *et al.* 2010). Unfortunately, choosing to fallow may not be rational over longer time scales, because cutting back on rotational crops ultimately reduces long-term resilience to drought by reducing the formation of soil organic matter (West and Post 2002), which is important for retention of soil moisture (Hudson 1994). This is consistent with the observation that adverse events that are low-probability, high-consequence, and primarily observable through statistics, are less likely to elicit evasive actions than those that have immediate, visible effects (Weber 2006).

Nitrogen Price Adaptations

Although rotations were more widely viewed as a benefit for weed and pest suppression than for mitigating the effects of high nitrogen prices, their status as the second-most cited mitigation technique (behind cutting back on application rates) points to their future potential. Simply reducing the amount of nitrogen applied has the advantage of a quick reduction in costs, however it may deplete the pool of soil N, resulting in lower yields. Leguminous rotations, however, are able to supply a significant quantity of N to the cash crop, albeit only after use in rotation for six years (Miller *et al.* 2015, O'Dea *et al.* 2015). Whether by emphasizing the reduced costs of pest control or by promotion as a way to reduce nitrogen costs, pulse crops are the most viable method for increasing resilience to high nitrogen prices. Both justifications fit in with the primary concern of farmers being economic viability. Furthermore, leguminous rotations simultaneously assist in building soil organic matter.

Adaptability and Interacting Stressors

Fluctuations in the climatic and economic variables discussed above oscillate at different speeds and frequencies, yet all are somewhat unpredictable. Prices appear to rise and fall with less variability than the Palmer drought index, giving farmers a better possibility of adapting through the gradual incorporation of pulse crops or other methods of increasing nitrogen use efficiency in times of lower prices. However, with respect to drought, the high unpredictability makes adaptation far more difficult, and it excludes mitigation strategies and experimentation at the time that they are most needed. Implementation of strategies that could increase resilience through crop rotation appear to be slowly increasing, with 51,000 acres devoted to pulse crops in 1998 and greater than 700,000 (12.4% of NGP cropland) acres in 2013 (USDA NASS). However, adoption is interrupted during periods of drought, and it remains to be seen whether the use of pulses continues to expand.

Periods of intense stress, when price variability is high and soil moisture are limited, are thus unlikely to be advantageous times for increasing farmer adaptability.

Farmers' economic flexibility to experiment is also more limited during these periods due to lower net revenues. Although farmers are constantly exposed to a variety of information sources, their economic conservatism will likely trump their belief in the value of rotations. Furthermore, their peers are unlikely to provide constructive demonstrations of rotational crop performance during such periods, thus they may be less inclined to experiment with new rotations. It has been argued by some economists that farmers are correct in this hesitation because the costs of experimentation outweigh the value of information gained by waiting for the trajectory of future conditions to become clear (Lombardi 2009). Yet while this "option value" would be rational for stressors that have somewhat predictable signals, it would only be partially true for prices and would not hold true for climatic stressors that are highly variable and uncertain for specific locations.

Thus there exists a conflict between short and long-term economic and agronomic rationality that ultimately serves to decrease the resilience to these stressors during times of drought. Drought mitigation through the improvement of soil organic matter requires 20-60 years (West and Post 2002), and increasing the nitrogen supplying power of soil requires at the very least two to three cropping cycles (O'Dea *et al.* 2015) hence economic incentives may be required to maintain rotations even in the presence of drought. These incentives could be aligned with efforts to increase carbon sequestration, as increased levels of organic matter equate to higher levels of carbon stored in the soil. Increasing rotational complexity could therefore simultaneously increase nitrogen and sequester an average of 20 ± 12 g Carbon m^{-2} yr^{-1} (West and Post 2002). However, without incentives, even producers (such as organic farmers) who may have a stronger long-term motivation to increase organic matter and who are aware of the benefits in doing so, are subject to the short-term need to maximize profits (Knutson 2011). Therefore, market development for drought-tolerant crops or policy incentives to increase long-term drought resilience may be required to shift farmer behavior.

Conclusion

Dryland agricultural systems in the NGP are constrained by fluctuating nitrogen and wheat prices, and by sporadic, intense drought. The options for mitigating the effects of these stressors are limited, and may be inaccessible when conditions are unfavorable and highly unpredictable. However, during periods when drought is not amplifying the effects of price pressures, several trends, if nurtured, may facilitate more resilient agricultural systems in this region.

First, farmers' belief in the value of rotations may be harnessed to achieve the simultaneous goals of reducing reliance on fertilizer inputs and increasing soil moisture retention, which could be achieved, for example, through legume-based rotations that increase soil fertility and soil water retention. Second, if farmers are incentivized to experiment even under duress, then there will be greater potential for finding agronomic options that are optimal under stressful conditions. Furthermore, if failure of small agronomic trials is less stigmatized, it will reinforce the culture of small-scale on-farm experimentation, in turn unearthing the most drought-tolerant practices over the long term.

Without an acceleration of the use of rotations or other mitigation strategies, it is unclear whether periods of intense, unpredictable stress, could have catastrophic impacts. In the marginal agricultural climatic region of the NGP, many farmers have been forced to exit during high total stress conditions. This analysis suggests that such outcomes are still possible. If the climatic and economic thresholds that govern crop production in these marginal agricultural systems become more unpredictable, then an even greater number of North American farming systems could be vulnerable to bankruptcy. Thus, effective strategies to increase the resilience of dryland agricultural systems, particularly those that use crop rotations to increase soil organic matter and nitrogen may provide increased resilience of NGP agriculture.

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References

Antle J.M.1983. Incorporating risk in production analysis. *American Journal of Agricultural Economics* 65: 1099–1106.

Berkes F., Armitage D., & Doubleday N. 2007. Synthesis: adapting, innovating, evolving. In: Armitage D, Berkes F, Doubleday N (eds) *Adaptive co-management: collaboration, learning and multi-level governance*. UBC Press, Vancouver.

Bradshaw B., Dolan H., & Smit B. 2004. Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. *Climatic Change* 67: 119-141.

Bureau of Labor Statistics. 2015. Consumer Price Index – all urban consumers. Accessed from http://download.bls.gov/pub/time.series/cu/cu.data.1.AllItems

Burgess M**.**, Miller P., & Jones C.A. 2012. Pulse crops improve energy intensity and productivity of cereal production in Montana, U.S.A. *Journal of Sustainable Agriculture* 36: 699-718.

Cassman K.G., Dobermann A., & Walters D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio* 31:132-140.

Cox T.S., Glover J.D. Van Tassel D.L., Cox C.M., & DeHaan L.R. 2006. Prospects for developing perennial grain crops. *Bioscience* 56: 649-659.

Cutter S. 1996. Vulnerability to environmental hazards. *Progress in Human Geography* 20: 529-539.

Delgado J.A., Secchi S., Groffman P., Nearing M.A., Goddard T., Reicocky D., Lal R., Salon P., Kitchen N.R., Rice C., & Towery D. 2011. Conservation practices to mitigate and adapt to the effects of climate change. *Journal of Soil and Water Conservation Society* 66(a): 118A-129A.

Dillman D.A. 2000. Mail and internet surveys: the tailored design method. 2nd Edition. New York: John Wiley Co.

Duliere V., Zhang Y., Salathe Jr., & Eric P. 2013. Changes in twentieth-century extreme temperature and precipitation over the western United States based on observations and regional climate model simulations. *Journal of Climate* 26: 8556-8575.

Hatfield J.L., Boote K.J., Kimball B.A., Ziska L.H., Izaurralde R.C., Ort D., Thomson A.M., & Wolfe D. 2011. Climate impacts on agriculture: implications for crop production. *Agronomy Journal* 103, 351–370.

Howden S.M., Soussana J.F., Tubiello F.N., Chhetri N., Dunlop M., & Meinke H. 2007. Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences* 104: 19691-19696.

Hudson B.D. 1994. Soil organic matter and available water capacity. *Journal of Soil and Water Conservation* 49:189-194.

Karl T.R. 2009.Global climate change impacts in the United States. Accessed from http://downloads.globalchange.gov/usimpacts/pdfs/climate-impacts-report.pdf.

Knutson C.L., Haigh T., Hayes M.J., Widhalm M., Nothwehr J., Kleinschmidt M., & Graf L. 2011. Farmer perceptions of sustainable agriculture practices and drought risk reduction in Nebraska, USA. *Renewable Agriculture an d Food Systems* 26: 255-266.

Lobell D.B., Burke M.B, Tebaldi C., Mastrandrea M.C., Falcon W.P., & Naylor R.L. 2008. Prioritizing Climate Change Adaptation Needs for Food Security in 2030. *Science* 319: 607-610.

Lombardi D. 2009. Business Investment under Uncertainty and Irreversibility. *Oxonomics* 4: 25 – 31.

Malhi S.S., Soon Y.K., Grant C.A., Lemke R.L., & Lupwayi N.Z. 2010. Influence of controlled-release urea on seed yield and N concentration, and N use efficiency of small grain crops grown on Dark Gray Luvisols., *Canadian Journal of Soil Science, 90*: 363-372.

Marra M., Pannell D.J., & Ghadim, A.A. 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems* 75: 215-234.

Mason R.G. 1964. The use of information sources in the process of adoption. *Rural sociology* 29: 40-52.

Maxwell J.A. 2013. *Qualitative Research Design: An Interactive Approach 3rd Edition*. Thousand Oaks, CA: Sage.

McLeman R., Mayo D., Strebeck E., Smit B. 2008. Drought adaptation in rural eastern Oklahoma in the 1930s: lessons for climate change adaptation research. *Mitigation and Adaptation Strategies for Global Change* 13: 379-400.

Miles M.B. & Michael Huberman A.. 1994. *Qualitative Data Analysis: An Expanded Sourcebook*. Thousand Oaks, CA: Sage

Miller P.R., Bekkerman A., Jones C.A., Burgess M.H., Holmes J.A. & Engel R.E. 2015. Pea in rotation with wheat reduced uncertainty of economic returns in Southwest Montana. *Agronomy Journal* 107: 541-550.

Mishra A.K. & El-Osta H.S. 2002. Managing risk in agriculture through hedging and crop insurance: what does a national survey reveal? *Agricultural Finance Review* 62: 135–148.

Montana Dept. of Agriculture. 2014. North central Montana dryland agricultural model. Retrieved from http://agr.mt.gov/agr/Producer/CropTools/Models/Forms/NC_MT_Dryland_Budgets_2014.xls

National Climatic Data Center. Historical Palmer z-index data. Retrieved from ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-zndxdv-v1.0.0-20150904.

Nielsen D.C., Unger P.W., & Miller P.R. 2005. Efficient water use in dryland cropping systems in the Great Plains. *Agronomy Journal* 97: 364–372.

O'Dea J.K., Jones C.A., Zabinski C.A., Miller P.R. & Keren, I.N. 2015. Legume, cropping intensity, and N-fertilization effects on soil attributes and processes from an eight-year-old semiarid wheat system. *Nutrient Cycling in Agroecosystems* 102: 179-194.

Piringer G. & Steinberg L.J. 2006. Reevaluation of energy use in wheat production in the United States. *Journal of Industrial Ecology* 10: 149-167.

Pittman J., Wittrock V., Kulshreshtha S., & Wheaton E. 2011. Vulnerability to climate change in rural Saskatchewan: Case study of the Rural Municipality of Rudy No. 284. *Journal of Rural Studies* 27: 83-94.

Quiring S.M., & Papakryiakou T.N.2003. An evaluation of agricultural drought indices for the Canadian Prairies. *Agricultural and Forest Meteorology* 118:49-62.

Rogers E.M. & Beal G.M. 1958. The importance of personal influence in the *adoption* of technological changes. *Social Forces* 36: 329-335.

Roling N.G. & Jiggins J. 1998. The ecological knowledge system. In: Roling NG, Wagemakers MAE (eds) Facilitating sustainable agriculture: participatory learning and adaptive management in times of environmental uncertainty. Cambridge University Press, UK

Ruttan V.W. 1996. What happened to technology adoption-diffusion research? *Sociologia Ruralis* 36: 51-73.

Saltiel J., Bauder J.W., & Palakovich S., 1994. Adoption of sustainable agricultural practices: diffusion, farm structure, and profitability. Rural Sociology 59, 333–349.

Sunding D, Zilberman D. 2000. The agricultural innovation process: research and technology adoption in a changing agricultural industry. In: Gardner B, Rausser GC (eds) Handbook of agricultural and resource economics. Elsevier, Amsterdam, pp 207–261.

Tanaka D.L., Schillinger W.F., Papendick R.I., & McCool D.K. 2010. Soil and water conservation advances in the semiarid northern great plains. Soil and Water Conservation Advances in the United States, pp. 47–79.

Tarnoczi T. 2011. Transformative learning and adaptation to climate change in the Canadian Prairie agro-ecosystem. *Mitig. Adapt Strateg. Glob. Change* 16: 387-406.

Tarleton M. & Ramsey D. 2008. Farm-level adaptation to multiple risks: climate change and other concerns. *Journal of Rural and Community Development* 3: 47-63.

USDA National Agricultural Statistics Service. 2015a. Wheat prices. Retrieved from http://www.ers.usda.gov/datafiles/Wheat_Wheat_Data/Yearbook_Tables/Domestic_and_International_Prices/WheatYearbookTable18.xls

USDA National Agricultural Statistics Service. 2015c. Fertilizer use and price. Retrieved from http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx

USDA National Agricultural Statistics Service. 2015b. Census of agriculture 1964-2012. Retrieved from http://www.agcensus.usda.gov/Publications/

USDA National Agricultural Statistics Service Montana Office. 2011. State-wide Fertilizer Usage.

Velandia M., Rejesus R.M., Knight T.O., & Sherrick B.J. 2009. Factors affecting farmers' utilization of agricultural risk management tools: the case of crop insurance, forward contracting, and spreading sales. *Journal of Agricultural and Applied Economics* 41: 107–123.

Weber E.U. 2006. Experience-based and description-based perceptions of long-term risk: why global warming does not scare us (yet). *Climatic Change* 77: 103-120.

West T.O. & Post W.M. Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal* 66:1930-1946.

CHAPTER SIX

CONCLUSION: SYNTHESIS OF AGRICULTURAL VULNERABILITY

The overarching goal of this dissertation was to understand how economic variability and a changing climate will affect the resilience of Montana's dryland agricultural systems. In the previous chapters, several key analytical building blocks were contributed to this end, including a framework to integrate site-specific uncertainty on individual farms while optimizing inputs, a practical application of this framework to real farm data while considering farmer risk preferences, and a behavioral analysis of farmer adaptive capacity in the face of uncertainty. To conclude, this chapter will integrate the previous content and will address the question of resilience by simulating economic responses to price and precipitation variability at local and state-wide scales.

In chapter three, a framework was proposed to site-specifically analyze the impact of uncertain weather conditions, prices, fertilizer input choices, and crop responses on farmer yields and profitability. The demonstrated Bayesian simulation methodology accounted for spatial relationships between variables and incorporated experimentation and updating steps that improved input optimizations year after year.

In chapter four, the framework was modified to include crop rotations, and was applied to precision agricultural data from an actual farm near Great Falls, Montana to identify optimal input and crop rotation strategies for different farmer risk preferences. Regardless of farmers' level of risk aversion, winter wheat-pea rotations resulted in higher value (utility) for the farmer than winter wheat-fallow and winter wheat-winter wheat rotations. For most levels of risk adversity, it was also optimal to apply no nitrogen fertilizer, although this result may have been an artifact of high levels of residual nitrogen from over-fertilization in previous years. Irrespective of farmer choices for rotations or input levels, net returns always straddled the line between profitability and loss, reflecting the inherent risks of farming in this region.

The modeling approach from the first two sections relied on data from past observations to calculate optimal management choices. The derived input-yield-net return relationships could be used to forecast future bioeconomic responses under a range of scenarios. However, if future climatic and economic conditions shift beyond the historical range of variability (Keane 2009), this approach may produce inaccurate predictions. Therefore, it was important to identify how, in novel scenarios, farmers might adapt to maintain profitability, which was explored in chapter five.

Currently, farmers do not appear to have many adaptations to the highly unpredictable stress associated with drought in the dryland systems of Montana. More options are recognized for managing unfavorable price conditions. Farmers are exposed to a wide variety of information sources, so beneficial adaptations are likely to be assimilated quickly, especially if the tendency to experiment with new practices is encouraged. However, when the stressors become too intense, this ability to adapt is highly constrained, and farmers may shift, and return to more conservative practices such as wheat-fallow. These fall-back cropping strategies were generally sufficient to withstand past occurrences of drought but may fail catastrophically under extreme conditions. Furthermore, they do not improve the buffering capacity of the agricultural systems to future stressors, thus are insufficient solutions for long-term resiliency.

The final step towards understanding the resilience of Montana's dryland agricultural systems required the disparate results presented above to be synthesized into an analysis that could be understood on local scales and in a broader spatial context. To remind the reader of the research question and hypothesis motivating this integration, they are reiterated below:

RESEARCH QUESTION: *Are Montana's dryland small-grain farms resilient under current management regimes given economic and climate variability, and how/why might that change in the future?*

HYPOTHESIS: *the cost of inputs along with uncertainty in prices and driving environmental variables coupled with current decision-making processes will make these agricultural systems less resilient.*

Thus far, quantitative data have been presented that examined uncertainty and profitability on a scale specific to one farm. Qualitative data that addressed individual farmer adaptability and more generalized adaptive capacity were also investigated. Still missing from this analysis was the consideration of these results within the context of resilience, defined as: *the ability of farmers to persist and to endure variability in wheat prices, costs of inputs and insurance, climate uncertainty, changes in governmental programs, and social factors while continuing to produce crops as a primary source of livelihood*.

Considering the site-specific data presented in chapter four, it is clear that the specific farm under study, given current management regimes and the various forms of uncertainty integrated in the analysis, is vulnerable to fluctuations in prices and precipitation. Vulnerability is defined as the level of harm resulting from perturbation or stress. This definition encompasses risk to the farmer, sensitivity of livelihoods to those risks, options for adaptation, and resulting losses in well-being (Turner *et al.* 2003). For this location, the risk to the farmer is high, the economic sensitivity to drought or price changes is significant, and the resulting economic damages could be large (ignoring crop insurance payments). This vulnerability is primarily driven by low potential yields, which increase the likelihood that stressors will cause the farm to become unprofitable. It must be emphasized that a number of assumptions about fixed costs to the farmer and similarity of the studied fields to the whole farm may modify this assessment of vulnerability. However, given current knowledge, the outlook on vulnerability is certainly less than positive. The remaining questions on this localized scale are the exact degree of sensitivity to fluctuations in bioeconomic variables and the degree to which vulnerability corresponds to a lack of resilience.

Methods

To provide an answer, the equations and associated uncertainty from the site-specific analysis were extended using simulation, and a new county-level analysis developed. The general procedure, for local (site-specific) and county-level scales, was to simulate alternative scenarios of growing season precipitation, rotations, wheat prices, and nitrogen prices to assess impacts on economic resilience. Only major wheat producing counties (26 out of 56) in Montana were included in the analysis (Appendix D)

At the site-specific or local scale, the equations and derived parameters from chapter four were used as the basis for simulation. For all scenarios, one homogeneous field was assumed for simplicity, using a single value for Topographic Wetness Index equal to the average value across all fields (given its significant, yet minimal impact on yields in Chapter 4). The mean value of the random intercepts for all fields was also applied. For the fixed parameters, the posterior modes were used to facilitate comparison to the county-level data (analyzed with Frequentist, not Bayesian methods), however the entire distributions were also run through the simulation to validate that the use of posterior modes did not change the conclusions. The two-year net return function applied in the simulations was nearly identical (see Appendix D) to the function in chapter four, but utilities were not calculated.

In brief, the county-level analysis used the same simulation methodology to forecast net returns for alternative growing season precipitation, price, and rotation scenarios, and were performed at the whole-county scale (assuming homogeneity). The regression equations underlying the simulation were linear, with yield as the dependent variable and precipitation, a maximum temperature indicator variable, year (to account for technological advances) and a precipitation by county interaction as independent variables. Yield and weather data used for the regressions were based on county-level historical records for dryland wheat (USDA NASS 2015) and a dataset of historical growing season weather for each county. Two-year net returns were calculated with the same values as used in the site-specific simulation. However, a yield penalty was imposed on the continuous wheat rotation scenarios, which was based on the observed yield differences for continuous wheat from the site-specific study. Details of these inputs and the statistical analysis are provided in Appendix D.

At the site-specific and county-level scales, a nitrogen fertilization level of 120 kg ha^{-1} was assumed. Also at both scales, a range of inflation-adjusted nitrogen and wheat prices was simulated using a copula function (Sklar 1959, Genest and MacKay 1986) that accounted for the correlation between the two time series. The use of the copula function is explained in Appendix D, where the county-level regressions are also described in detail.

Results

Quantitative Site-Specific Vulnerability

When growing season precipitation was below 15 cm, all rotations resulted in negative two-year net returns for the farmer (Figure 6.1). Net returns were the lowest for continuous wheat rotations, and highest for wheat-pea rotations. At 20 cm of precipitation, wheat-pea rotation net returns were still higher for most nitrogen and wheat prices, although continuous wheat rotations were associated with a greater range of net returns (Figure 6.2). At the highest level of precipitation, which is unrealistic at this location, continuous wheat performed the best for the majority of price scenarios, although it also performed the worst when the wheat price was very low. These patterns of variability in net return were validated when the uncertainty from the posterior distributions was included in the simulations, even though the range of observed net returns widened (figure 6.3).

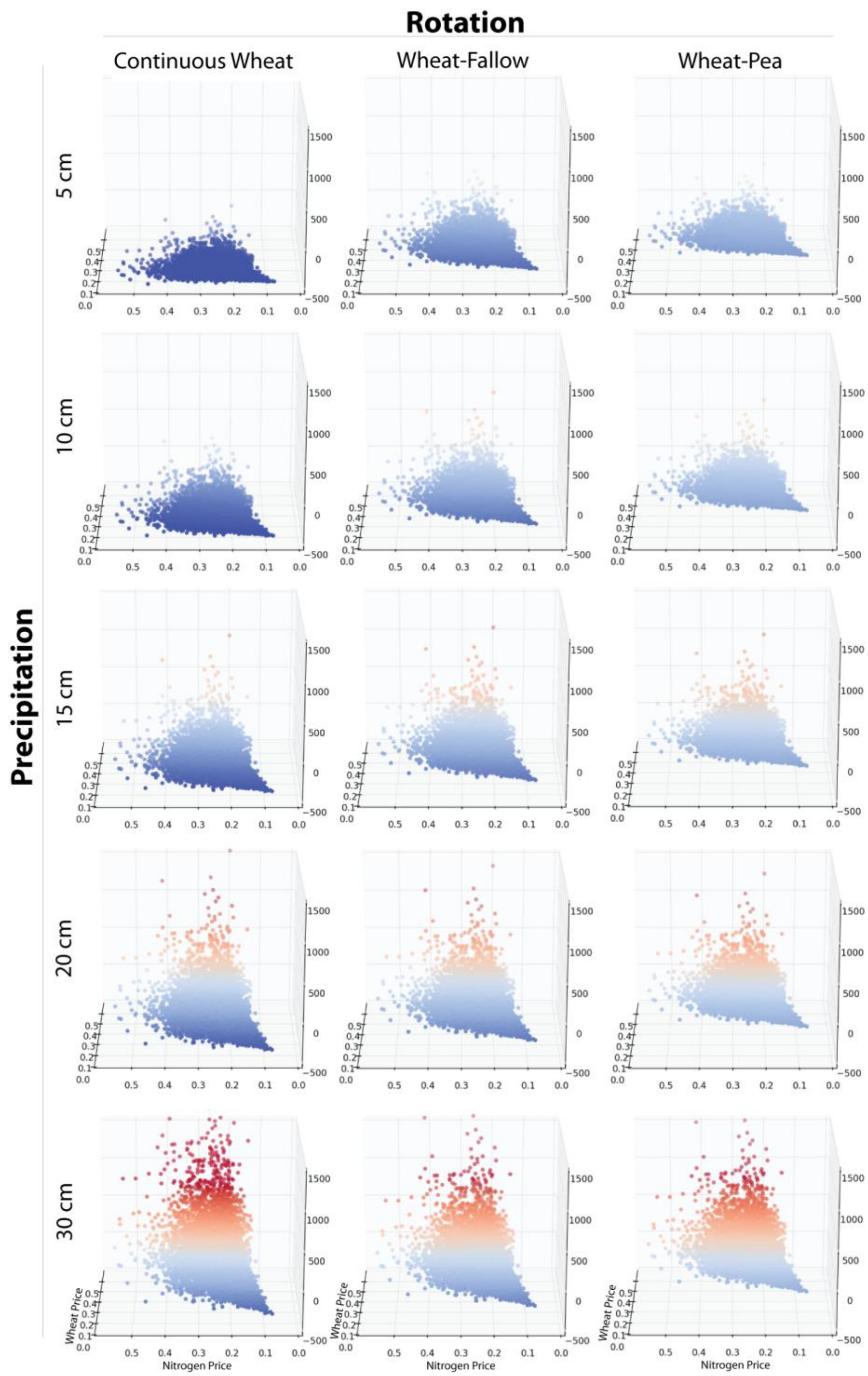

Figure 6.1. Simulated two-year net returns based on the localized economic and crop yield models. 10,000 simulations of wheat and nitrogen prices were drawn from the copula functions and combined with estimated yields for different rotations and precipitation scenarios to calculate net returns. Blue/red colors correspond with the z-axis, where blue is negative and red is positive. The 3d scatterplots are rotated for maximum visibility of the net returns.

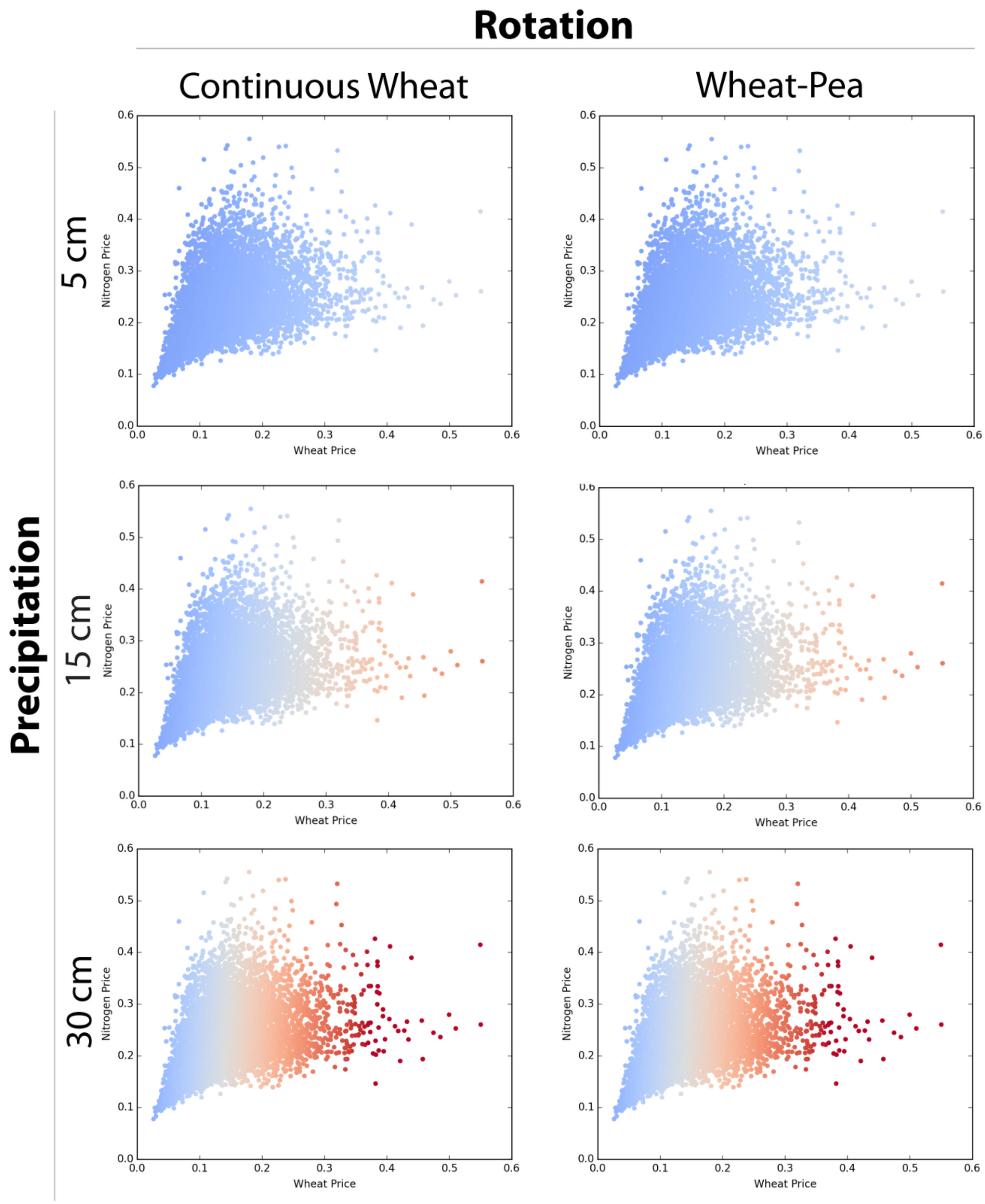

Figure 6.2. Birds-eye view of figure 6.1, illustrating the relationship between nitrogen prices, wheat prices, and two-year net returns (blue = negative net return, red = positive net return). Only two rotations and reduced precipitation scenarios are shown for clarity.

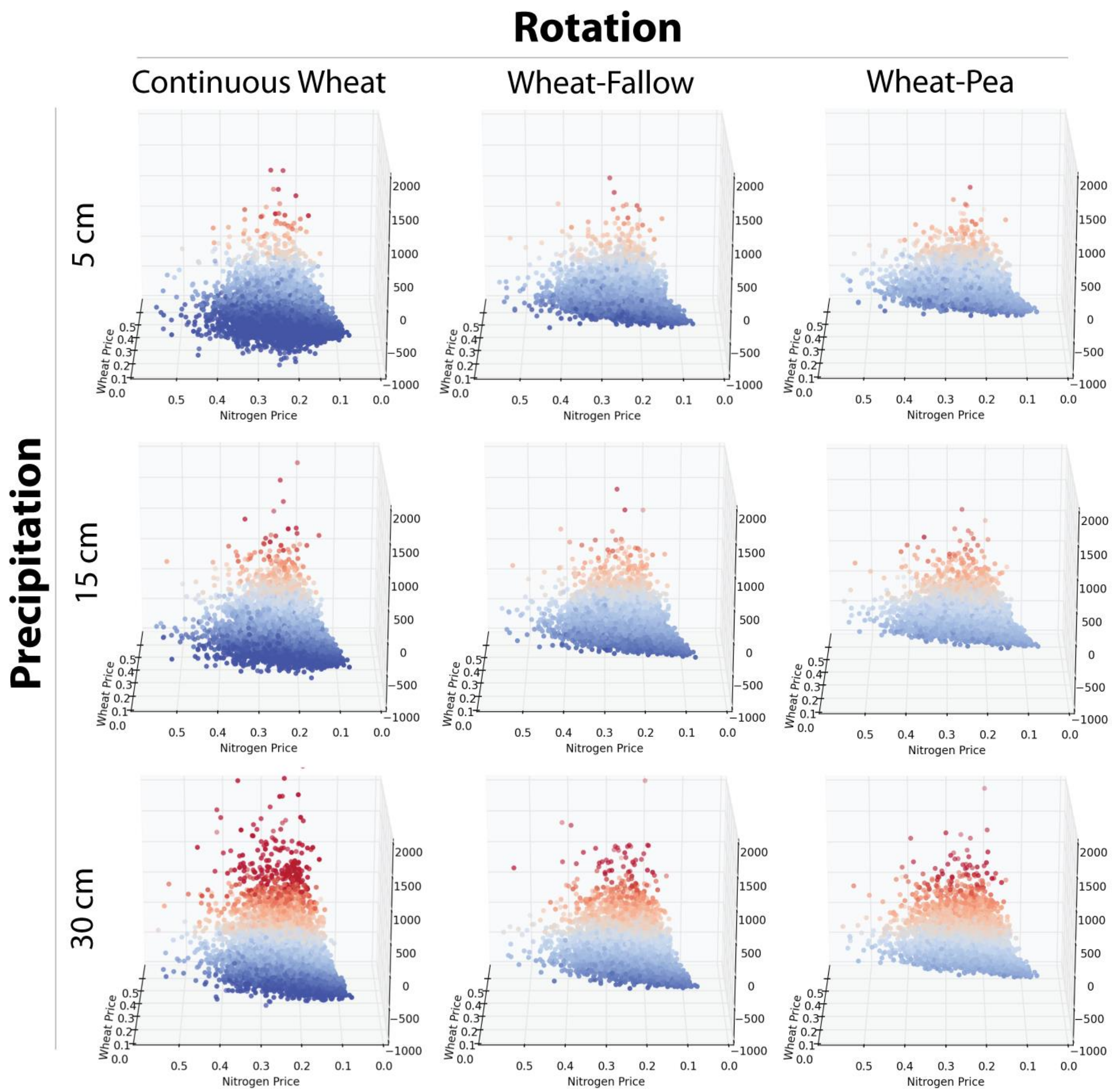

Figure 6.3. Simulated two-year net returns at the localized scale. Equations that generated figures 6.1 and 6.2 were modified for this figure to include the full posterior distribution uncertainty from the site-specific yield model. The full suite of precipitation scenarios is truncated for brevity.

The visualizations in Figure 6.1 and Figure 6.2 confirm the vulnerability of the farm fields under study to fluctuations in precipitation, as net returns were low or negative, even at the average level of growing season precipitation for this site (14.8 cm). Wheat prices had a disproportionate impact on net returns over nitrogen prices, reflecting the relatively small contribution of nitrogen prices to overall costs. However, as one traces a vertical line in Figure 6.2 across multiple nitrogen prices (holding wheat prices constant), a small decrease in net returns is visible. The combined impact of the price fluctuations was dampened at lower levels of precipitation, mirroring the low yields and low variability associated with such pessimistic scenarios.

Quantitative County-Scale Vulnerability

The results for Judith Basin County, a wheat-producing county in central Montana with growing season precipitation near average for the state, are displayed in figure 6.4 to illustrate the detailed relationship between prices, precipitation, rotation and two-year net returns at the county level. Net returns were always higher under all rotations than in the site-specific analysis. Similar to the site-specific results, continuous wheat encompassed a wider range of net returns over all price scenarios, while wheat-pea rotations reduced the variability in economic outcomes. The relative impact of wheat prices and nitrogen prices was the same as in the site-specific analysis, which was expected as the same functional form of net return equation was used.

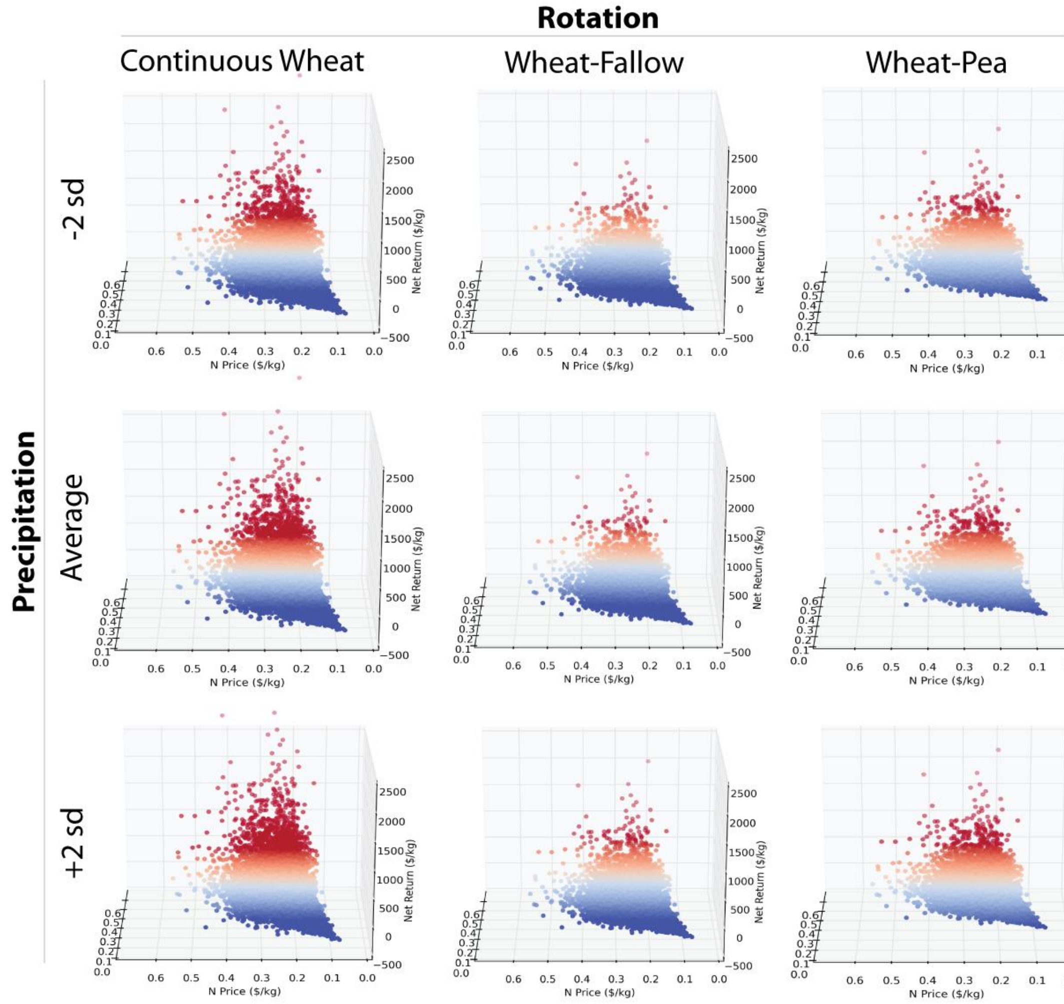

Figure 6.4. County-level two-year net returns for alternative rotations used in Judith Basin county, MT under the mean (21.5 cm yr^{-1}), +2 standard deviation (34.3 cm yr^{-1}), and -2 standard deviation (8.7 cm yr^{-1}) precipitation values for that county.

Across counties, the differences in net returns for alternative price-precipitation scenarios were less pronounced (Figure 6.5; for clarity only 3 counties across a precipitation gradient are shown). The wettest county, Flathead, displayed the highest net returns, while the driest county in this three-county comparison, Daniels, displayed the lowest. These discrepancies may solely be attributable to the differing absolute levels of growing season precipitation, but are also likely to be influenced by soil depth, water holding capacity, and other climatic factors.

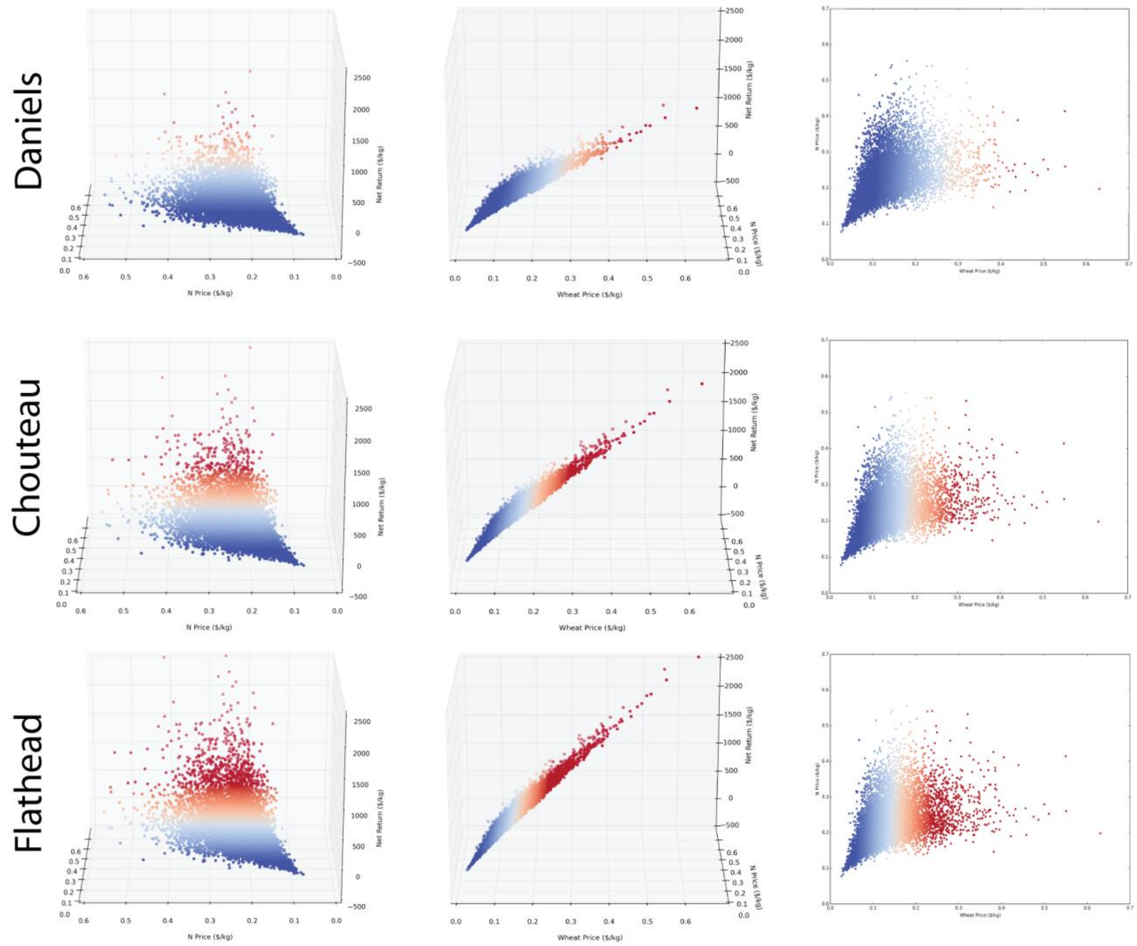

Figure 6.5. Two-year net return responses to alternative nitrogen and wheat price scenarios across counties representing a gradient in precipitation (high to low: Flathead (μ=26.7 cm, σ=6.2 cm) > Chouteau (μ=16.7 cm, σ=45.3 cm) > Daniels (μ=13.7 cm, σ=4.9 cm), evaluated for a wheat-fallow rotation at +2 standard deviations of growing season precipitation greater than normal. Two oblique perspectives and one bird's eye perspective are displayed.

Visualized spatially, the differences between counties and scenarios were more pronounced (figures 6.5-6.7). As before, wheat-pea rotations performed the best under unfavorable prices and very well under favorable prices, and were successful at mitigating the impacts of low precipitation. On the other end of the spectrum, continuous wheat rotations performed the worst under unfavorable prices and the best under favorable prices when the level of precipitation was relatively high. Wheat-fallow rotations fell somewhere in the middle by reducing variability, but never excelled under any scenario. A clear spatial separation between western and eastern Montana counties was visible, with western counties performing better under almost every scenario.

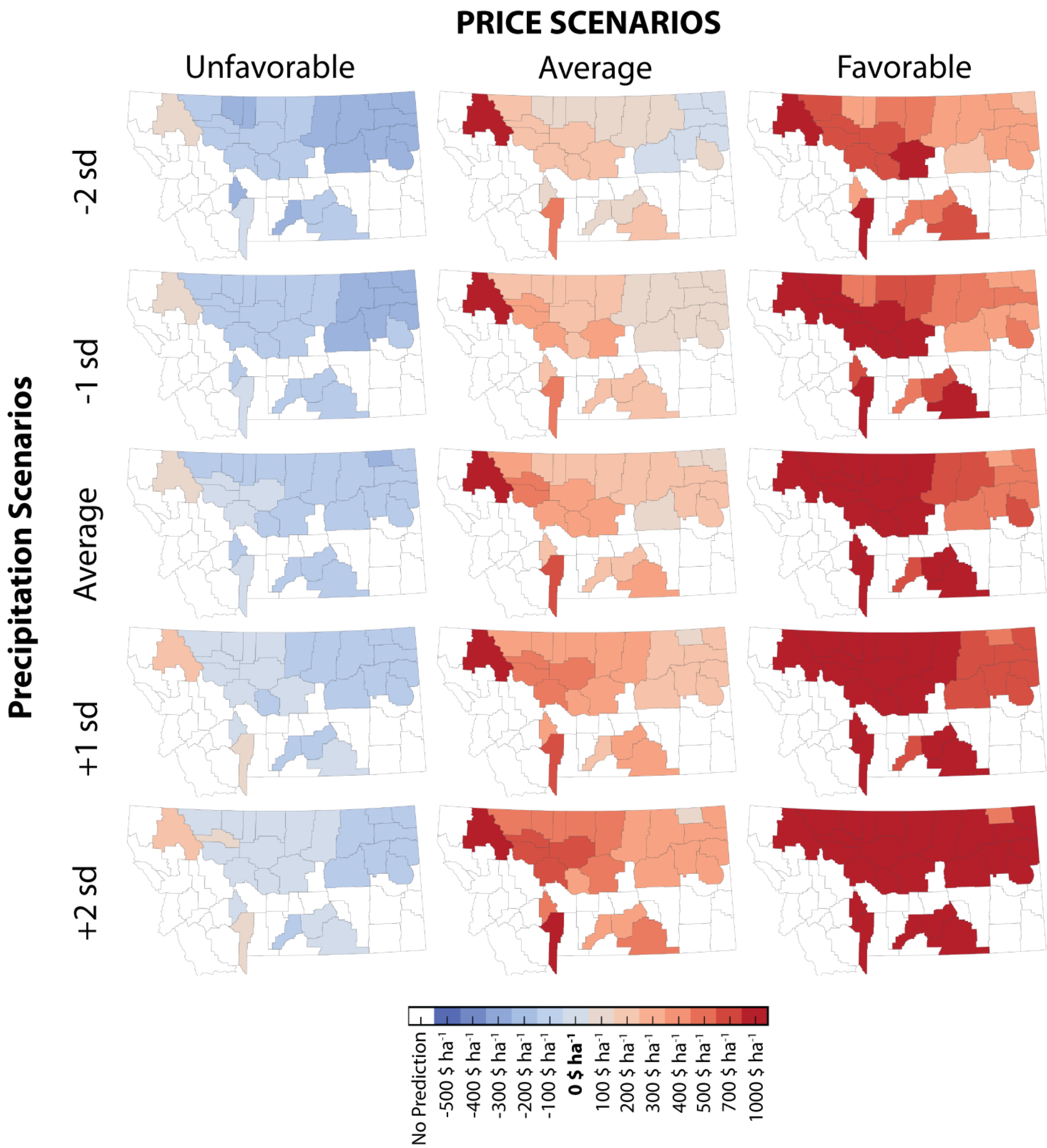

Figure 6.6. Two-year net returns for significant wheat-producing counties in Montana under different price and precipitation scenarios, for a continuous wheat rotation. Unfavorable prices represents where net returns were one standard deviation below average (as caused by low wheat prices and/or high nitrogen prices), and the opposite held true for favorable prices. Precipitation averages and standard deviations are calculated relative to the historical dataset for each distinct county.

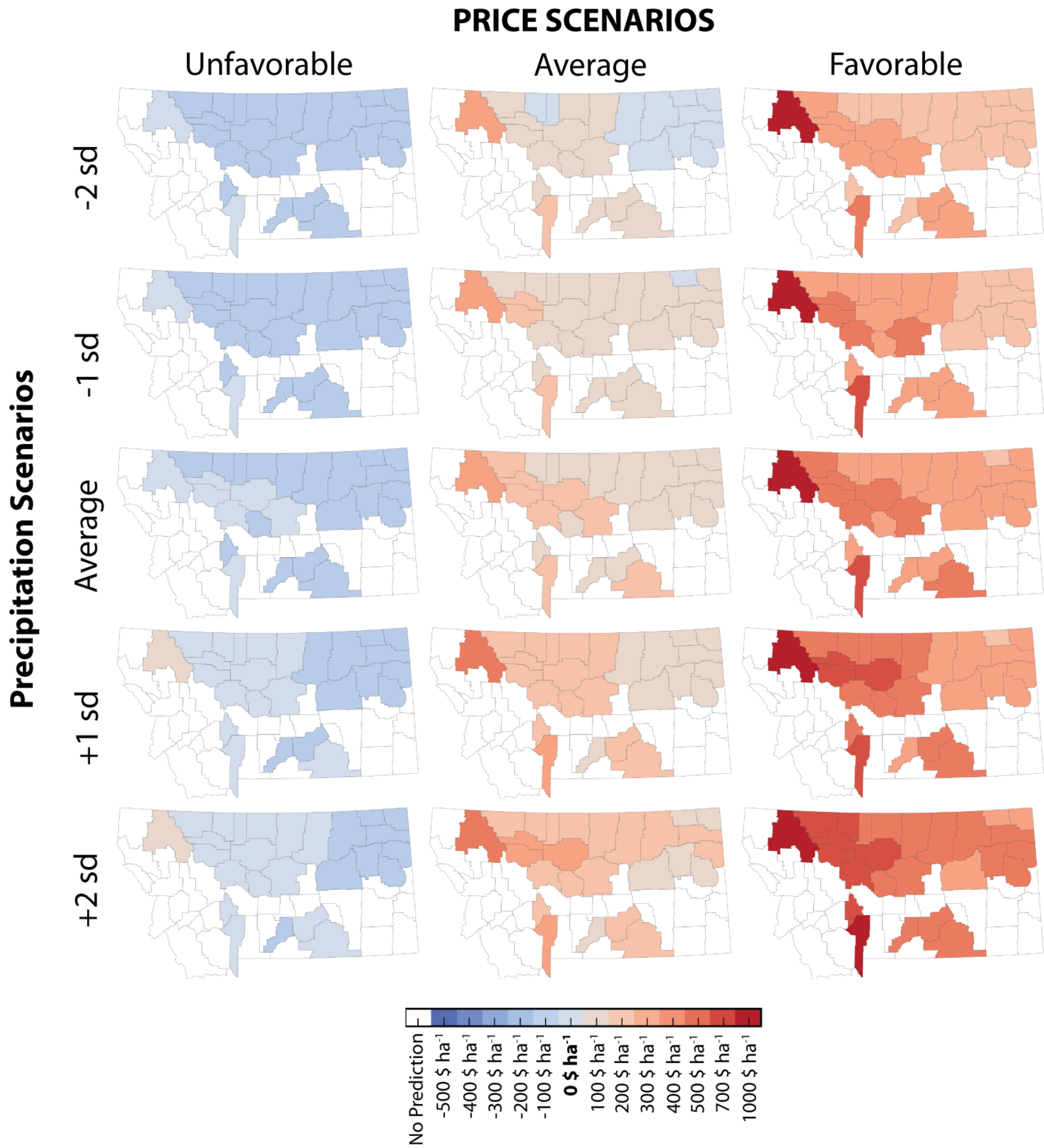

Figure 6.7. Two-year net returns for significant wheat-producing counties in Montana under different price and precipitation scenarios, for a wheat-fallow rotation.

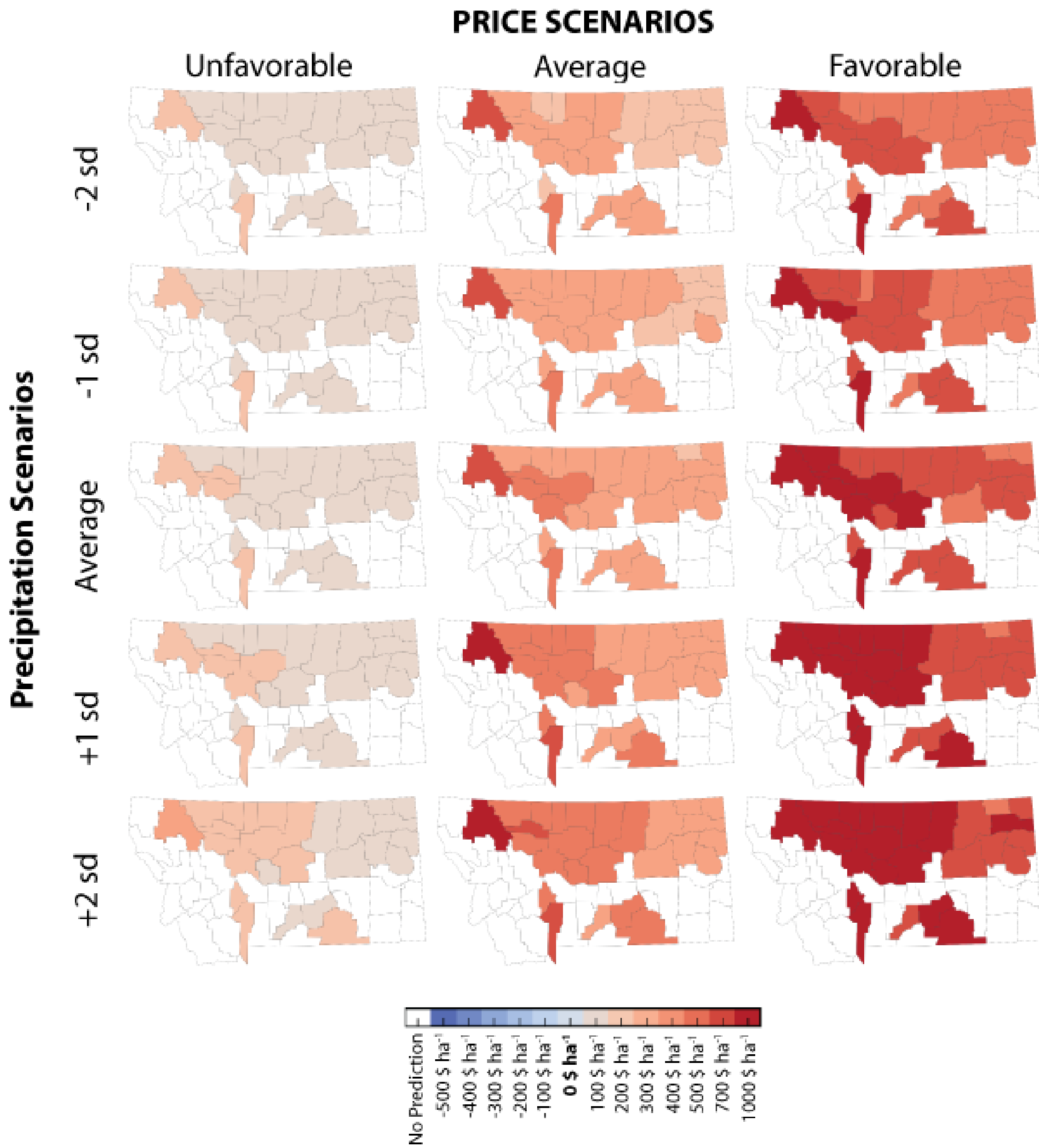

Figure 6.8. Two-year net returns for significant wheat-producing counties in Montana under different price and precipitation scenarios, for a wheat-pea rotation.

Discussion

Summary of Vulnerability

In general, the site-specific and county-level results were very similar. The exception to this similarity was the higher magnitude of the county-level two-year net returns under all scenarios. This discrepancy in net returns may have been caused by shallow, rocky soils at the localized site, which could reduce the amount of potential water storage in the soil and prevent roots from accessing deep sources of moisture necessary for higher yields.

At both scales, wheat-pea rotations reduced vulnerability to economic and climatic variability, but the degree of reduction was highly dependent on site-specific factors that may limit potential yields. Continuous wheat rotations maintained the potential for high payoffs under favorable price conditions and high levels of precipitation, but under normal conditions or worse, wheat-pea rotations performed substantially better and reduced risk for the farmer.

The degree of vulnerability was thus highly dependent upon the rotation used by the farmer, which can either minimize or maximize the impact of economic and precipitation fluctuations. Location also has a significant impact on vulnerability. However, for all locations, many realistic price scenarios exist that could negatively impact economic well-being, as evidenced by the large area of blue visible in each of the scatter plots. Any efforts to reduce that variability of net returns, whether through rotations, moisture conservation, or trimming of costs, would be highly beneficial.

Resilience

Given the impact of variability on farmer net returns in Montana and the resulting levels of vulnerability, are the farmers of this state resilient to economic and climatic change?

If Montana's farmers continue to use wheat-fallow rotations, fluctuations in prices and precipitation will likely continue to erode their profits (Table 6.1). Conversely, if wheat-pea or other wheat-legume rotations are used more frequently, future price shocks or droughts will have a lower probability of significantly impacting farmer economic well-being. Finally, if wheat is cropped continuously year after year, farmers will likely earn large amounts of money under favorable conditions, but will also suffer significant losses during periods of stress.

Table 6.1. Summary of impacts on resilience and profitability of alternative rotation-price-precipitation scenarios.

	Probability of Reducing Resilience		**Profitability**	
Rotation	Fluctuations in Prices	Fluctuations in Precipitation	Low-stress scenario	High-stress scenario
Continuous Wheat	High	High	Very High	Very Low
Wheat-Fallow	High	Moderate	Moderate	Low
Wheat-Pea	Moderate	Low-Moderate	High	Moderate

In Montana, summerfallow continues to be heavily used in Major Land Resource Area (MLRA) 52 (Miller *et al.* 2015), which generally corresponds to the north-central region of the state. This region is generally more profitable, but, as the results show, less resilient. Conversely, in northeastern Montana (MLRA 53a), which tends to have lower overall yields, pulses have been much more widely adopted (Miller *et al.* 2015). The spatial patterns of continuous cropping are unknown. As a result, it appears that northeastern Montana is reasonably resilient under current management regimes given economic and climatic variability. If, under climate change, temperatures were to increase or precipitation to decrease, these spatial patterns in resilience may become even more pronounced.

However, the picture of resilience is still not complete. As discovered in chapter five, adaptability of individual farmers can potentially mitigate the impacts of stressors, especially if the farmers have a strong bias towards experimentation and a belief in the value in rotations. Therefore, even if a producer was using wheat-fallow or continuous wheat as their rotation (perhaps to take advantage of high wheat prices), they may be able to quickly implement a more profitable agronomic practice in the event of extreme stress.

Nevertheless, if farmers are not already experimenting with alternative crops and management strategies, historical evidence suggests it would be unlikely that they would suddenly shift course during periods of drought or low wheat prices. In the survey results presented in chapter five, 53% of respondents were not experimenting with pulses or alternative crops (excluding corn and forage/grass). If that percentage is relatively accurate, then it implies that significant proportions of Montana's dryland wheat farms are at risk, and may suffer serious losses when the next drought or economic downturn inevitably arrives.

In their widely cited paper on the meaning of resilience, Carpenter *et al*. (2001) partition resilience into: "(a) the amount of change the system can undergo (and implicitly, therefore, the amount of extrinsic force the system can sustain) and still remain within the same domain of attraction (that is, retain the same controls on structure and function); (b) the degree to which the system is capable of self-organization (versus lack of organization, or organization forced by external factors); and (c) the degree to which the system can build the capacity to learn and adapt." By all these metrics, diversified rotations, frequent use of on-farm experimentation, and use of diverse peer learning networks all appear to characterize resilient farms and farmers in Montana. Yet resilience is not always desirable, and may be associated with ossified systems that have deleterious environmental and social consequences. Fortunately, in this instance, the resilient agricultural systems in Montana also tend to be more environmentally sustainable, and confer many other benefits associated with diversification such as pest suppression and buffering against extreme events (Lin 2011). The analysis presented here does not claim that these 'resilient' systems are environmentally sustainable or socially just in the absolute, but it does posit that they are improvements over the status quo.

This may not always be the case, and the agroecosystems that dominate the Northern Great Plains may not adopt resilient systems quickly enough, after which collapse and rebuilding will follow (Gunderson and Holling 2002). However, by continuously assessing these systems at small and large scales using the ever-expanding stream of agricultural data, impending catastrophes may potentially be detected and mitigated. Further, by expanding the scope of assessment to include more environmental and social factors, and by increasing the adaptive capacity of farmers in general, Montana's agricultural systems of the future will become more resilient, just, and sustainable.

Epilogue

During the implementation of the research for this dissertation, there were numerous times when it felt as though I was piling assumption upon assumption, with little solid ground underneath. At various points, I am sure that I made all parties involved in my work somewhat uncomfortable, whether by stretching the boundaries of data manipulation or by forcing different disciplines to coexist within the same analytical framework. Certainly, I am sure that if I had chosen a research topic that was more concrete, elemental, and well defined, my task, though not easy, would have been much more straightforward. Yet I am unable to narrow my perspective sufficiently to take on research of that nature, and I do not find myself well suited for it.

My personal history has been characterized by the mixing of many different perspectives, cultural and philosophical, and I have carried the tendency to embrace conflicting truths throughout my adult life. So when I decided to enter graduate school, I naturally tended to home in on "big picture" questions that were more broadly focused. When the topic of dryland agriculture had been chosen, I naturally gravitated towards trying to understand its characteristics and sustainability/resilience on a larger scale, rather than dissecting individual components in isolation. To be clear, I greatly respect those who dedicate their lives to understanding the fundamental nature of life and matter. However, especially in the realms of ecology and agriculture that are characterized by amorphous dynamics, evolving interactions, and messy statistical relationships, I personally believe that narrow approach can only go so far. Individual choices made by farmers must be placed within the broader context of food systems analysis, and the optimal choices for today will necessarily be different in new locations or novel bioclimatic environments.

My attempt to adopt a holistic view of agriculture in this dissertation is undoubtedly only a first, incomplete step, and it holds little significance within the broader scope of agroecological thought and scholarship. Many details were neglected that would be critical to include in future analyses, especially related to environmental externalities and social justice. However, I believe that I have made a worthwhile contribution to the relatively new study of agriculture that is data driven but still tethered to the whims of individual farmers and the tyranny of site-specific variability. And although I have asserted myself as a systems scientist, I still have put substantial effort into understanding the fine details of agricultural variability, albeit more through the lens of data analysis than traditional laboratory work.

I must give an incredible amount of credit to my major advisor, Dr. Bruce Maxwell, and co-advisor, Dr. Lisa Rew, for giving me the space and freedom to attempt such an interdisciplinary project. Much of the reason for my decision to stay at Montana State was driven by the knowledge that I would not be forced into a narrow analysis that fit within the confines of my advisors' preconceptions. This is not to say that they have been lacking in advice and guidance – quite the contrary. My point is to emphasize that they have had faith in me to execute this difficult project, and that, despite challenges and setbacks, they have supported me in this endeavor completely.

I have acquired substantial knowledge, skills, and confidence during the course of this work, yet I still cannot foresee the exact way in which it will be applied. Nevertheless, I have grown to appreciate my unique niche of agriculture, ecology, statistics, technology, and interdisciplinary analysis. My tendencies are such that I know I will stretch myself to apply my skills for the betterment of agriculture and the environment. This path will not be linear, but it will be guided by moral intuition and the desire to put my knowledge to good use. I look forward to this future, with deep respect and recognition for this important chapter in my life.

References

Carpenter S.R., Walker B., Anderies J.M., & Abel N. 2001. From metaphor to measurement: resilience of what to what? *Ecosystems* 4: 765-781.

Genest C. & MacKay J. 1986. The joy of copulas. *The American Statistician* 40: 280-283.

Gunderson L.H. & Holling C.S. 2002. Panarchy: understanding transformations in systems of human and nature. Island Press, Washington, D.C.

Keane R.E., Hessburg P.F., Landres P.B., & Swanson F.J. 2003. The use of Historical Range of Variability (HRV) in landscape management. *Forest Ecology and Management* 258: 1025-1037.

Lin B.B. 2011. Resilience in agriculture through crop diversification: adaptive management for environmental change. *Bioscience* 61: 183-193.

Miller P.R., Bekkerman A., Jones C.A., Burgess M.H., Holmes J.A. & Engel R.E. 2015. Pea in rotation with wheat reduced uncertainty of economic returns in Southwest Montana. *Agronomy Journal* 107: 541-550.

Turner B.L., Kasperson R.E., Matosn P.A., McCarthy J.J., Corell R.W. & Christensen, L. 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences* 100: 8074-8079.

Sklar A. 1959. Fonctions de répartition à n dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris* **8**: 229–231.

REFERENCES CITED

Ahmed F., Al-Mamun H.A., Hossain Bari A.S.M., Hossain E., & Kwan P. 2012. Classification of crops and weeds from digital images: a support vector machine approach. *Crop Protection* 40: 98-104.

Allen P.G. 1994. Economic forecasting in agriculture. *International Journal of Forecasting* 10: 81–135.

Anselin L., Bongiovanni R., & Lowenberg-DeBoer J. 2004. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *American Journal of Agricultural Economics* 86: 675–687.

Antle J.M.1983. Incorporating risk in production analysis. *American Journal of Agricultural Economics* 65: 1099–1106.

Archontoulis S.V. & Miguez F.E. 2013. Nonlinear regression models and applications in agricultural research. *Agronomy Journal* 105: 1-13.

Arrow K., 1965, *Aspects of the Theory of Risk-Bearing*. Helsinki: Yrjö Jahnssonin Säätiö Foundation.

Banerjee S., B. P. Carlin, & A. E. Gelfand. 2004. Hierarchical modeling and analysis for spatial data. Chapman & Hall/CRC, New York, NY.

Bates D., Maechler M., & Walker S. 2015. *lme4: Linear mixed-effects models using Eigen and S4.*

Battisti B. & Naylor R.L. 2009. Historical warnings of future food insecurity with unprecedented seasonal heat. *Science* 323: 240–244.

Baxter S.J., Oliver M.A., & Gaunt J. 2003. A geostatistical analysis of the spatial variation of soil mineral nitrogen and potentially available nitrogen within an arable field. *Precision Agriculture* 4: 213–226.

Bekkerman A. 2015. Costs and Revenue for several crop rotations in Montana. *Unpublished data*.

Berkes F., Armitage D., & Doubleday N. 2007. Synthesis: adapting, innovating, evolving. In: Armitage D, Berkes F, Doubleday N (eds) *Adaptive co-management: collaboration, learning and multi-level governance*. UBC Press, Vancouver.

Berry J.K., Delgado J.A., Pierce F.J., & Khosla R. 2005. Applying spatial analysis for precision conservation across the landscape. *Journal of Soil and Water Conservation* 60: 363–370.

Besag J. 1974. Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society. Series B (Methodological)*: 192–236.

Beven K.J. & Kirkby M.J. 1979. A physically based, variable contributing area model of basin hydrology / Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. *Hydrological Sciences Bulletin* 24: 43–69.

Biermacher J. T., B. W. Brorsen, F. M. Epplin, J. B. Solie, and W. R. Raun. 2009. The economic potential of precision nitrogen application with wheat based on plant sensing. Agricultural Economics 40:397–407.

Birch C.P. 1999. A new generalized logistic sigmoid growth equation compared with the Richards growth equation. *Annals of Botany* 83: 713–723.

Blackmore S. 1999. Remedial correction of yield map data. *Precision agriculture* 1: 53–66.

Boehlje M.D., Gloy B.A. & Henderson J.R. 2013. U.S. farm prosperity: the new normal or Reversion to the Mean. *American Journal of Agricultural Economics* 95:310-317.

Bongiovanni R.G., Robledo C.W., & Lambert D.M. 2007. Economics of site-specific nitrogen management for protein content in wheat. *Computers and Electronics in Agriculture* 58: 13–24.

Bourennane, H., Nicoullaud, B., Couturier, A., & King, D. 2004. Exploring the spatial relationships between some soil properties and wheat yields in two soil types. *Precision Agriculture* 5: 521–536.

Bradshaw B., Dolan H., & Smit B. 2004. Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. *Climatic Change* 67: 119-141.

Brand, F.S. & Jax, K. 2007. Focusing the meaning (s) of resilience: resilience as a descriptive concept and a boundary object. *Ecology and Society* 12: 23.

Brevik E. C., T. E. Fenton, & A. Lazari. 2006. Soil electrical conductivity as a function of soil water content and implications for soil mapping. Precision Agriculture 7:393–404.

Bureau of Labor Statistics. 2015. Consumer Price Index – all urban consumers. Accessed from http://download.bls.gov/pub/time.series/cu/cu.data.1.AllItems

Burgess, M., P. Miller, & C.A. Jones. 2012. Pulse crops improve energy intensity and productivity of cereal production in Montana, U.S.A. *Journal of Sustainable Agriculture* 36: 699-718.

Cambardella C.A. & Karlen D.L. 1999. Spatial analysis of soil fertility parameters. *Precision Agriculture* 1: 5–14.

Campbell, H.W. 1907. Campbell's soil culture manual. 3rd ed. Woodruff-Collins Press Printers and Binders, Lincoln, NE.

Campbell C.A., Selles F., Zentner R.P., De Jong R., Lemke R., & Hamel C. 2006. Nitrate leaching in the semiarid prairie: effect of cropping frequency, crop type, and fertilizer after 37 years. *Canadian Journal of Soil Science* 86: 701-710.

Cao Q., Cui Z., Chen X., Khosla R., Dao T.H., & Miao Y. 2012. Quantifying spatial variability of indigenous nitrogen supply for precision nitrogen management in small scale farming. *Precision Agriculture* 13: 45–61.

Carolan, M.S., 2006. Do You See What I See? Examining the Epistemic Barriers to Sustainable Agriculture. *Rural sociology* 71: 232–260.

Carpenter S.R., Walker B., Anderies J.M., & Abel N. 2001. From metaphor to measurement: resilience of what to what? *Ecosystems* 4: 765-781.

Cassman K.G., Dobermann A., & Walters D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio* 31:132-140.

Chen C., Neill K., Burgess M., & Bekkerman A. 2012. Agronomic benefit and economic potential of introducing fall-seeded pea and lentil into conventional wheat-based crop rotations. *Agronomy Journal* 104: 215-224.

Christopherson, S., Michie, J., & Tyler, P. 2010. Regional resilience: theoretical and empirical perspectives. *Cambridge Journal of Regions, Economy and Society* 3: 3–10.

Cliff A.D & Ord J.K. 1981. *Spatial Processes*. London: Pion.

Cochran V., Danielson J., Kolberg R., & Miller P. 2006. Dryland cropping in the Canadian Prairies and the U.S. northern Great Plains. Pages 293-339 *in* Peterson G.A., Unger W., and Payne W.A. eds. Dryland Agriculture. Agronomy Monograph No. 23, 2nd ed., ASA, Madison, WI.

Corwin D. L. & S. M. Lesch. 2003. Application of soil electrical conductivity to precision agriculture. Agronomy Journal 95:455–471.

Corwin D. L. & S. M. Lesch. 2005. Apparent soil electrical conductivity measurements in agriculture. Computers and Electronics in Agriculture 46:11–43.

Cox T.S., Glover J.D. Van Tassel D.L., Cox C.M., & DeHaan L.R. 2006. Prospects for developing perennial grain crops. *Bioscience* 56: 649-659.

Cressie N. 1993. *Statistics for spatial data*. Canada: Wiley.

Cressie N. & C. K. Wikle. 2011. Statistics for spatio-temporal data. John Wiley & Sons, Inc., Hoboken, NJ.

Crews T.E. & Peoples M.B. 2004. Legume versus fertilizer sources of nitrogen: Ecological tradeoffs and human needs. *Agriculture Ecosystems & Environment* 102: 279-297. DOI: 10.1016/j.agee.2003.09.018.

Cutter, S. 1996. Vulnerability to environmental hazards. *Progress in Human Geography* 20: 529-539.

Delgado J.A., Secchi S., Groffman P., Nearing M.A., Goddard T., Reicocky D., Lal R., Salon P., Kitchen N.R., Rice C., & Towery D. 2011. Conservation practices to mitigate and adapt to the effects of climate change. *Journal of Soil and Water Conservation Society* 66(a): 118A-129A.

Diaz R.J. & Rosenberg R. 2008. Spreading dead zones and consequences for marine ecosystems. *Science* 321: 926–929.

Dillman D.A. 2000. Mail and Internet Surveys: The Tailored Design Method. 2nd Edition. New York: John Wiley Co.

Dinkins C.P. & Jones C. 2013. Developing fertilizer recommendations for agriculture. MontGuide 200703AG. Montana State University Extension Publications.

Dulière V., Zhang Y., & Salathé E.P. 2013. Changes in twentieth-century extreme temperature and precipitation over the western united states based on observations and regional climate model simulations. *Journal of Climate* 26: 8556–8575.

Engel R., Jones C., & Wallander R. 2011. Ammonia volatilization from urea and mitigation by NBPT following surface application to cold soils. *Soil Sci Soc Am J.* 75: 2348-2357.

Florin M. J., McBratney A. B., & Whelan B. M.. 2009. Quantification and comparison of wheat yield variation across space and time. European Journal of Agronomy 30:212–219.

Florin M. J., McBratney A. B., Whelan B. M., & Minasny B.. 2010. Inverse meta-modelling to estimate soil available water capacity at high spatial resolution across a farm. *Precision Agriculture* 12:421–438.

Folke C. 2006. Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change* 16: 253–267.

Fonnesbeck C., Patil A., Huard D., and Salvatier J.. 2012. PyMC.

Franzen D.W. & Peck T.R. 1995. Site-specific management for agricultural systems. ASA-CSSA-SSSA publications.

Gelman A. & Rubin D.B. 1992. Inference from iterative simulation using multiple sequences. *Statistical Science*: **7**: 457–472.

Gelman A., Carlin J. B., Stern H. S., & Rubin D. B.. 2004. Bayesian data analysis. Second Edition. Chapman & Hall/CRC, New York, NY.

Genest C. & MacKay J. 1986. The joy of copulas. *The American Statistician* 40: 280-283.

GLO Records, n.d. Bureau of Land Management General Land Office. http://www.glorecords.blm.gov/ PatentSearch/

Godfray H.C.J., Beddington J.R., Crute I.R., Haddad L., Lawrence D., Muir J.F., Pretty J., Robinson S., Thomas S.M., & Toulmin C. 2010. Food security: the challenge of feeding 9 billion people. *Science* 327: 812–818.

Grant G.D. Spring wheat yield response to nitrogen, 1993-2006. *Unpublished data.*

Griffin T.W., Dobbins C.L., Vyn T.J., Florax R.J.G.M., & Lowenberg-DeBoer J.M. 2008. Spatial analysis of yield monitor data: case studies of on-farm trials and farm management decision making. *Precision Agriculture* 9: 269–283.

Guirguis K.J. & Avissar R. 2008. An analysis of precipitation variability, persistence, and observational data uncertainty in the Western United States. *Journal of Hydrometeorology* 9: 843–865.

Gunderson L.H. & Holling C.S. 2002. Panarchy: understanding transformations in systems of human and nature. Island Press, Washington, D.C.

Hall K.D., Guo J., Dore M., & Chow C.C. 2009. The progressive increase of food waste in America and its environmental impact. *PLoS ONE* 4: 1-6.

Hansen Z.K. & Libecap G.D. 2004. The allocation of property rights to land: US land policy and farm failure in the northern Great Plains. *Explorations in Economic History* 41,:103–129.

Hansen N.C., Allen B.L., Baumhardt R.L., & Lyon D.J. 2012. Research achievements and adoption of no-till, dryland cropping in the semiarid US Great Plains. *Field Crops Research* 132: 196-203.

Hatfield J.L., Boote K.J., Kimball B.A., Ziska L.H., Izaurralde R.C., Ort D., Thomson A.M., & Wolfe D. 2011. Climate impacts on agriculture: implications for crop production. *Agronomy Journal* 103, 351–370.

Heiniger R.W., McBride R.G., & Clay D.E. 2003. Using soil electrical conductivity to improve nutrient management. *Agronomy Journal* 95: 508–519.

Henderson, J., Gloy, B., Boehlje, M. 2011. Agriculture's boom-bust cycles: is this time different? *Economic Review of the Federal Reserve Bank of Kansas City, Fourth Quarter*: 83-105.

Hiemstra P.H., Pebesma E.J., Twenhöfel C.J.W., & Heuvelink G.B.M. 2009. Real-time automatic interpolation of ambient gamma dose rates from the Dutch radioactivity monitoring network. *Computers & Geosciences* 35: 1711–1721.

Hoffman M.D. & Gelman A. 2011. The no-U-turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *The Journal of Machine Learning Research* 15: 1593–1623.

Holling C.S. 1973. Resilience and stability of ecological systems. *Annual review of ecology and systematics* 4: 1–23.

Howden S.M., Soussana, J.F., Tubiello, F.N., Chhetri, N., Dunlop, M. & Meinke, H. 2007. Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences* 104: 19691-19696.

Hudson B.D. 1994. Soil Organic Matter and Available Water Capacity. *Journal of Soil and Water Conservation* 49:189-194.

James G., Witten D., Hastie T., & Tibshirani R. 2013. *An Introduction to Statistical Learning with Applications in R.* Springer, New York.

Janzen H.H., Campbell C.A., Izaurralde R.C., Ellert B.H., Juma N., McGill W.B. & Zentner R.P. 1998. Management effects on soil C storage on the Canadian prairies. *Soil and Tillage Research* 47: 181-195.

Jiang P., He Z., Kitchen N.R., & Sudduth K.A. 2008. Bayesian analysis of within-field variability of corn yield using a spatial hierarchical model. *Precision Agriculture* 10: 111–127.

Jones J.W., Hoogenboom G., Porter C.H., Boote K.J., Batchelor W.D., Hunt L.A., Wilkens P.W., Singh U., Gijsman A.J., & Ritchie J.T. 2003. The DSSAT cropping system model. *European journal of agronomy* 18: 235–265.

Jung W. K., Kitchen N. R., Sudduth K. A., Kremer R. J., & Motavalli P. P.. 2005. Relationship of apparent soil electrical conductivity to claypan soil properties. Soil Science Society of America Journal 69:883–892.

Kantanantha N., Serban N., & Griffin P. 2010. Yield and price forecasting for stochastic crop decision planning. *Journal of Agricultural, Biological, and Environmental Statistics* 15: 362–380.

Karl T.R. 2009.Global climate change impacts in the United States. Accessed from http://downloads.globalchange.gov/usimpacts/pdfs/climate-impacts-report.pdf.

Keane R.E., Hessburg P.F., Landres P.B., & Swanson F.J. 2003. The use of Historical Range of Variability (HRV) in landscape management. *Forest Ecology and Management* 258: 1025-1037.

Keller M., Gutjahr C., Möhring J., Weis M., Sökefeld M., & Gerhards R. 2014. Estimating economic thresholds for site-specific weed control using manual weed counts and sensor technology: An example based on three winter wheat trials: Yield effect of weeds, herbicides and thresholds for site-specific weed control. *Pest Management Science* 70: 200–211.

Kerry R. & Oliver M.A. 2003. Variograms of ancillary data to aid sampling for soil surveys. *Precision Agriculture* 4: 261–278.

Khosla R., Inman D., Westfall D.G., Reich R.M., Frasier M., Mzuku M., Koch B., & Hornung A. 2008. A synthesis of multi-disciplinary research in precision agriculture: site-specific management zones in the semiarid western Great Plains of the USA. *Precision Agriculture* 9: 85–100.

King J.A., Dampney P.M.R., Lark R.M., Wheeler H.C., Bradley R.I., & Mayr T.R. 2005. Mapping potential crop management zones within fields: use of yield-map series and patterns of soil physical properties identified by electromagnetic induction sensing. *Precision Agriculture* 6: 167–181.

Kloppenburg J. 1991. Social theory and the de/reconstruction of agricultural science: local knowledge for an alternative agriculture. *Rural sociology* 56: 519–548.

Knutson C.L., Haigh T., Hayes M.J., Widhalm M., Nothwehr J., Kleinschmidt M., & Graf L. 2011. Farmer perceptions of sustainable agriculture practices and drought risk reduction in Nebraska, USA. *Renewable Agriculture an d Food Systems* 26: 255-266.

Koch B., Khosla R., Frasier W.M., Westfall D.G., & Inman D. 2004. Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones. *Agronomy Journal* 96: 1572–1580.

Kravchenko A. N., Robertson G. P., Thelen K. D., & Harwood R. R.. 2005. Management, topographical, and weather effects on spatial variability of crop grain yields. *Agronomy Journal* 97:514–523.

Kühn J., Brenning A., Wehrhan M., Koszinski S., & Sommer M.. 2008. Interpretation of electrical conductivity patterns by soil properties and geological maps for precision agriculture. *Precision Agriculture* 10:490–507.

Kunkel H.O. 1988. Issues of academic disciplines in agricultural research. *Agriculture and Human Values* 5: 16–25.

Lambert D. M., Lowenberg-DeBoer J., & Malzer G. L.. 2006. Economic Analysis of Spatial-Temporal Patterns in Corn and Soybean Response to Nitrogen and Phosphorus. *Agronomy Journal* 98:43.

Lanning S.P., Kephart K., Carlson G.R., Eckhoff J.E., Stougaard R.N., Wichman D.M., Martin J.M., & Talbert L.E. 2010. Climatic change and agronomic performance of hard red spring wheat from 1950 to 2007. *Crop Science* 50: 835.

Larney F.J., Lindwall C.W., Izaurralde R.C. & Moulin, A.P. 1994. Tillage systems for soil and water conservation on the Canadian Prairie. p. 305-328. *In* Conservation tillage in temperate agroecosystems. CRC Press, Boca Raton.

Lawrence P.G., Rew L.J., & Maxwell B.D. 2015. A probabilistic Bayesian framework for progressively updating site-specific recommendations. *Precision Agriculture* 16: 275–296.

Lin B.B. 2011. Resilience in agriculture through crop diversification: adaptive management for environmental change. *Bioscience* 61: 183-193.

Lindstrom M.J., Nelson W.W., & Schumacher T.E. 1992. Quantifying tillage erosion rates due to moldboard plowing. *Soil and Tillage Research* 24: 243-255.

Liu Y., Swinton S.M., & Miller N.R. 2006. Is site-specific yield response consistent over time? Does it pay? *American Journal of Agricultural Economics* 88: 471–483.

Lobell D.B., Burke M.B, Tebaldi C., Mastrandrea M.C., Falcon W.P., & Naylor R.L. 2008. Prioritizing Climate Change Adaptation Needs for Food Security in 2030. *Science* 319: 607-610.

Lombardi D. 2009. Business Investment under Uncertainty and Irreversibility. *Oxonomics* 4: 25 – 31.

Long D.S., Whitmus J.D., Engel R.E., & Brester G.W. 2015. Net Returns from Terrain-Based Variable-Rate Nitrogen Management on Dryland Spring Wheat in Northern Montana. *Agronomy Journal* 107: 1055.

Long J.A., Lawrence R.L., Miller P.R., & Marshall L.A. 2014. Changes in field-level cropping sequences: Indicators of shifting agricultural practices. *Agriculture, Ecosystems & Environment* 189: 11–20.

Lorenz, E.N. 1963. Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences* 20: 130–141.

Macmillan R.A., Pettapiece W.W., Nolan S.C., & Goddard T.W. 2000. A generic procedure for automatically segmenting landforms into landform elements using DEMs, heuristic rules and fuzzy logic. *Fuzzy Sets and Systems* 113: 81–109.

MacMynowski D.P. 2007. Pausing at the brink of interdisciplinarity: power and knowledge at the meeting of social and biophysical science. *Ecology and Society* 12: 20.

Malhi S.S., Soon Y.K., Grant C.A., Lemke R.L., & Lupwayi, N.Z. 2010. Influence of controlled-release urea on seed yield and N concentration, and N use efficiency of small grain crops grown on Dark Gray Luvisols., *Canadian Journal of Soil Science,* 90: 363-372.

Mallarino A.P. & Wittry D.J. 2004. Efficacy of grid and zone soil sampling approaches for site-specific assessment of phosphorus, potassium, pH, and organic matter. *Precision Agriculture* 5: 131–144.

Mamo M., Malzer G. L., Mulla D. J. Huggins D. R., & Strock J.. 2003. Spatial and temporal variation in economically optimum nitrogen rate for corn. *Agronomy Journal* 95:958–964.

Marotz-Baden R. 1988. Income, economic satisfaction, and stress in two-generational farm families. *Journal of Family and Economic Issues* 9: 331–356.

Marra M., Pannell D.J., & Ghadim, A.A. 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems* 75: 215-234.

Mason R.G. 1964. The use of information sources in the process of adoption. *Rural sociology* 29: 40-52.

Maxwell J.A. 2013. *Qualitative Research Design: An Interactive Approach 3rd Edition*. Thousand Oaks, CA: Sage.

Maxwell B.D., Luschei E.C. 2005. Justification for site-specific weed management based on ecology and economics. *Weed Science* 53: 221–227.

May R.M. 1977. Thresholds and breakpoints in ecosystems with a multiplicity of stable states. *Nature* 269: 471–477.

Maynard L.J., Harper J.K., Hoffman L.D., & others. 1997. Impact of risk preferences on crop rotation choice. *Agricultural and Resource Economics Review* 26: 106–114.

McCormick S., Jordan C., & Bailey J.S. 2009. Within and between-field spatial variation in soil phosphorus in permanent grassland. *Precision Agriculture* 10: 262–276.

McLeman R., Mayo D., Strebeck E., & Smit B. 2008. Drought adaptation in rural eastern Oklahoma in the 1930s: lessons for climate change adaptation research. *Mitigation and Adaptation Strategies for Global Change* 13: 379-400.

Meyer-Aurich A., Gandorfer M., Weersink A., & Wagner P. 2008. Economic analysis of site-specific wheat management with respect to grain quality and separation of the different quality fractions. *12th Congress of the European Association of Agricultural Economists*, Ghent, Belgium.

Miles M.B. & A. Michael Huberman. 1994. *Qualitative Data Analysis: An Expanded Sourcebook.* Thousand Oaks, CA: Sage

Miller P.R. & Holmes J.A. 2005. Cropping sequence effects of four broadleaf crops on four cereal crops in the northern Great Plains. *Agronomy journal* 97: 189–200.

Miller P.R., Bekkerman A., Jones C.A., Burgess M.H., Holmes J.A. & Engel R.E. 2015. Pea in rotation with wheat reduced uncertainty of economic returns in Southwest Montana. *Agronomy Journal* 107: 541-550.

Mishra A.K. & El-Osta H.S. 2002. Managing risk in agriculture through hedging and crop insurance: what does a national survey reveal? *Agricultural Finance Review* 62: 135–148.

Mo K.C. 2010. Interdecadal Modulation of the Impact of ENSO on Precipitation and Temperature over the United States. *Journal of Climate* 23: 3639–3656.

Mock C.J. 1996. Climatic Controls and Spatial Variations of Precipitation in the Western United States. *Journal of Climate* 9: 1111–1125.

Monjardino M., McBeath T., Ouzman J., Llewellyn R., & Jones B. 2015. Farmer risk-aversion limits closure of yield and profit gaps: A study of nitrogen management in the southern Australian wheatbelt. *Agricultural Systems* 137: 108–118.

Montana Dept. of Agriculture. 2014. North central Montana dryland agricultural model. Retrieved from http://agr.mt.gov/agr/Producer/CropTools/Models/Forms/NC_MT_Dryland_Budgets_2014.xls

Montana Department of Agriculture. 2015. Wheat Prices. Retrieved from http://wbc.agr.mt.gov/wbc/Producers/Pricing.html.

Moran P.A. 1950. Notes on continuous stochastic phenomena. *Biometrika* 37: 178-81.

Mortensen D.A. 1999. Site-specific Crop Management: Filling Critical Gaps. USDA Agricultural Outlook Forum.

National Climatic Data Center. Historical Palmer z-index data. Retrieved from ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-zndxdv-v1.0.0-20150904.

Nielsen D.C., Unger P.W. & Miller P.R. 2005. Efficient water use in dryland cropping systems in the Great Plains. *Agronomy Journal* 97: 364–372.

O'Dea J.K., Jones C.A., Zabinski C.A., Miller P.R. & Keren I.N. 2015. Legume, cropping intensity, and N-fertilization effects on soil attributes and processes from an eight-year-old semiarid wheat system. *Nutrient Cycling in Agroecosystems* 102: 179-194.

.

Odum E.P. 1989. Input management of production systems. *Science* 243, 177–182.

Ostrom E. 2009. A general framework for analyzing sustainability of social-ecological systems. *Science* 325:419-422.

Padbury G., Waltman S., Caprio J., Coen G., McGinn S., Mortensen D., Nielsen G., & Sinclair R. 2002. Agroecosystems and land resources of the northern Great Plains. *Agronomy Journal* 94: 251–261.

Patzold S., Mertens F. M., Bornemann L., Koleczek B., Franke J., Feilhauer H., & Welp G.. 2008. Soil heterogeneity at the field scale: a challenge for precision crop protection. *Precision Agriculture* 9:367–390.

Percival D.B. & Rothrock D.A. 2005. "Eyeballing" trends in climate time series: A cautionary note. *Journal of climate* 18: 886-890.

Phalan B., Onial M., Balmford A., & Green R.E. 2011. Reconciling food production and biodiversity conservation: land sharing and land sparing compared. *Science* 333: 1289-1291.

Pinheiro J., Bates D., DebRoy S., Sarkar D., & R Core Team. 2015. *NLME: Linear and Nonlinear Mixed Effects Models.*

Piringer G. & Steinberg L.J. 2006. Reevaluation of energy use in wheat production in the United States. *Journal of Industrial Ecology* 10: 149-167.

Pittman J., Wittrock V., Kulshreshtha S., & Wheaton E. 2011. Vulnerability to climate change in rural Saskatchewan: Case study of the Rural Municipality of Rudy No. 284. *Journal of Rural Studies* 27: 83-94.

Popper K.R. 1959. The logic of scientific discovery. Hutchinson, London.

Power A.G. 2010. Ecosystem services and agriculture: tradeoffs and synergies. *Philosophical Transactions of the Royal Society B: Biological Sciences* 365: 2959–2971.

Pratt J.W. 1964. Risk aversion in the small and in the large. *Econometrica,* 32: 122-136.

Pricing :: Montana Wheat & Barley Committee. 2013. http://wbc.agr.mt.gov/wbc/Producers/Pricing.html.

Quiring S.M. & Papakryiakou T.N.2003. An evaluation of agricultural drought indices for the Canadian Prairies. *Agricultural and Forest Meteorology* 118:49-62.

R Core Team. 2012. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Robertson, G.P. & Swinton, S.M. 2005. Reconciling agricultural productivity and environmental integrity: a grand challenge for agriculture. *Frontiers in Ecology and the Environment* 3: 38–46.

Rogers E.M. and Beal G.M. 1958. The importance of personal influence in the *adoption* of technological changes. *Social Forces* 36: 329-335.

Roling N.G. & Jiggins J. 1998. The ecological knowledge system. In: Roling NG, Wagemakers MAE (eds) Facilitating sustainable agriculture: participatory learning and adaptive management in times of environmental uncertainty. Cambridge University Press, UK

Ruttan V.W. 1996. What happened to technology adoption-diffusion research? *Sociologia Ruralis* 36: 51-73.

Sadler E.J., Sudduth K.A. & Jones J.W. 2007. Separating spatial and temporal sources of variation for model testing in precision agriculture. *Precision Agriculture* 8: 297–310.

Salmon S.C., Mathews O.R., & Leukel R.W.. 1953. A half century of wheat improvement in the United States. *Adv. Agron.* 5: 1–151.

Saltiel J., Bauder J.W., & Palakovich S. 1994. Adoption of Sustainable Agricultural Practices: Diffusion, Farm Structure, and Profitability1. *Rural Sociology* 59, 333–349.

Schabenberger O. & Gotway C.A. 2004. *Statistical Methods for Data Analysis*. Boca Raton: Chapman & Hall/CRC Press.

Scheffer M., Carpenter S., Foley J.A., Folke C., & Walker B. 2001. Catastrophic shifts in ecosystems. *Nature* 413: 591–596.

Schlather M. 2012. RandomFields: simulation and analysis of random fields.

Schoennagel T., Veblen T.T., Romme W.H., Sibold J.S., & Cook E.R. 2005. ENSO and PDO variability affect drought-induced fire occurrence in Rocky Mountain subalpine forests. *Ecological Applications* 15: 2000–2014.

Sepaskhah A.R., Fahandezh-Saadi S., & Zand-Parsa S. 2011. Logistic model application for prediction of maize yield under water and nitrogen management. *Agricultural Water Management* 99: 51–57.

Shahandeh H., Wright A.L., & Hons F.M. 2011. Use of soil nitrogen parameters and texture for spatially-variable nitrogen fertilization. *Precision Agriculture* 12: 146–163.

Shahandeh H., Wright A.L., Hons F.M., & Lascano R.J. 2005. Spatial and Temporal Variation of Soil Nitrogen Parameters Related to Soil Texture and Corn Yield. *Agronomy Journal* 97: 772-782.

Shaner D.L., Khosla R., Brodahl M.K., Buchleiter G.W., & Farahani H.J. 2008. How Well Does Zone Sampling Based on Soil Electrical Conductivity Maps Represent Soil Variability? *Agronomy Journal* 100: 1472-1480.

Sheffield J., Barrett A.P., Colle B., Nelun Fernando D., Fu R., Geil K.L., Hu Q., Kinter J., Kumar S., Langenbrunner B., & others. 2013. North American Climate in CMIP5 Experiments. Part I: Evaluation of Historical Simulations of Continental and Regional Climatology. *Journal of Climate* 26: 9209–9245.

Simmons A.J. & Hollingsworth A. 2002. Some aspects of the improvement in skill of numerical weather prediction. *Quarterly Journal of the Royal Meteorological Society* 128: 647–677.

Sklar A. 1959. Fonctions de répartition à n dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris* 8: 229–231.

Stan Development Team. 2014. *RStan: the R interface to Stan.*

Strang V. 2009. Integrating the social and natural sciences in environmental research: a discussion paper. *Environment, Development and Sustainability* 11: 1-18.

Strunz S. 2012. Is conceptual vagueness an asset? Arguments from philosophy of science applied to the concept of resilience. *Ecological Economics* 76: 112–118.

Sudduth K.A. & Drummond S.T. 2007. Yield editor: software for removing errors from crop yield maps. *Agronomy Journal* 99: 1471-1482.

Sunding D & Zilberman D. 2000. The agricultural innovation process: research and technology adoption in a changing agricultural industry. In: Gardner B, Rausser GC (eds) Handbook of agricultural and resource economics. Elsevier, Amsterdam, pp 207–261.

Suppe, F. 1987. The limited applicability of agricultural research. *Agriculture and Human Values* 4: 4–14.

Tanaka D.L., Schillinger W.F., Papendick R.I., & McCool D.K. 2010. Soil and water conservation advances in the semiarid northern great plains. Soil and Water Conservation Advances in the United States, pp. 47–79.

Tarleton M. & Ramsey D. 2008. Farm-level Adaptation to Multiple Risks: Climate Change and Other Concerns. *Journal of Rural and Community Development* 3: 47-63.

Tarnoczi T. 2011. Transformative learning and adaptation to climate change in the Canadian Prairie agro-ecosystem. *Mitig. Adapt Strateg. Glob. Change* 16: 387-406.

Thöle H., Richter C., & Ehlert D. 2013. Strategy of statistical model selection for precision farming on-farm experiments. *Precision Agriculture* 14: 434-449.

Thrikawala S., Weersink A., Fox G., & Kachanoski G. 1999. Economic feasibility of variable-rate technology for nitrogen on corn. *American Journal of Agricultural Economics* 81: 914–927.

Tilman D., Cassman K.G., Matson P.A., Naylor R., & Polasky S. 2002. Agricultural sustainability and intensive production practices. *Nature* 418: 671–677.

Tomek W.G. & Peterson H.H. 2001. Risk management in agricultural markets: a review. *Journal of Futures Markets* 21: 953–985.

Turner B.L., Kasperson R.E., Matosn P.A., McCarthy J.J., Corell R.W. & Christensen, L. 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences* 100: 8074-8079.

USDA ERS - Commodity Costs and Returns. 2012. http://www.ers.usda.gov/data-products/commodity-costs-and-returns.aspx#.UnuxUeIltLN.

USDA National Agricultural Statistics Service Montana Office. State-wide Fertilizer Usage. 2011.

USDA National Agricultural Statistics Service. 2015. Census of Agriculture 1964-2012. Retrieved from http://www.agcensus.usda.gov/Publications/

USDA National Agricultural Statistics Service. 2015. Fertilizer use and price. Retrieved from http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx

USDA National Agricultural Statistics Service. 2015a. Wheat prices. Retrieved from http://www.ers.usda.gov/datafiles/Wheat_Wheat_Data/Yearbook_Tables/Domestic_and_International_Prices/WheatYearbookTable18.xls

Velandia M., Rejesus R.M., Knight T.O., & Sherrick B.J. 2009. Factors affecting farmers' utilization of agricultural risk management tools: the case of crop insurance, forward contracting, and spreading sales. *Journal of Agricultural and Applied Economics* 41: 107–123.

Weber E.U. 2006. Experience-Based and Description-Based Perceptions of Long-Term Risk: Why Global Warming Does Not Scare Us (Yet). *Climatic Change* 77: 103-120.

West T.O. & Post W.M. Soil Organic Carbon Sequestration Rates by Tillage and Crop Rotation. *Soil Science Society of America Journal* 66:1930-1946.

Whelan B.M., Taylor J.A., & McBratney A.B. 2012. A "small strip" approach to empirically determining management class yield response functions and calculating the potential financial "net wastage" associated with whole-field uniform-rate fertiliser application. *Field Crops Research* 139: 47–56.

Wiles L.J. 2008. Beyond patch spraying: site-specific weed management with several herbicides. *Precision Agriculture* 10: 277–290.

Wilson M.L. 1928. Dry farming in the north central Montana "Triangle." *Bulletin 66. Montana Agricultural Experiment Station*, Bozeman, MT.

Wisner R.N., Blue E.N., & Baldwin E.D. 1998. Preharvest Marketing Strategies Increase Net Returns for Corn and Soybean Growers. *Applied Economic Perspectives and Policy* 20: 288–307.

Yang W., Bryan B.A., MacDonald D.H., Ward J.R., Wells G., Crossman N.D., & Connor J.D. 2010. A conservation industry for sustaining natural capital and ecosystem services in agricultural landscapes. *Ecological Economics* 69: 680–689.

Zentner R.P., Lafond G.P., Derksen D.A., Nagy C.N., Wall D.D., & May W.P. 2004. Effects of tillage method and crop rotation on non-renewable energy use efficiency for a thin Black Chernozem in the Canadian Prairies. *Soil and Tillage Research* 77: 125–136.

APPENDICES

APPENDIX A

PRECISION AG DATA CLEANING AND SYNTHESIS

Sensors used for precision agriculture generate enormous amounts of data for any given year, and significant portions of those data can be erroneous (Blackmore, 1999). Given the sheer volume of data, it is impractical to manually remove erroneous data points, and doing so can also introduce bias if the basis for removal is purely heuristic. Therefore, a set of automated steps were used in order to clean data from the yield monitor and fertilizer spreader. These were generally based on Sudduth and Drummond (2007).

Yield Data

Grain Flow Delay (Lag Correction)

Between the time that the header on a combine harvests an area of crop, and the time when the harvested grain passes by the yield monitor, a substantial time lag exists. This lag causes the GPS coordinate logged at the time of the header pass to be associated with grain that was collected at a previous location and time. Previous studies have shown simple time delays to be adequate for delay correction (Birrell et al. 1996 in Sudduth and Drummond 2007). The cooperating farmer for this study stated that he usually corrected the data associated with the four fields using a lag of three points (i.e. the GPS coordinate for the point t was matched with the yield value from point $t - 3$, where 3 is the difference in sequential order of the points), which was associated with a time delay averaging 9 seconds. To clean the data used for this study, a three-point lag delay was used as the starting value, after which positive and negative adjustments to the lag were made until patterns apparent in successive combine passes were spatially adjacent. The lag adjustments were made by programmatically holding sequences of geographically adjacent points in memory (from the same combine pass), then adjusting the yield values accordingly.

Headlands correction

To correct for alterations in angular momentum, velocities, header width and volume at the end of each combine transect, and for anomalous levels of machinery traffic, 120 feet (two cells) of data were removed at each edge of the field.

Velocity Correction

Anomalously large velocities suggest either dead-heading across the field, and anomalously low velocities suggest encountered obstacles that may cause the measured yields to be lower than actual. The equipment used by the cooperating farmer did not log velocities, however the distance between points was used as a proxy for velocity, because the time between GPS measurements was constant. Therefore, minimum and maximum between-point distance (calculated trigonometrically) filters were implemented, and were set at 2 meters and 50 meters.

Minimum Swath

Data with header width recordings lower than full width were removed.

Standard Deviation

Yield data outside +- 3 standard deviations of the mean for each year were removed.

Minimum Yield

The minimum yield filter was used only to remove values that were negative, as very low values were occasionally observed in the fields.

Maximum Yield

Yields greater than 5000 kg/ha were removed as productivity has never been observed by the farmer to be this high in any of the observed fields.

Cell-based Filters

Despite all of the above filters, there were still instances in which erroneous points were observed where the combine was stopped and still recorded measurements, where the driver had not turned off the yield monitor after harvesting, etc. Therefore, cell-based filters were implemented. When more than two yield points associated with each 18.3 by 18.3 m cell were above 670 kg/ha (10 bu/ac) and more than two-thirds of those points were above that same 670 kg/ha threshold, it was highly likely that remaining points in the cell below the threshold were erroneous. In such a case, the points below the threshold were removed. This function was implemented within the PostGIS spatial database.

Fertilizer and Apparent Electrical Conductivity Data

Fertilizer and apparent electrical conductivity data are not subject to the same errors as yield data for several reasons. First, no lag exists between measurement of the applied level of fertilizer or EC_a measurement and the GPS measurement. Second, although the fertilizer values are logged 'as-applied', the values are solely determined by the output of the rate controller and are not verified with external measurements. Since the rate controller is programmed not to exceed pre-specified values, no minimum, maximum, and standard deviation filtering is necessary. With EC_a, data cleaning is not always standard, however we applied a +- 3 standard deviation to measurements within a field.

Data Synthesis Procedure

Fertilizer data were averaged for each cell (median) to prevent skewing by high or low values that may not have represented the average for that area or that were associated with multiple equipment passes over the same cell. In contrast, yield data were run through an automated kriging procedure (Hiemstra et al., 2009) to obtain one smoothed estimate for each cell, and to fill in missing values. Each field-year was visually examined to confirm that the missing values did not follow any specific geospatial patterns (i.e. were randomly distributed), which could have otherwise biased the subsequent statistical procedures.

APPENDIX B

MODELING STATISTICAL CHOICES, PACKAGES AND SELECTION

In an ideal setting, a Bayesian approach would be used for modeling because it enables the calculation of posterior probabilities that facilitate probabilistic risk analysis, and because it can be updated on an annual basis as more data become available (Lawrence *et al.* 2015). However, even with a powerful computer (64 GB RAM) and no autocorrelative structure being estimated, each model run with 10,000 iterations required 1.5 days to run, which greatly impeded model selection with a large number of candidate models. Therefore, the top five non-linear models were selected under the Frequentist approach, and were subsequently analyzed with Bayesian methods. Model estimation was initially attempted using the pymc statistical package available in the python programming language, however a lack of convergence forced migration to the software Stan, which is accessible through R (RStan) and provides a more efficient Monte-Carlo sampler that enabled convergence (Hoffman and Gelman 2011; Stan Development Team, 2014). To provide an even more substantial aid to convergence, it was necessary to standardize the independent variables in the non-linear term. Convergence was evaluated with the R-hat statistic (Gelman and Rubin 1992), and by visually examining trace plots from the MCMC sampler.

Using frequentist statistical tools, non-linear model estimation ran significantly faster (a few minutes), however it was not possible to estimate crossed random effects simultaneously with the non-linear model using currently available statistical packages (Pinheiro *et al.* 2015). Therefore all of the non-linear model combinations were tested with either a field-specific random effect or a year-specific random effect, but not both.

In contrast, estimating crossed random effects for linear models was possible using the lme4 package in R (Bates *et al.* 2015).

To compare the non-linear Bayesian, non-linear frequentist, and linear frequentist models, k-fold cross-validation (CV) was used (James *et al.* 2013), with prediction accuracy estimated by the mean squared error (MSE) of the validation set. CV divides the observed data into a training set and test set, with the size of the test set equal to the number of observations divided by the number of folds. The training set is then used to estimate the model, and the test set is used for calculating MSE. Due to the time required for estimating the Bayesian models, only one number of folds was used (six), however for the frequentist models four through ten folds were used for calculation of the CV to ensure that the optimal models were not sensitive to the number of folds.

Bayesian models produce posterior distributions for parameters by default and Frequentist models do not. Therefore to obtain posterior distributions, the top Frequentist models were bootstrapped to obtain 'posterior' estimates of the parameters that could be used in a similar probabilistic fashion to the Bayesian posterior estimates. The primary distinction between the bootstrapped estimates and the Bayesian posterior is that the bootstrapped estimates are not proper (i.e. do not integrate to one); propriety was enforced at a later step using a kernel density estimator

APPENDIX C

MONTE-CARLO SIMULATION PROCEDURE AND MODEL SELECTION

Simulation Procedure

The steps involved were as follows:

1. Choose previous field use: wheat crop, pea crop, fallow
2. Select the EC and TWI values for one cell
3. Draw a random value from each of the posterior parameter distributions
4. Draw a random value from the historical distribution of growing season precipitation
5. Calculate $Yield_i$
6. Draw a random value from the historical distributions of wheat price and nitrogen price. Individual farms are assumed to be price takers and, therefore, prices and yields are assumed to be independent.
7. Combine the random draws with the sequence of fertilizer values (0 – 200 kg ha^{-1} in steps of 20), the fixed costs, and estimates for the previous crops' (or fallow) revenue into an estimate of net return.
8. Repeat steps three to seven 1000 times for each cell
9. Repeat for each cell and for each previous crop option

Applying the sequence of fertilizer values facilitated optimization at a later step, bypassing the need to run a net return maximization algorithm.

Top Models

The top three frequentist models and top one Bayesian model were relatively similar in terms of CV error. Acknowledging the likelihood that the best models still could be improved and that future computational advances may promote a different subset of models, it was deemed valuable to carry multiple models through the analysis to assess whether the results were invariant to parameterization.

The top frequentist models chosen were model 23 and model 8; both were non-linear. Across different numbers of folds, these top models were consistent (Figure 7.1).

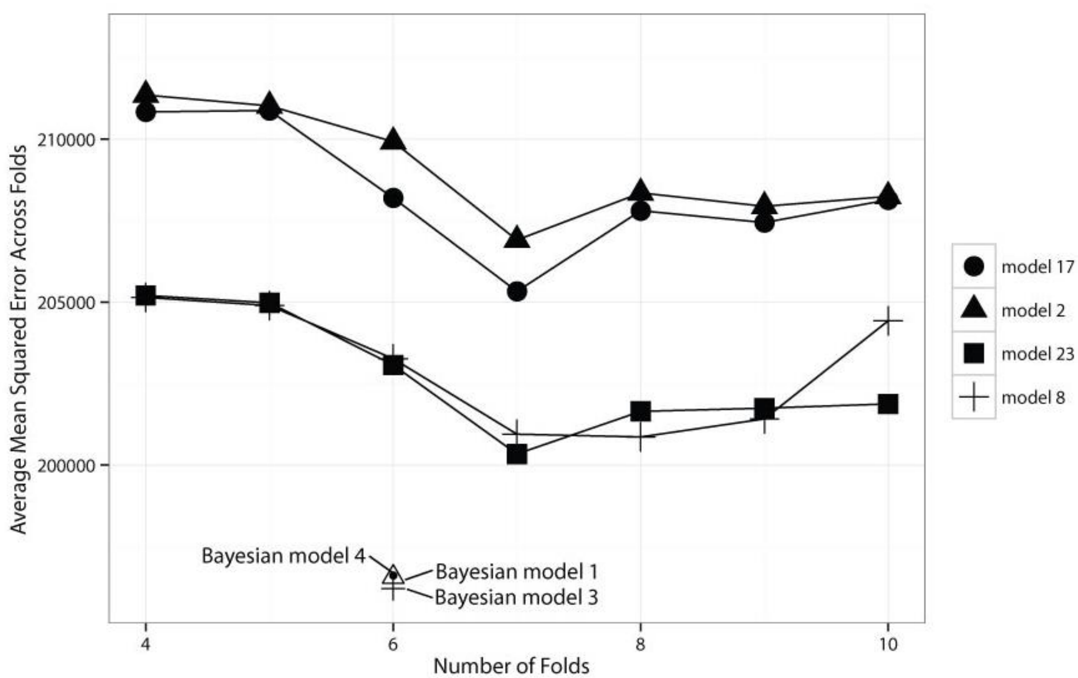

Figure 7.1. Mean squared error on the test dataset for the top four Frequentist models with four to ten-fold Cross-Validation (3/4 to 9/10 of the data used as the training dataset and ¼ to 1/10 of the data used as the test dataset), and the top Bayesian models at six folds.

The Bayesian models outperformed the frequentist models where evaluated at six folds. The practical difference between the Bayesian models was minimal, with the top model (model 3) residual error at 444 kg ha^{-1}, and the residual error for model 1 equal to 451 kg ha^{-1}. The equations for these models were as follows:

FREQUENTIST MODELS:

Model 8	$Yield_{ij} = \frac{\beta max * precip_j}{1 + \exp(-\beta_1 * QuantN_{ij} - \beta_2 * EC_{a,i})} + Fallow_{j-1} + Peas_{j-1} + year_j$
Model 23	$\frac{\beta max * precip_j}{1 + \exp(-\beta_1 * QuantN_{ij} - \beta_2 * EC_{a,i} - \beta_3 * TWI)} + Fallow_{j-1} + Peas_{j-1} + year_j$

BAYESIAN MODELS:

Model 4	$Yield_{ij} = \frac{\beta max * precip_j}{1 + \exp(-\beta_1 * QuantN_{ij} - \beta_2 * TWI_{a,i})} + Fallow_{j-1} + Peas_{j-1} + field_k + year_j$
Model 1	$Yield_{ij} = \frac{\beta max * precip_j}{1 + \exp(-\beta_1 * QuantN_{ij} - \beta_2 * EC_{a,i} - \beta_3 * TWI_i)} + Fallow_{j-1} + Peas_{j-1} + field_k + year_j$

The indicator variable for previous crop was retained in all of the top models. Within the frequentist models, the year random effect provided improved predictive ability over the field random effect. Posterior boxplots for the Bayesian models and histograms for the frequentist model parameters are shown in fig 2 - 5. Yield differences associated with using continuous wheat, wheat-pea, or wheat-fallow as rotations are displayed in Table 7.1.

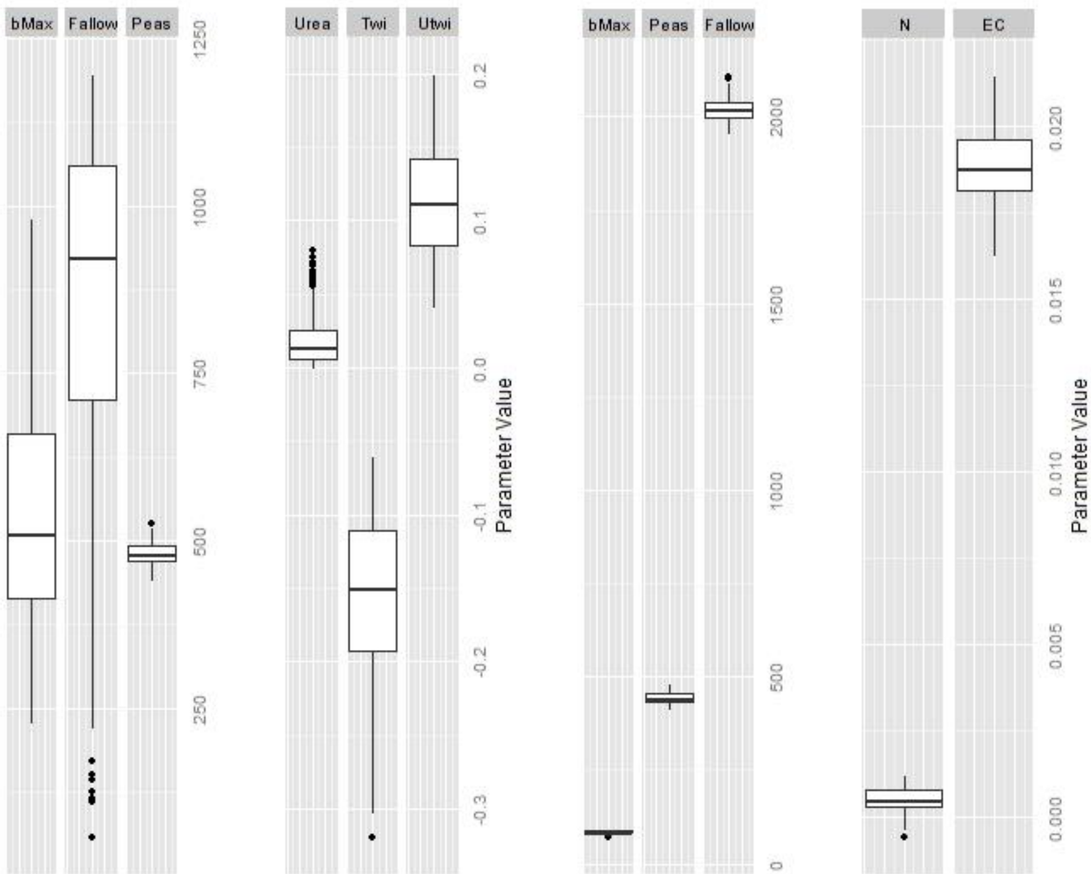

Figure 7.2. Boxplots of bootstrapped 'posterior' distributions for the parameters from model 23 (left two panels) and model 8 (right two panels).

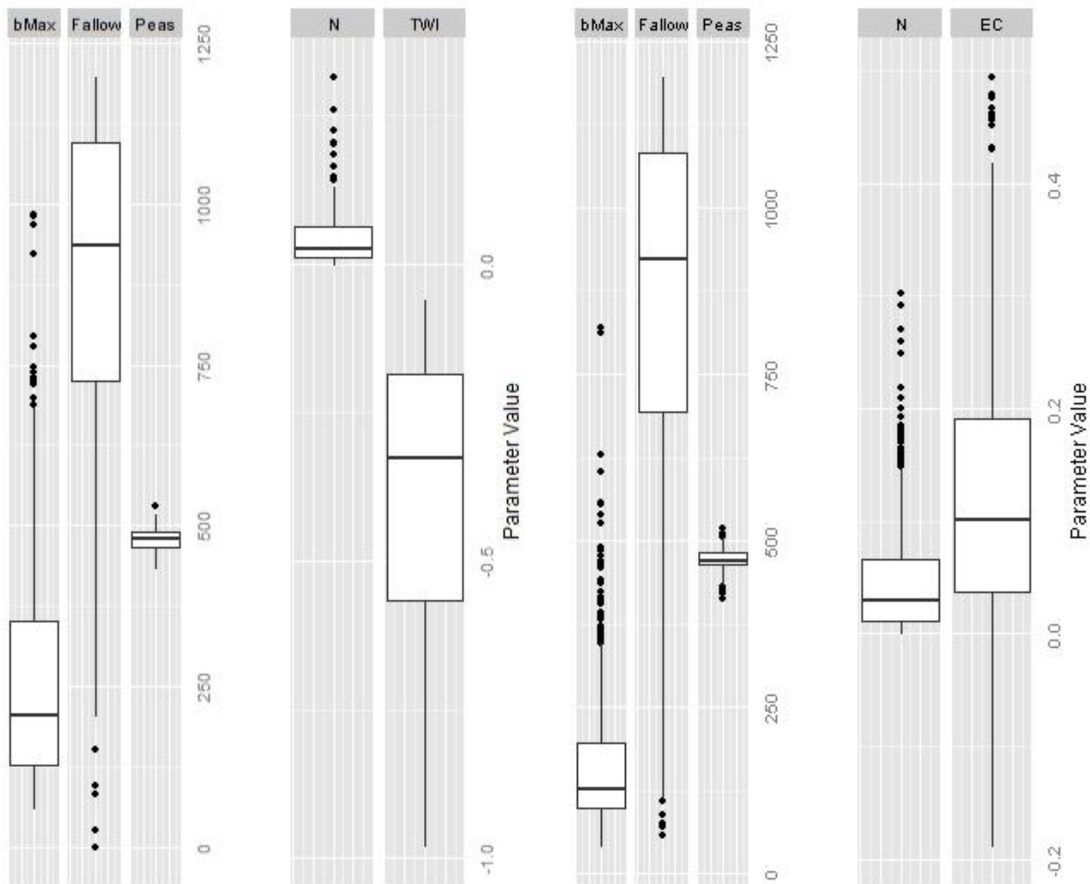

Figure 7.3. Boxplots of posterior distributions for the parameters from Bayesian model 4 (left two panels) and model 1 (right two panels).

Table 7.1. Yield increases (kg ha^{-1}) from using peas and fallow as the previous crop as compared to wheat (continuous wheat).

Model	Peas	Fallow
23	440.7	2403.5
8	443.6	2021.5
4	471.7	868.5
1	472.6	861.1

APPENDIX D

CHAPTER SIX SUPPLEMENT: REGRESSIONS AND PRICE SIMULATIONS

County-Level Regressions

Weather data were obtained from a gridded, 1/16° interpolated dataset spanning the years 1950 – 2013 (Livneh *et al.* 2013). The gridded dataset consisted of monthly total precipitation, maximum temperature, minimum temperature, and average temperature. County-level yield data for non-irrigated winter wheat were also obtained for this time span from the USDA NASS Quickstats database (USDA NASS 2015). Only counties consistently producing over 6700 MT (100,000 bushels) per year were included in the analysis, which in this case was 26 out of 56 total.

Weather data were aggregated at the same scale as the yield data by subsetting and averaging the 1/16° weather observations at the county level. Following this, the growing season precipitation (April-May-June) associated with biomass production was calculated. Additionally, the maximum and minimum temperatures were extracted for June when frosts or heat waves would likely have the largest impact on yields due to anthesis. These minimum and maximum temperatures were transformed into binary indicator variables based on temperatures dropping below zero or going above the critical threshold for impacts on anthesis, from 28 – 32 degrees Celsius.

The merged weather-yield dataset (divided into winter and spring wheat) was analyzed using multiple linear regression, with predictors of precipitation, the minimum temperature indicator, the maximum temperature indicator, year (to account for improved yields from breeding and increased herbicide/fertilizer use), county, and a county X precipitation interaction.

The maximum temperature cutoff was selected based on the lowest AIC value achieved; thus the cutoff was 29 degrees Celsius. The residuals from the regression were examined and displayed constant variance, hence no corrections for heteroscedasticity were necessary. However, corrections for serial correlation were necessary due to temporal autocorrelation in the residuals. The time series was weakly stationary, thus first-differencing was unnecessary (Dickey-Fuller statistic = -6.9, p-value=0.01). Using the Box-Jenkins Methodology (1970), an autoregressive moving-average (ARMA) model was derived, with values for p and q of 3 and 3, respectively.

All of the predictors were strongly associated with yield (in kg ha^{-1}) at the 0.05 level except for the minimum temperature indicator (Table 7.2). There was evidence that individual counties were associated with unique levels of baseline yields (winter wheat: likelihood ratio = 953 on 25 degrees of freedom, $p < 0.0001$) and that each county was uniquely responsive to precipitation (winter wheat: likelihood ratio = 74 on 25 degrees of freedom, $p < 0.0001$).

Table 7.2. Coefficients for winter wheat yield (kg ha^{-1}). County-level coefficients omitted.

Coefficient	Estimate	Std. Error	P-Value
Intercept	1021.9	147.9	-
Precipitation	2.5	0.7	< 0.001
Tmax	-793.4	148	< 0.001
Year	20.2	2.2	< 0.001

For winter wheat, each 1 mm increase in precipitation was associated with a 2.5 kg ha^{-1} increase in yields, thus each cm increase in growing season precipitation was associated with a 25 kg ha^{-1} increase in yields and the average county-level precipitation of 17.6 cm was associated with 1461 kg ha^{-1} of yield (intercept + precipitation effect) . Whenever the temperature was elevated above 29 degrees for winter wheat in June, there was a corresponding decrease of 793.4 kg ha^{-1} of yield. Finally, there was a consistent yearly increase of 20.2 kg ha^{-1} since 1950, which is presumably associated with the positive effects of breeding and increased fertilizer and herbicide application levels.

Nitrogen and Wheat Price Copula

In order to simulate realistic prices for nitrogen and wheat for the resilience analysis, it was necessary to account for the dependence between the two time series, which have a correlation coefficient of 0.65. If both prices were simulated independently, then unrealistic combinations would be sampled, such as wheat prices equal to \$0.30 kg^{-1} and nitrogen fertilizer prices equal to \$0.05 kg^{-1}. To accomplish this, a copula approach (Sklar 1959, Genest and MacKay 1986) was used to synthesize the multivariate distribution for the two time series. Both price datasets were obtained from the USDA NASS Quickstats database (USDA NASS 2015). The nitrogen price dataset was weighted by the average mix of fertilize use is Montana as calculated in Chapter 5. Both datasets were adjusted for inflation using the consumer price index (BLS CPI, “All Urban Areas”, 2015), with 1982-84 as the baseline.

Using the copula library in R (R Core Team 2015; Hofert *et al.* 2015), empirical distributions were fit to each of the time series, after which they were transformed to uniform marginal distributions. Next, normal, Gumbel, and Clayton copulas were fit to the marginal distributions using maximum likelihood. These three copula forms were compared using goodness-of-fit tests and visualization of the observed versus fitted values. Neither the normal nor Gumbel copula functional forms produced p-values less than 0.05, but the Clayton copula was strongly significant (0.002, correlation parameter $\alpha = 1.738$).

Finally, to generate values for nitrogen and wheat prices for use in the simulation, the rCopula() function was used to randomly create 10,000 values of correlated nitrogen and wheat prices. These 10,000 values were assumed to adequately represent all of the possible combinations of prices that might impact agricultural systems.

Net Return Calculation

Net returns were calculated identically to the procedure outlined in Chapter four, with two exceptions. First, because the price data were normalized to 1982-84 as the baseline year using the Consumer Price Index (CPI), fixed costs were necessarily adjusted by the CPI as well. However, net returns were later re-adjusted back to 2013 dollars for interpretability. Second, data on yield differences between rotations was not available at the county scale, thus several assumptions about productivity were made. Wheat-fallow yields were assumed to respond identically to changes in precipitation and changes in technology as wheat-pea. However, the potential negative impact of continuous cropping on yields is well known, thus yields under this rotation were adjusted downwards by 500 kg ha^{-1}, which was approximately the yield differences observed in Chapter 3.