Incorporating Risk into Climate Adaptation:
Decision Analysis for Crop Switching in a Changing Climate

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Abstract

Decision analysis informs a question common to all enterprise strategies: under changing conditions when does it make sense to change operations? Risk and decision analytic approaches would seem useful to the problem of adapting to a changing climate, and are increasingly called for by assessments of the problem. Formal decision analysis is founded on a set of economic and management principles applied to a decision-maker's realistic structure of options and outcomes under uncertainty, and can inculcate a mixed-methods approach of both prescriptive and diagnostic instruments including goals ranging from optimizing to satisficing. We test a suite of decision analysis criteria and methods, including expected utility, regret analysis, risk aversion, sensitivity analysis and the value of obtaining more information, for the case of a potential change in crops in the Northern Great Plains, where the warming climate already appears to have created opportunities for increased production via crop switching, from spring to winter wheat. Results indicate that warming climate over recent decades has brought winter wheat almost to

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parity with traditional spring wheat on average, but with larger downside risks of complete crop failure exacerbated by financial vulnerability due to lack of insurance. Even weak expectations of future insurance availability encourages switching, and the benefits of winter wheat in most years support switching and self-insuring.

Key Words: Decision analysis, climate risk, adaptation, wheat production

1 Introduction

The growing need for adaptation to climate change has brought calls for analysis of the adaptation decision process (Melillo et al. 2014), and for decision support to improve climate risk management (Moss et al. 2014); both approaches invoke, implicitly or explicitly, the methods of formal risk and decision analysis. A "risk approach" is increasingly invoked in discussions of climate change, along with a turn toward decision analysis and decision support. Risk and decision analysis were mentioned prominently in NRC's America's Climate Choices, IPCC AR5, and the third U.S. National Climate Assessment, yet these reports lacked details on how to apply risk and decision theory and methods to climate adaptation. Recent reviews lay out decision analysis approaches that can contribute theoretical and diagnostic insights to the larger project of understanding, predicting, and improving adaptation (Dow et al., 2013; Jones and Preston, 2011; Kunreuther et al., 2013). Decision analysis can improve treatment of adaption in impact studies and the conceptual foundations and tools are in place (Heal and Millner, 2014), but decision processes remain implicit in most adaptation studies. Here we explicate those methods in application to a realistic case of adaptation.

2 Decision Analysis of Climate Adaptation

Decision analysis, codified by Raiffa (1968), Howard (1988) and others, and intersected with risk analysis to improve handling of uncertainty in decisions and policies (Morgan and Henrion, 1990), provides an axiomatic yet flexible tool kit for analyzing the adaptation process. While some economists have explored decision analysis frameworks even for global climate policy (Drouet et al., 2015; Heal and Millner, 2014; Smith, 2010), decision analysis seems most "appropriate for studies at the local scale where climate predictions are the least informative…..and where location-specific policies are often needed." (Heal and Millner, 2014, p. 131). Such "decision-centered approaches" (Schneider et al. 2000; Wise et al. 2014) can complement top-down and integrated modelling with greater consideration of "individual behaviour, decision-making and adaptive learning" (Arneth et al. 2014, p. 511).

Various forms of decision analysis have been applied to climate change, including expected utility (Kunreuther et al), decision-scaling, a form of sensitivity analysis (Brown et al., 2012), , robust decision-making (Lempert and Groves, 2010). In contrast to general equilibrium econometric studies also applied to agricultural responses to climate change (Antle et al., 2004), decision analysis tends to focus on the decision agent (Schneider et al., 2000), and thus is not generalizable to equilibrium outcomes across an industry sector or region. An important capability of decision analysis is to make transparent and available to the decision-maker the role of singular events and extremes, and to illustrate the difference between expected value outcomes based on mean vs. extremes; this allows both the decision-maker and the decision modeler to include the effect of extremes/singular events or not, based on the decision structure and the decision-maker's risk and regret functions.

Decision analysis can enhance attention to risk and risk-taking behavior, making it useful at this stage of climate change analysis. The importance of stochastic variability, and extremes, in adaptation studies, projections, and, in theory, in adaptation itself (Sexton and Harris, 2015), is being more recognized as the literature [methodology, approach, epistemology] shifts toward a risk framework, as described earlier. This is important in this study because we wish to test the effect of occasional complete crop loss, that is discreet loss events whose probability is changing over time. Time-transgressive studies are especially needed to allow for slow change and learning by the adaptive agents, and some decision tools, especially those taught in business schools like risk registers and options analysis (Clemen and Reilly, 2013), deal explicitly with changing conditions and decisions over time, as we do in this study.

Here we apply decision analysis to farmer adaptation behavior, with focus on the role of risk and risk aversion in crop choices. The question is: When does it make sense to switch production systems as their relative advantages and risks change with changing climate? It is important to note that in decision analysis the notion of a choice that "makes sense" is defined as part of the decision structure, and may be based on criteria that range from maximizing, to optimizing, to satisficing. We pursue this in a case where climate change appears to be creating opportunities for increased production via crop switching, from spring to winter wheat, in the northern Great Plains.

3 Adaptation in Agricultural Studies

A large literature explores adaptation, innovation, technology adoption, and risk management in agriculture, and these instruments have been directed to climate impacts and adaptation in agriculture for decades (Kaiser et al., 1993). Climate adaptation can be incorporated into agricultural studies as incremental adjustments in crop management (Antle et al. 2004; Easterling et al. 2003; Porter et al. 2014), and crop models can be used with various production choices (e.g., planting date) to evaluate whether adaptation can compensate for climate-induced yield reductions. A recent meta-analysis of cereal crop adaptation studies for the IPCC's fifth assessment (Porter et al. 2014) showed that incremental adaptations such as changes in planting dates could increase yields 15-18% above the climate-decremented trend (see also: Challinor et al. 2014). But the assessment also noted that more fundamental changes, like type of crop or expansion into regions previously too cold, were not readily included in crop models.

Efforts are increasing to simulate adaptation in Crop impact studies, like the Agricultural Model Intercomparison and Improvement Project (Rosenzweig et al. 2013), are putting more effort into simulating adaptation (Challinor et al. 2014; Rotter 2014).

Howden et al. (2007) argued that "practices at the management unit level will be a key component in adapting agriculture to climate change," echoing the agent-centered approaches by Schneider et al. (2000). It is also in farmer choices that risks are clearly manifest, and a large, decades-deep literature addresses risk in farmer decision-making (Great Plains Council 1955; Just 2003), its role in innovation (Marra et al. 2003), and the *prima facie* salience of risk management in farmer response to climate change. Decision analysis lends itself to analyzing farm level adaptation (Just 2003; United States Department of Agriculture 2012) and the effect of extreme events on decisions (Antón et al. 2013; Travis and Huisenga 2013). Other approaches to simulating farmer choices, including innovation adoption cohorts (Ruttan, xxxx; Chhetri et al. 2010), represenattive agricultural pathways (Antle et al. 2014), and the growing stable of risk modeling tools (Hoag 2010; see also http://www.rightrisk.org/), can be applied for both research and decision-support.

We draw on these approaches, applying farm-level risk and decision analysis to crop switching adaptation.

4 Crop switching in the northern Great Plains

Limited empirical data, and farmer and extension agent testimonies, suggest that winter wheat is making inroads into the long-standing dominance of spring wheat in North Dakota, especially over the last 20 years (Knutson 2011; Swenson 2006a). This may be the early stages of adaptation to a warming climate in the northern Great Plains, as suggested by Porter et al. (2014) and in media stories (Ydstie 2014).

Adaptation in this case takes advantage of conditions that create opportunities for higher pay-off crops. The switch from spring to winter wheat offers several benefits, but also entails residual risk of total crop loss due to winterkill. Winterkill risk has traditionally been so large that winter wheat was rarely grown, and is not eligible for crop insurance, in North Dakota. So this analysis addresses the changing advantages of cropping systems in which residual climate risk adheres to an increasingly attractive alternative.

4.1 Production patterns

The general pattern of Great Plains wheat production was established over a century ago. Farmers chose winter wheat (sown in the fall, dormant over the winter, and maturing in early summer) in the southern and central Plains because it could be harvested before the hottest part of the summer (Malin 1944). Colder winters further north did not support the over-wintering crop, and spring wheat (sown in spring and harvested in late-summer or early fall), came to dominate the northern Great Plains. Spring wheat is susceptible to occasional drought and mid-summer heat, delayed or prevented planting due to wet spring conditions, and some risk of loss to early frosts, but it evades winterkill.

4.2 Winter wheat expansion

Winter wheat in this setting mostly avoids drought and heat hazards. The crop is already in the fields during spring, taking advantage of early moisture and warmth, and is harvested before peak summer heat. The net effect of winter wheat's phenology is 20% or more yield over spring wheat (Alberta Wheat Commission 2013). By tracking the few farmers who grow at least some winter wheat, Swenson (2006a) finds that the crop provides up to 30% more yield and 10% better net economic returns in some districts, rough values also supported by the representative crop production budgets on which we based the simulations below. Swenson (2006b) noted that winter wheat abandonment was declining, especially since the mid-1990s, to around 20% through 2005, and that more farmers are growing at least some winter wheat.

This crop trend may be associated with the region's warming trend over the last half-century (Romero-Lankao et al., 2014); the northern Plains having especially warmed, in all seasons, over the past three decades (Ballard et al. 2014; Walsh et al. 2014). The instrumental record shows winter warming for North Dakota's central climate division (Fig. 1), the focus of this study. The warming has been noted by farmers (Ydstie 2014), documented in plant flowering phenology (Dunnell and Travers, 2011) and wildlife studies (Ballard et al. 2014), and shows up in some agronomic studies (Hu et al. 2005). Ballard et al. (2014) noted the "post-1980s winter warming" as the "most striking" trend in the region's climate over the past century.

Warming has not obviated the chance of extremely cold winters (Fig. 1), and the limited data available on winterkill suggest occasional extensive winter loss, with widespread crop abandonment in the coldest winters shown in Fig. 1, as evident in this agricultural news report from spring, 2014:

> "Winterkill in this area is severe!" reports a farmer from Ward County, N.D. "I have never seen such a large complete loss due to winterkill before. Winterkill is around 100% damage in all fields in this area. Stubble cover and maturity of the plants did not make a difference." (Shafer, 2014)

The northern Great Plains experienced an extremely cold winter in 2013-14 (Fig. 1), indicating that crop-damaging cold spells can be part of even a warming climate, and must be factored into adaptation choices.

Thus, the crux challenge for winter wheat in the north is potential winterkill from freeze damage (Cox et al. 1986; Fowler 2012; Graybosch and Peterson 2010; Skinner and Bellinger 2010). Little research is available that dis-entangles the effects of cultivar hardiness, management, and weather and climate in the spread of winter wheat, and winter loss is a complex phenomenon affected by diurnal and seasonal temperatures, snow cover, wind, crop residue, and soil moisture (Alberta Wheat Commission 2013; Cox et al. 1986; Skinner and Bellinger, 2010). Laboratory studies indicate that temporary warmth followed by cold late in the winter is especially damaging, but plants exposed to a freeze-thaw cycle early in the winter can better tolerate subsequent freezing (Skinner and Bellinger 2010).

Such technical uncertainties notwithstanding, the advantages of winter wheat, along with a warming climate, appear to be enticing more North Dakota farmers to switch (Swenson 2006a). The capital investment in switching is small, so the key decision factors are comparative returns and uncertainty about future yields. Also important to many farmers is that crop insurance is unavailable for winter wheat in North Dakota, reflecting the past threat of winterkill.

5 Modeling the decision to switch crops

Our main approach to climate adaptation modeling is to adopt and modify extant, in-use decision tools, and to simulate them over time with scenarios of climate change and, in this case, the potential for extremes that cause total loss, while applying alternative decision criteria. The extant decision tools applied here are farm budget spreadsheets developed by university extension economists for farmers in the region (Swenson and Haugen 2013), and the risk assessment and management templates provided to producers in the region by a consortium of agricultural researchers and advisors through the "Risk Navigator" ( ) and "AgSurvivor" ( ) programs, and documented in Hoag (2xxx). We implemented a suite of expected utility decision models for North Dakota wheat production using *@Risk*, a business risk and decision analysis software (see: http://www.palisade.com/) that maintains a spreadsheet frontend that will be familiar to most producers while allowing for more sophisticated simulation analysis. The models are available from the corresponding author and an archival website (http://wwa.colorado.edu/resources/tools/decision_models/index.html), and detailed in the Electronic Supplementary Material. Here we briefly describe model development and key simulation parameters.

5.1 Decision structuring

A standard first step of decision analysis is decision-structuring: defining the choices, uncertainties, and outcomes for a given decision problem. Farmers make short-term, often repetitive, as well as long-term decisions, affected by the environment, technology, markets, policy, and personal preferences. Minor adjustments in production and marketing account for many of the decisions, while choices like what crop to plant are made more rarely. The switch from spring to winter wheat, while not transformative, does require change in seasonal allocation of labor, production costs, and marketing, and subjects the farmer to new production and financial risks.

The model simulates the crop switch decision as a choice between expected value of crops:

$$EV = (yield * price) - production\ cost \tag{1}$$

Detailed annual farm budget spreadsheets (Supplementary Table 1) developed by North Dakota State University (NDSU) extension service (see: http://www.ag.ndsu.edu/farmmanagement/crop-budget-archive; Swenson and Haugen 2013) are applied to a typical 2,000 acre dryland wheat farm in North Dakota's south central district, as in a previous study (Travis and Huisenga 2013) and similar to a farm analyzed in Hoag (2010). We follow the practice of farm finance analysts (Hoag 2010; Swenson and Haugen 2013) and modify the farm budgets in order to focus on the crop enterprise, omitting indirect costs, like land rent and machinery debt servicing, to calculate a net return to operating costs, mainly inputs like seed and fertilizer. Most farm income comes from crop production, and maximizing return from the crop enterprise remains the main strategy for farming success (Hoag 2010; Swenson 2010; Taylor et al. 2011), making it a logical target for expected value decision analysis.

As with the crop cost or risk calculators that farmers use, we apply statistical distributions to yield and price. Crop yields in the model are a skewed distribution based on 2003-2013 data for the South Central district. Prices, which are notoriously difficult to predict and range widely for a variety of reasons, are set at 2014 values or treated as a uniform distribution bounded by the lowest and highest prices in the 2006-2014 series of NDSU crop budgets (Supplementary Table 1).

Crop switching represents a move from one crop budget and yield distribution to another. In the base runs we hold production parameters at 2014 levels and vary the rate of winterkill and availability of insurance for winter wheat in 5,000 Monte Carlo simulations to compare EV of spring and winter wheat. Next we developed 30-year "Representative Agricultural Pathways" (RAPs) similar to the approach applied in AgMIP (Antle et al. 2014). Returns vary over these time series as yields, insurance costs, and the probability of crop loss change. For the base run we decremented winter-kill probability from .3 to .05 (to match the spring wheat loss rate) assuming that warming continues linearly over the 30 years, and imputed an insurance instrument in the simulations after different thresholds of loss rate were reached (e.g., .2 or .1, which occur roughly 8 and 16 years into the simulation, respectively). We plot annual net crop income as well as calculate a net present value (NPV) of future years as:

$$NPV = \sum_{i=0}^{n} \frac{x_i}{(1+r)i} \tag{2}$$

The discount rate r is set at 3%. To create a time series of NPVs, n is reset each year to the remaining annual steps, making each year the start of a shorter planning horizon that eventually reduces to zero years. This is akin to the risk-adjusted NPV (rNPV) used in financial analysis, and is especially useful in climate impact studies because the crop loss risk is explicitly calculated, not assumed to be reflected in the discount rate. A time series of NPVs allows comparison among different NPV trajectories, for example with or without insurance becoming available at some time in the simulation.

With these three approaches (base, annual EV, and NPV) we simulate a farmer making choices on recent outcomes, as well as a forward-looking farmer weighing a stream of expected returns as described in Hoag et al. (2010). The main questions are whether the farmer should switch crops given the difference, when would this occur, and how do different levels of risk tolerance and risk transference affect the decision. The simplest decision criterion trips the crop switch when EV from winter wheat exceeds spring wheat, as with Trade-Off Analysis (TOA) applied to farmer choices by Antle et al. (2014). The switch makes increasing sense as the differential, or opportunity cost, between the adaptive (switching) and non-adaptive (non-switching) farm increases (Antle et al., 2014; see also Travis and Huisenga, 2013).

The continued (though slowly reducing) likelihood of extremely cold winter conditions makes the crop switch decision risky, as does the lack of insurance for winter wheat. Agricultural extension reports from North Dakota (Swenson, 2006a; Swenson, 2006b) estimate that winter wheat abandonment has varied around 18% in recent years. Rather than simply comparing the average efficiency of cropping systems, farmers considering the switch to winter wheat know that they are taking on the risk of total crop loss due to winterkill, a risk not present in the traditional spring wheat system. The model simulates total crop loss via a "risk register" (Donnelly et al., 2012) that inserts a bivariate distribution of zero yield into the production simulation at a given probability, illustrated in Supplementary Fig. 1. If winter wheat is becoming less subject to total loss, the crop budgets indicate that its production and cost benefits will eventually surpass spring wheat and make switching worthwhile. Improving performance might eventually warrant insurance coverage for winter wheat, and thus the RAPs include an emergent hypothetical insurance instrument. The opportunity cost at which the switch occurs is sensitive to the difference between mean conditions and the rate of crop failure, thus invoking also the decision-maker's risk tolerance.

5.2 Risk tolerance

Decision modeling at the farm scale offers the potential to reflect farmers' tolerance for risk, also known as risk aversion (Holt and Laury, 2002; Pratt, 1964). In decision analysis, risk aversion is assessed by translating monetary values into utilities via a function whose shape reflects the risk-reward relationship. Choice of risk tolerance parameters remains something of an art, approached in different styles: laboratory and field elicitation (Holt and Laury, 2002) and rule-of-thumb approximations from analysis of past decisions (Howard, 1988; Pratt, 1964).

We implement risk aversion in the model, both to make the decision point more realistic and to estimate a hypothetical winter wheat crop insurance premium, via the mixed methods approach taken in the agricultural risk literature (Hoag and Keske, 2010). From the literature we know that the risk utility function will be at least slightly concave (e.g., risk-averse rather than risk-seeking), but modern production systems like those simulated here tend to exhibit only mild risk aversion, especially in the context of subsidized crop insurance (Parsons and Hoag, 2010). Our goal in specifying risk aversion in the simulation is to estimate an efficient premium for winter wheat insurance that might emerge in the future. We do this by translating EV of winter wheat production into utilities (as described by Clemen and Reilly 2013, 637-657):

$$U(x) = 1 - e^{-x/R} \tag{3}$$

x is the expected value of net crop income
e is the constant 2.71828 (base of the natural logarithm)
R is the risk tolerance, and sets the concavity of the utility curve.

We estimate *R* by the Pratt Approximation (Pratt, 1964), roughly 1.25 times net income, and by the risk tolerance elicited for a 2,000 acre dryland wheat farm analyzed in Hoag and Keske

(2010). R is in dollars, and defines the certainty equivalent (CE), the value of the enterprise minus risk, which allows calculation of a risk premium:

$$RP = EVr - CE \tag{4}$$

EVr is the expected value with risk, and RP is the amount the farmer is willing to pay to eliminate the risk for a given risk aversion, thus it is equivalent to an efficient insurance premium.

4.3 Crop insurance module

Availability and structure of insurance is an important element of crop choices among farmers (Antón et al., 2013). Yield and revenue insurance is widely used in the U.S., especially for dryland crops, but winter wheat insurance is not available in North Dakota (Diersen, 2012; Swenson, 2006a). Presumably, if winter wheat expands as the climate warms, then a winter wheat-specific insurance program will be fashioned by the USDA's Risk Management Agency, since its goal is to provide insurance where actuarially feasible (see: http://www.rma.usda.gov/help/faq/basics.html). Thus, a realistic RAP must allow for an insurance instrument to emerge.

Our hypothetical insurance policy is structured along the lines of "Yield Protection" policies offered in South Dakota, where more winter wheat is grown and insured (Diersen, 2012); it is described in detail in the supplementary material. We cannot know what risk-priced winter wheat insurance would cost in North Dakota's climate future, so we estimated premium prices first as multiples (up to 3) of the spring wheat premium to reflect the difference in risk, and next by a premium calculated via the econometric method based on risk aversion, as described above.

6 Results

Results include simulations comparing spring and winter wheat outcomes based on 2014 production budgets for different rates of winterkill, 30-year simulations to test the pace of adaptation, and sensitivity runs to test insurance instruments and the role of risk aversion in adaptation decisions.

6.1 Base runs

Winter wheat abandonment has ranged from roughly 10 to 30%, two to six times larger than spring wheat. So winterkill is simulated via the risk register to force total crop loss into the simulations based on a bivariate sampling between .3 and .1 probability of zero yield, with spring wheat's catastrophic loss set at its recent rate of .05. Winter wheat in the initial runs is produced without insurance protection such that if the risk register calls for complete loss then no yield and no income accrue.

6.2 With and without winter wheat insurance

Base runs, using 2014 NDSU crop budgets and the yield distributions as specified above and in the supplementary material, are shown in Fig. 2. Results for spring wheat and three rates of winter wheat failure with and without hypothetical insurance (Fig. 2a), show that winter wheat outcomes range widely compared to spring wheat, due to higher probability of complete crop loss and lack of insurance. A 30% chance of winterkill without insurance creates a large downside risk that comports with the historical fact that winter wheat was rarely grown in North Dakota. Winter wheat very slightly out-performing spring wheat only at low (e.g., .1 to .2) probabilities of winterkill and only if insurance were available. In only about 40% of the time could winter wheat under these conditions be expected to equal or exceed the returns of spring wheat (Fig. 2b). Winter wheat with only a .1 probability of winterkill out-performs spring wheat

70% of the time, and offers almost a 35% chance of netting over $200K, while spring wheat might net $200K only 20% of the time.

A less risk-averse farmer might try winter wheat at .1 probability of winterkill even without insurance to enjoy the higher mean and maximum outcomes (half of the crops ought to outperform spring wheat), while bearing the lower tail in which perhaps 1-in-5 crops would result in a negative crop income.

A crop insurance scheme is likely to emerge if winter wheat becomes more viable. We simulate insurance that covers 75% of expected revenue if the winter wheat is abandoned, at various probabilities of winterkill and premiums that are multiples of the spring wheat premium. The right-hand plots in Fig 2a show results for the 2014 base budget with this insurance costing 1.5 times the spring wheat premium. Insurance truncates large losses, but also slightly depresses the top income because the premium increases operating costs. Under these conditions winter wheat provides similar or slightly better returns than spring wheat at .2 and .1 winterkill probabilities. Somewhere between .2 and .1 probability of winterkill, winter wheat and spring wheat produce similar net return prospects, supporting the suggestion by Swenson and others that winter wheat might perform better than spring wheat right now, at just under 20% abandonment rates.

6.3 What price for insurance?

Risk aversion analysis (Table 1) points to an efficient premium price for spring and winter wheat insurance. Spring wheat at its recent .05 probability of crop loss requires a risk premium (calculated by equations 3 and 4) of $16.89, close to the actual $15.40 cost of an all-peril policy in 2014. An equivalent policy for winter wheat, were one available, should cost $32.30 at .3 probability of winterkill, and $10.21 at .2 winterkill probability. If the rate of winterkill were to decrease further, the risk premium becomes negative, meaning the farmer should not be willing to pay anything for insurance, and could efficiently self-insure.

6.4 Sensitivity analysis

Sensitivity analysis, variously termed stress testing, bottom-up analysis, or decision scaling, can reveal the effect of different choices in decision analysis (Morgan and Henrion, 1990, chapter 8). Standard sensitivity analysis of the base runs gives expected results: returns are most sensitive to prices, which vary widely, and to yields. The decision scaling method described by Brown et al. (2012), reveals the relationship between the yield benefit from winter wheat compared to spring wheat (Fig 3a), and tolerance for cost of hypothetical winter wheat insurance (Fig 3b). Across the range of winterkill probabilities, the winter-to-spring wheat yield ratio need only reside around 1.2 to allow winter wheat to statistically dominate spring wheat in expected value even at .3 likelihood of winterkill. At the current yield premium, winter wheat producers should be willing to pay a premium for insurance coverage up to 2 times the spring wheat cost (Fig 3b), keeping in mind that insurance is only about 10% of production costs. This sensitivity analysis also suggests that the winter wheat production frontier is theoretically quite close to, and perhaps already overlaps with, spring wheat in North Dakota, suggesting why recent warming has apparently elicited increasing winter wheat production (Swenson, 2006b).

6.5 Value of adaptation as climate changes

The final set of model runs simulate a 30-year RAP in which the probability of winterkill starts at .3 and declines due to climate warming to roughly the rate of spring wheat, and in which crop insurance emerges at different loss probabilities and with different premium rates. The first RAP simulations (Fig. 4a) look for the point where winter wheat begins to offer better net return than spring wheat based on insurance scenarios. The RAP starts with a .3 probability of winterkill and insurance that emerges when the probability declines to .2, at a premium that is 1.5 times the spring wheat cost, a value that comports with the risk tolerance found above. Insurance offered at .2 probability of failure, even with premium rates 1.5 times current spring wheat rates, would advance the switch almost a decade. Insurance that emerges only when winter wheat risk declines to something close to spring wheat (.1 to .05) has little effect on crop switching, and farmers would benefit from the switch even without insurance.

When might a forward-looking farmer, observing successful experimentation with winter wheat but also recent set-backs like the 2014 crop loss, decide it is worth switching? Assuming that the relative advantages of production and price continue, the key factors in this decision are expected rates of crop loss and the potential emergence of winter wheat insurance. A forward-looking decision-maker would key on the net present value (NPV) of a choice, so we plot NPVs (at a 3% discount rate) for different RAPs (Fig 4b). Spring wheat exhibits the largest NPV at the start of all scenarios (first pointer in Fig 4b), given the .3 probability of winter wheat loss, but winter wheat NPV begins to exceed spring wheat in about 5 years (second pointer in Fig 4b) if insurance is offered at a .2 loss rate, and in about 12 years if insurance emerges at a .1 probability of winterkill. Farmers might ride these waves of improved NPV as they move through time, switching crops when winter wheat starts to dominate the NPV curve.

7 Conclusions

Warming climate in the Northern Great Plains has brought winter wheat almost to parity with more traditional spring wheat, but farmers making the switch face residual risks of occasional winter kill and financial vulnerability due to lack of insurance. A slight further reduction in winter kill risk, and insurance priced even at 1.5 times the spring wheat premium, would make winter wheat an attractive adaptation in the warming climate.

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Crop	Prob. of loss	Risk premium
Spring wheat	.05	$16.89
Winter wheat	.3	$32.30
Winter wheat	.2	$10.21
Winter wheat	.1	$-36.32

Table 1 Risk premiums for spring and winter wheat calculated for a moderately risk-averse farmer. Current spring wheat insurance in the study area costs about $15.00. Winter wheat at .1 probability of failure performs so well that the farmer is better off without paying for insurance.

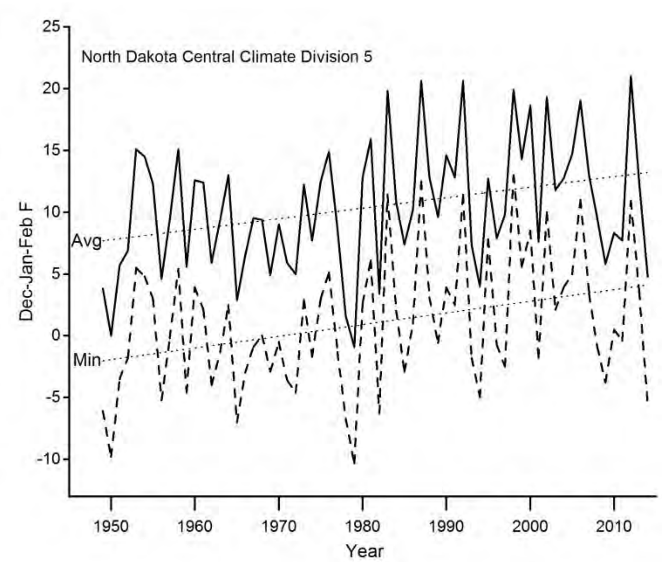
Figure Captions

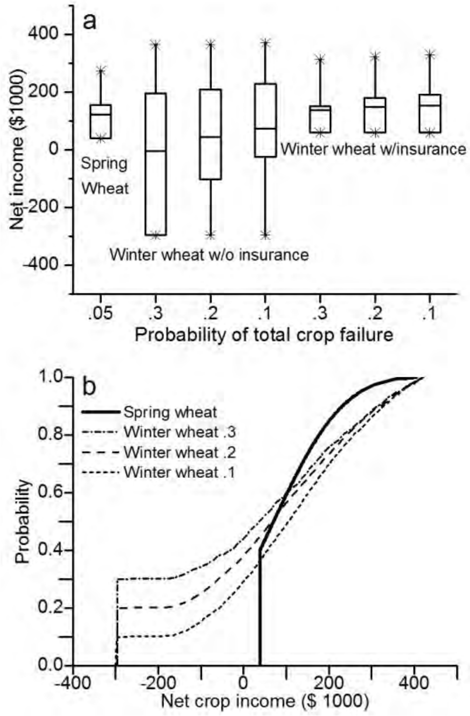
Fig. 1 Average temperatures and average monthly minima, December-January-February, North Dakota central climate division. From NOAA's National Climate Data Center at: http://www.ncdc.noaa.gov/cag/time-series/us

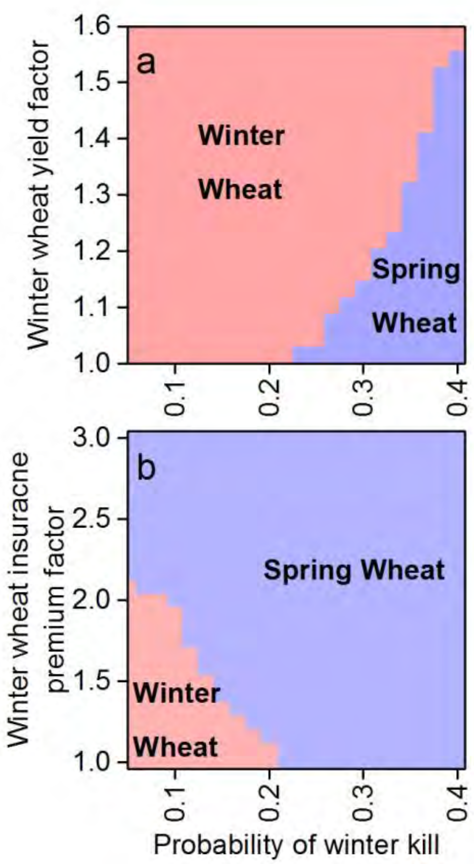
Fig. 2 (a) Cumulative distributions of net crop income for a simulated 2,000 acre dryland farm, south central crop district of North Dakota, 2014 crop budgets: winter wheat (WW) at .3, .2 and .1 probability of total crop failure (without insurance) compared to spring wheat (all spring wheat simulations include insurance and .05 probability of crop loss). (b) Distribution of spring wheat and winter wheat at .3, .2, .1 and .05 probability of total crop failure, without and with crop insurance. Boxes are 25th to 75th percentiles, whiskers extend to 1% and 99% percentiles, central line is the mean.

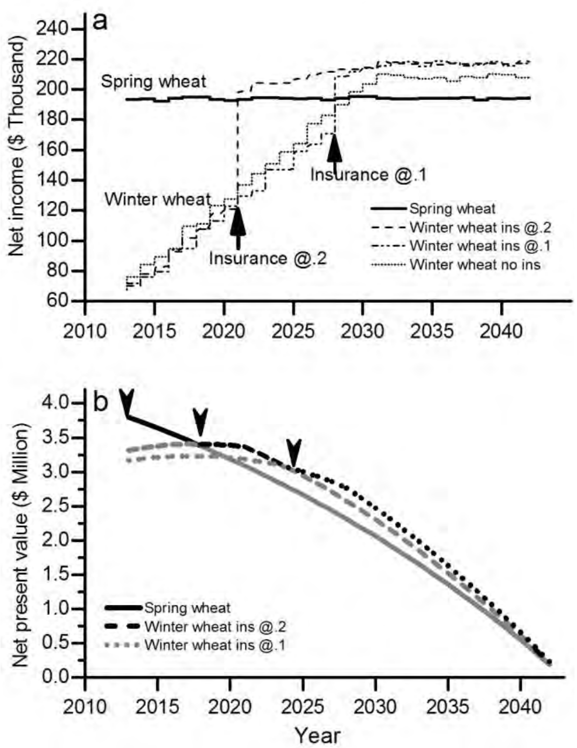
Fig 3 Strategy regions where either winter or spring wheat stochastically dominate the optimal choice based on expected value: (a) the yield improvement that winter wheat must show over spring wheat to dominate the optimal choice at different rates of winter wheat failure, and (b) where winter wheat is a good choice based on its additional insurance premium cost (from 1 to 3 times the rate for spring wheat).

Fig. 4 Simulated time series of (a) net income and (b) net present value for spring vs. winter wheat at different rates of changing winter wheat failure and with winter wheat insurance emerging at different times.




a
Net income ($1000)
Spring
Wheat
Winter wheat w/insurance
Winter wheat w/o insurance
Probability of total crop failure
b
Spring wheat
Winter wheat .3
Winter wheat .2
Winter wheat .1
Probability
Net crop income ($ 1000)


a
Winter wheat yield factor
Winter
Wheat
Spring
Wheat
b
Winter wheat insuracne
premium factor
Spring Wheat
Winter
Wheat
Probability of winter kill



a
Net income ($ Thousand)
240
220
200
180
160
140
120
100
80
60
Spring wheat
Winter wheat
Insurance @.1
Insurance @.2
Spring wheat
Winter wheat ins @.2
Winter wheat ins @.1
Winter wheat no ins
2010
2015
2020
2025
2030
2035
2040
b
Net present value ($ Million)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Spring wheat
Winter wheat ins @.2
Winter wheat ins @.1
2010
2015
2020
2025
2030
2035
2040
Year