Crop Selection in Permanent No-till in Northwest Kansas of the High Plains
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Background

This paper is structured somewhat differently than most in that background and research results are presented first, followed by a more detailed description of underlying research in a lengthy appendix. This should allow the reader to immediately see results. Yet, sufficient detail is provided later to allow other researchers to assess the research, other critical thinkers to react with additional questions, and future work to easily build upon this effort. In order to get this project started, in this first draft, many of the required assumptions have not yet benefitted from a thorough consensus-forming assessment of the co-authors. But, since the framework is now in place, that can come with future drafts. So, as with all simulation work, readers should bring a critical eye to our work reported here.

In the last couple of decades many non-irrigated farms in western Kansas have changed from a wheat-fallow rotation to a rotation involving wheat, followed by grain sorghum (milo) or corn, followed by fallow. Typically, in this rotation, the fallow period preceding wheat involves tillage, whereas the fallow period ahead of corn or milo involves no-till. In the last few years, more and more farms in the area appear to be adopting no-till for their entire system, that is, ahead of wheat as well as ahead of row crops. Additionally, these managers who rely on permanent no-till are considering other crops besides wheat, milo, and corn, and whether to increase cropping intensity beyond two crops in three years. Moreover, they are wondering whether a fixed or opportunistic crop rotation should be used, where an opportunistic system allows crop selection dynamically based on some measure of soil water. Finally, both expected profit and expected risk (variation in annual profit over years) are important considerations for managers hoping to improve their management of permanent no-till in western Kansas.

Traditionally, agronomic research is based on controlled experiments across multiple years. But, cropping systems are difficult to study in this framework because there are numerous combinations of tillage method, crop, and crop sequence that might be considered. Moreover, weather can greatly impact the findings, so that a study must be ongoing across many years in order to reach reliable inferences about the future. Such studies are further complicated by the fact that more than one year's weather might impact a crop yield due to long fallow periods and soil water. Finally, there might be effects that trend across time, especially related to no-till. Despite the associated difficulties, useful tillage studies have occurred in the High Plains. For example, Alan Schlegel conducts a long-term (starting in 1991) study of tillage systems (conventional, reduced, and no-till) in a wheat-milo-fallow rotation near Tribune Kansas.

Because directly relevant information is scarce, farm managers wish to extract as much decision-making information as considered appropriate from agronomic studies. How far can a study's results be extrapolated geographically? Can inferences be made about other crops than those studied? Yet, both researchers and farm managers alike are quite familiar with a research study's limitations, especially those related to weather. For example, because of weather at the time in the High Plains, studies in the late 1990s often explicitly or implicitly recommended increased cropping intensity and more corn in lieu of milo, whereas studies in the drier 2000s regularly point to longer fallow periods and perhaps a retrenchment in the wheat direction. So, farm managers would like to extend research findings across time as well as space. After all, business decisions always are made looking to the future.

The more a researcher or decision maker wishes to extend research findings across crops, space, and time, the less likely it is that the results of some particular study are directly useful. Rather, computer-based crop yield simulation models are considered. But, such simulation models also have limitations. First, formalized simulation models from agronomy often are cumbersome to use due to their requiring numerous data, for example, daily or weekly weather and crop growth information. Others depend on minimal information so as to have broad reach across crops, time, and space, but are so simplified that they miss important yield-driving features. In each case, it is not uncommon for a user's reaction to be, "that's great but I don't believe the results." Such reactions point to the fact that all simulation models generally need considerable calibration so that they provide acceptable results. Yet, such calibration, if performed at too fine of a scale, brings the added risk that a model merely will give back results consistent with a user's preconception, with no learning actually taking place.

This research constructs a simple crop yield simulation modeling framework based on the following information (details in the appendix): a) yield and soil water information from Schlegel's tillage study, b) long term observed or estimated weather information, c) farmer understanding of corn/milo yield relationships, and d) researcher understanding of inferential mathematical model construction. We posit the following. Available soil water (ASW) at planting is a mathematical function of ASW at the previous harvest, along with rainfall and water loss during the time interval. Wheat and milo yields are a function of ASW at planting, along with rainfall and water loss during the growing period. ASW at harvest is a function of the same variables, plus harvest yield. So that we can extend our simulations to corn, we assume that expected corn yield can be derived from expected milo yield. We deal with the issue of model calibration in two ways. First, we attempt to keep calibration somewhat coarse, not trying to zero in on actual observations so that it appears that the model will simulate with no error. Secondly, we carefully document our calibration assumptions, in order to increase the probability that other researchers would reach similar conclusions, thereby diminishing the amount of intuition-based preconception bias we otherwise might inject into our models.

A couple of points about ASW are worth mention. First, the typical silt loam soils considered for the western Kansas locations examined generally have the ability to store about 2 inches of available water per foot of soil, thus 12 inches of ASW in a 0-6 foot profile. Available water is that amount that can be practically taken up by crops. Saturation levels of water in the soil are much more, perhaps double the 2 inches per foot of available soil water. Second, Schlegel used suitable procedures to actually measure available soil water in the profile. This likely results in measures considerably different than soil water approximated using a standard 6-foot ball rod, a method commonly used by farmers and crop consultants in the area. For example, it is not known whether being able to push the ball rod down 6 feet equates to 12 inches of ASW or something more or less than 12. So, if a manager desires to use ASW to guide crop selection in the manner considered here for one of our crop rotations studied, it might be more appropriate (for model consistency) to use weather data in the area to predict the ASW used in crop selection.

In this research we seek answers to questions about crop yields and profits across different crop rotations, and across 3 Kansas locations, Tribune (Greeley County), Colby (Thomas County), and Atwood (Rawlins County). Naturally, we hope that our findings have value outside of these 3 locations, but we leave that up to the reader to judge. Besides considering various fixed crop rotations, we also consider dynamic decisions, where crop selection is based on ASW at planting. The goal of this research is to provide more information to permanent no-till dryland crop producers in western Kansas regarding crop selection and rotation. We recognize that it does not substitute for actual long-term observations of crop yields in different systems. But, it should provide better insight into crop planning than simple experienced-based intuition alone, which is about the only alternative.

Fundamentally, this research considers crop yield to be a function of water. Essentially, water that falls as precipitation, but which does not disappear into the air or below the rooting zone or run off the field, is viewed as either enhancing crop yield or increasing the reserve of ASW in the soil. Weather determines rainfall and water loss. Since one of our objectives is to make inferences from a broad range of possible weather, we considered observed and estimated weather data over the 1932-2005 time period.

Crop rotations considered

Below are listed the crop rotations we examine in this research. We consider those historically or currently observed in western Kansas, as well as some variants, less frequently observed but perhaps worthy of examination. As a reminder, in this work, the only tillage practice considered is permanent no-till.

Rot1: WMF
This is the widely accepted wheat-milo-fallow rotation, resulting in 2 crops in 3 years, thus a cropping intensity of 66.67%. As a reminder, since this is a permanent no-till study, weeds are kept at bay during fallow periods with herbicides rather than tillage. Hence, some refer to the wheat crop following the milo in this rotation as chem-fallowed wheat.

Rot2: WCF
This is the, also widely accepted, wheat-corn-fallow rotation, with a cropping intensity of 66.67%. This rotation is the same as *Rot1*, only replacing the milo with corn.

Rot3: WCMF
This rotation is wheat-corn-milo-fallow, with a cropping intensity of 75%. It is sometimes heralded as one way to increase cropping intensity while saving the expected-to-be-high-in-ASW spring wheat stubble for the relatively more water-critical crop of corn.

Rot4: Opp
Opp stands for opportunity since this rotation determines the crop based on opportunistic management around water. Some suggest planting corn if soil water is high, milo if it is somewhat lower, or perhaps skip the spring-planted crop and go to wheat in the fall if water is even less plentiful in the spring. There are numerous ways that perceived opportunity might be operationalized in crop selection. To gain some understanding of possible potential, we consider only one arbitrary configuration across all three locations, described as follows. Following wheat, plant wheat back immediately if ASW (in a 6-foot profile) at wheat planting time exceeds 5 inches (i.e., ASW>5), else plant corn the next spring if planting-time ASW>6, else plant milo if ASW>4, else wait until the following fall to plant wheat. Following corn, plant wheat into the cornstalks that fall if ASW>3, else plant corn the next spring if ASW>5, else plant milo if ASW>4, else plant wheat the following fall. Following milo, plant corn the next spring if ASW>5, else milo if ASW>4, else wheat the following fall. In this rotation, cropping intensity is dynamically determined by the ASW-based crop selection rules, and by definition will range between 50% and 100%.

Rot5: WF
This is the historical wheat-fallow crop rotation, with a 50% cropping intensity.

Rot6: WW
This is continuous wheat, with a 100% cropping intensity.

Rot7: MM
This is continuous milo, with a 100% cropping intensity.

Rot8: CC
This is continuous corn, with a 100% cropping intensity.

Rot9: CM
This is a corn-milo rotation, with a 100% cropping intensity.

Note that the 100% cropping intensity rotations are generally not expected to be particularly profitable, otherwise we would see more such programs on dryland farms in western Kansas. Moreover, in the case of same-crop 100% cropping intensity, we make no attempt to deal with the issue of whether crop diseases (or increased weed pressure of difficult to control weeds in a particular continuous crop system, e.g., winter annual grasses in continuous wheat, or summer annual grasses in continuous milo) could be sufficiently held back to make such rotations viable in the long run. So, these continuous cropping rotations are considered to learn more about the potential of crops in the area, especially when we consider subsets of the weather data.

Crop yields distinguished

Though we consider only crops of wheat, milo, and corn, the length of the preceding fallow period can impact expected yields. So, if needed for description, each of the crops within the listed crop rotations can be distinguished according to the following.

WaF: wheat after fallow, as in following a wheat crop and a summer fallow period
WaM: wheat after milo, planted following a summer fallow period
WaC: wheat after corn, planted following a summer fallow period
WaW: wheat after wheat, planted in the same fall as preceding crop's harvest
WaS: wheat after a spring crop (only corn is considered), planted in the same fall (into cornstalks)
MaW: milo after wheat, planted following a summer fallow period
MaM: milo after milo, planted in the following spring
MaC: milo after corn, planted in the following spring
CaW: corn after wheat, planted following a summer fallow period
CaM: corn after milo, planted in the following spring
CaC: corn after corn, planted in the following spring

Results

One of our stated objectives is to use long-term historical weather for making inferences about the future. So, should we use the full 1932-2005 weather data to generate reliable inferences for the future? For example, of some concern is whether it is appropriate to start the series with the dust bowl of the 1930s. With only that concern, and no thorough examination of the data, we arbitrarily selected two 30-year weather normals, hence the 60-year period of 1946-2005, as the most relevant weather for inferences about the future. Figure 1, which depicts 1932-2005 annual rainfall across the three locations of interest, confirms that the 1946-2005 time period should be reasonable.

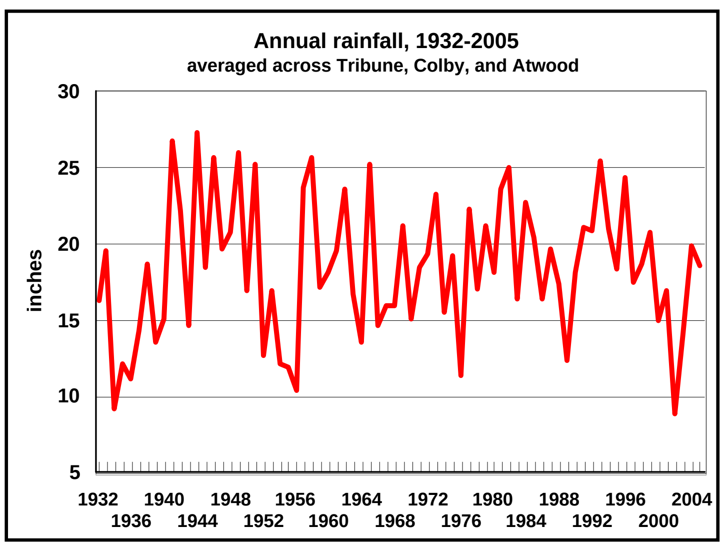

Figure 1

Each simulation scenario involves a particular crop rotation in a particular location, along with 150,000 years of weather data selected by re-combining actual weather data over the 1946-2005 time period. That is, we assert that each of the 150,000 years of simulated weather have the same likelihood of occurring in the future as any of the years of actual weather that did occur in the 1946-2005 period. The 150,000 years of simulated weather lead to simulated crop yields, which are assumed sold at prices of $4.43/bu, $3.29/bu, and $2.86/bu for wheat, corn, and milo, respectively. For computing simulated profit in each of the 150,000 years, all costs of crop production are considered, including land rent; costs are described in detail in the appendix. We assume a crop insurance program that protects the farm manager at 65% of expected yield. The 150,000-year average simulated profit is considered to be the expected profit for a scenario.

In each simulation scenario we also consider two measures of risk, standard deviation of profit and a measure we call *worst6*. The standard deviation essentially can be used as follows. We would expect annual profit to fall between expected profit and plus or minus one standard deviation about 2/3 of the time. Alternatively, we can say that 1 year in 6, we would expect profit to be less than expected profit less one standard deviation. The worst6 measure is the worst possible 6-year average annual profit in the 150,000-year simulation exercise. Computational work behind the scenes is described in the appendix.

Table 1. Simulation results using 1946-2005 weather data, Tribune

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	3	$30.58	$22.26	($6.97)
Rot2: WCF	1	$34.64	$33.88	($11.59)
Rot3: WCMF	2	$33.50	$28.59	($13.47)
Rot4: Opp	6	$23.58	$33.32	($27.36)
Rot5: WF	5	$25.53	$24.32	($7.12)
Rot6: WW	9	$4.77	$28.21	($35.07)
Rot7: MM	4	$29.99	$31.50	($14.57)
Rot8: CC	8	$16.45	$60.77	($43.56)
Rot9: CM	7	$21.51	$46.77	($29.93)

Table 2. Simulation results using 1946-2005 weather data, Colby

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	2	$35.89	$21.70	($2.55)
Rot2: WCF	4	$34.47	$33.24	($10.66)
Rot3: WCMF	3	$35.25	$27.99	($11.30)
Rot4: Opp	5	$34.20	$35.10	($26.24)
Rot5: WF	6	$32.12	$23.27	($2.20)
Rot6: WW	8	$24.29	$29.21	($19.12)
Rot7: MM	1	$39.24	$31.45	($7.01)
Rot8: CC	9	$20.15	$60.24	($39.39)
Rot9: CM	7	$27.97	$46.93	($24.23)

Table 3. Simulation results using 1946-2005 weather data, Atwood

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	5	$26.20	$16.50	($7.59)
Rot2: WCF	3	$29.66	$25.26	($11.02)
Rot3: WCMF	4	$26.43	$20.71	($15.42)
Rot4: Opp	6	$23.73	$26.79	($21.29)
Rot5: WF	2	$30.94	$19.66	($2.36)
Rot6: WW	1	$31.54	$24.59	($11.48)
Rot7: MM	7	$18.36	$21.51	($19.11)
Rot8: CC	9	$10.20	$44.16	($39.62)
Rot9: CM	8	$13.08	$34.09	($30.06)

Basic simulation results are reported in tables 1, 2, and 3, for Tribune, Colby, and Atwood, respectively. Dollar values are $/acre. The tables report rotation, rank of the rotation according to profit (1 is highest, 9 is lowest), expected annual profit (profit), along with the two measures of risk already discussed. For interested readers, corresponding mean simulated yields are reported in the appendix as tables A6-A8.

In studying the results reported in tables 1-3, a no-till farm manager should definitely bring his experienced-based intuition to bear. But, there are important reasons that he should also be willing to question that intuition during the study process. First, although farmers readily acknowledge the vagaries of weather, they generally draw heavily from their rather short time frame of weather reference for making inferences about the future. Second, few western Kansas farmers have multiple years of no-till experience, especially with permanent no-till and the no-till wheat portion of a crop rotation.

In addition to viewing tables 1-3 with an open mind, the numbers in the tables should be studied along several lines. First, although the rotations are ranked by profit, many rotations have profits that are not largely different from each other, meaning that small changes in expected prices might cause ranks to change. For example, table 3 reports the top-ranked rotation to be continuous wheat (WW), which might seem implausible to the Atwood-area farmer. But, it happens that expected corn yield in the WCF rotation of table 3 (a common rotation in the area, albeit not with *no-till* wheat) is 58.44 bu/acre. So, a $0.10/bu increase in expected corn price, while keeping expected wheat price constant, would lead to an annual increase in profit of $1.95/acre in this rotation that has corn every third year. This would be enough to make WCF the top ranked rotation. So, farm managers should not take the tables above as gospel, especially if they doubt the underlying assumptions or if something in the future causes those assumptions to no longer be appropriate. But, nor should the strong showing of WW in table 3 automatically be dismissed by those who have trouble believing it. The correct response for the Atwood-area farmer should be "perhaps I should take a look at more continuous wheat in my rotation." After all, the most learning comes when our biases are questioned, not when we merely seek out and find results that are consistent with our preconceptions.

Table 4. Simulation results using 1991-2005 weather data, Tribune

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	4	$25.53	$22.46	($11.13)
Rot2: WCF	1	$30.16	$34.49	($15.81)
Rot3: WCMF	2	$29.42	$28.99	($17.18)
Rot4: Opp	5	$22.25	$33.91	($27.38)
Rot5: WF	7	$20.65	$25.57	($11.33)
Rot6: WW	9	($0.25)	$28.92	($40.44)
Rot7: MM	3	$26.59	$31.17	($17.65)
Rot8: CC	8	$18.36	$61.20	($43.67)
Rot9: CM	6	$20.86	$47.03	($31.36)

Table 5. Simulation results using 1991-2005 weather data, Colby

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	7	$35.82	$24.53	($4.15)
Rot2: WCF	5	$41.63	$37.47	($8.75)
Rot3: WCMF	4	$44.23	$31.86	($9.35)
Rot4: Opp	6	$40.41	$40.40	($20.69)
Rot5: WF	8	$24.73	$26.28	($8.30)
Rot6: WW	9	$12.97	$32.90	($31.14)
Rot7: MM	2	$53.07	$36.93	$0.48
Rot8: CC	1	$54.97	$72.40	($23.19)
Rot9: CM	3	$52.67	$56.75	($12.35)

Table 6. Simulation results using 1991-2005 weather data, Atwood

rotation	profit rank	profit	stddev	worst6
Rot1: WMF	7	$34.32	$17.60	($2.62)
Rot2: WCF	3	$47.14	$29.07	$0.21
Rot3: WCMF	5	$45.08	$24.21	($4.67)
Rot4: Opp	4	$46.22	$34.36	($10.04)
Rot5: WF	8	$31.30	$18.45	($1.82)
Rot6: WW	9	$29.43	$22.90	($12.73)
Rot7: MM	6	$41.15	$25.93	($4.33)
Rot8: CC	1	$58.03	$55.15	($11.59)
Rot9: CM	2	$47.99	$42.25	($9.13)

The second point of note in tables 1-3 is risk. A WMF rotation is the least risky rotation for all three locations by the standard deviation measure. By the worst6 measure, WMF is either the least risky or second-least risky rotation across the locations. Moreover, it is an especially profitable rotation in Tribune and Colby, and not particularly unprofitable in Atwood either.

For comparison to tables 1-3, which used the long-term weather data spanning 1946-2005, tables 4-6 show simulation results associated with the calibration period 1991-2005 (associated yield information is shown in the appendix as tables A9-A11). The numbers shown in tables 4-6, especially the rotation rankings, likely are what would have emerged as intuition from a permanent no-till manager in each of the 3 locations had that manager been able to get past the not-so-great row crop yields in the 2000s due to recurring drought. Of course, had the manager only experienced no-till ahead of the corn or milo, as typically has been the case in western Kansas, it is not likely he would have acquired intuition consistent with the tables, even if he were able to get past the recency effect of drought.

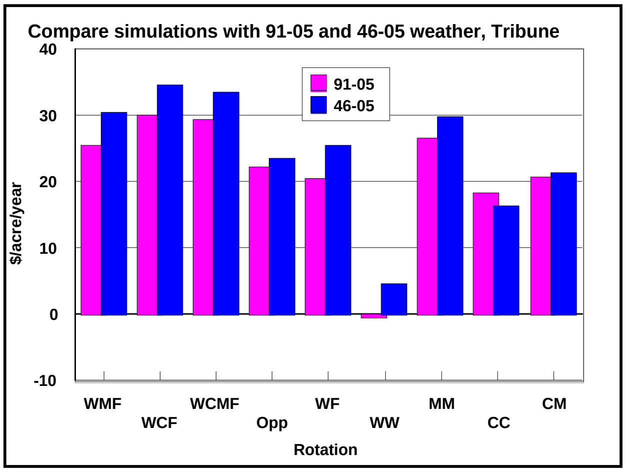

Figure 2

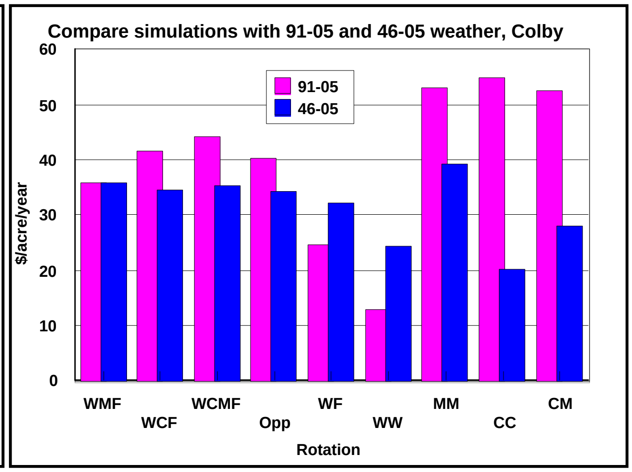

Figure 3

Figures 2 through 4 depict a graphical comparison of simulations using the calibration period of 1991-2005 with those using the longer-term 1946-2005 data for Tribune, Colby, and Atwood, respectively. The figures hint at where intuition based on recent weather might break down. For Tribune (figure 2), 1991-2005 intuition around permanent no-till may not serve the farm manager too poorly in the future assuming that the longer-term weather is a better indicator of future weather patterns. That is, profit rankings did not materially change across the two time periods of study. For Colby (figure 3), however, we begin to see some material differences. Likely, the permanent no-tiller there, thinking about the last 15 years, might over-rate cropping intensity – all three of the 100% cropping intensity programs of MM, CC, and CM did quite well in the 1991-2005 simulation period but relatively somewhat worse for the broader time period. Yet, MM still maintains its high-ranking status. Also, wheat seems to become relatively more profitable for the broader time period.

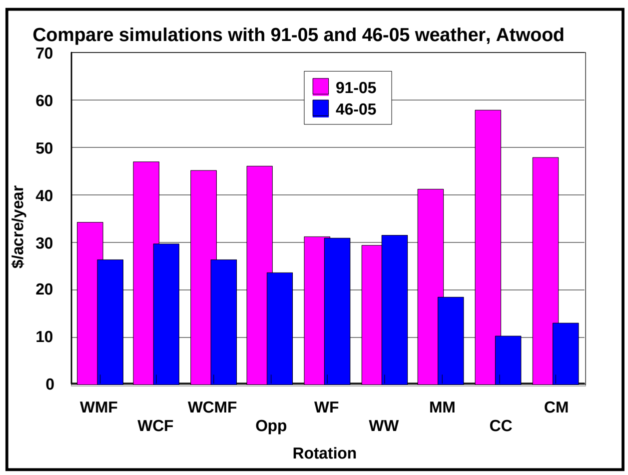

Figure 4

For Atwood (figure 4), the differences between the two simulation time periods are quite substantial. The recent 15-year period of 1991-2005 would suggest considerable benefits to corn and milo, and to intensive crop rotations as well. But, for the broader time period, wheat becomes king, both summerfallow wheat (WF) and continuous wheat (WW). Likely, this contrast between the two time periods will appear somewhat surprising to the Atwood-area farm manager. But, it is chiefly due to historical weather in the Atwood area being less favorable for crop production than more recent weather. In particular, the 1946-1990 period saw 5.6% less average annual rainfall at Atwood than the later 1991-2005 period. July rainfall was 21.0% lower. Meanwhile, neighboring Colby saw nearly identical annual rainfall across the two periods and Tribune had 8.1% higher annual rainfall in the earlier period as compared to the later one. Also, water loss, as measured by annual ETNE (described in appendix), was also slightly (0.5%) higher in the earlier period, whereas Colby had 2.1% *lower* ETNE for the earlier period.

In reference to figures 2-4, a few points are worth making about Opp, i.e., the water opportunity crop rotation, at least the way we had it configured and which already has been described. First, as a crop rotation, Opp was not outstanding in relative profitability, as we had perhaps hoped. But, it was not particularly bad either. Second, perhaps because of the low water thresholds used, Opp represented fairly high levels of cropping intensity: Tribune 92%, Colby 90%, and Atwood 86% (these values are reported in tables A6-A8 in the appendix). As such, the only rotations shown in the figure that were higher in intensity were the continuous cropping 100% intensity WW, MM, CC, and CM rotations. Of the Opp crops, 50% were wheat in Tribune, 33% in Colby, and only 21% in Atwood. It turned out that half those wheat crops in Tribune were WaW (wheat after wheat) and this is why Opp did not do well there. It should be noted that we did not spend a lot of time considering other water thresholds for crop selection in Opp. Nor, did we attempt to vary them by location. So, it is likely that additional simulation in this area would still be fruitful.

Summary and concluding remarks

Adoption of no-till farming practices ahead of milo or corn in western Kansas paralleled, and likely was accelerated by, especially favorable crop production in the late 1990s. Field studies at the time promoted more row crops and more cropping intensity. But, adoption of no-till ahead of the wheat crop in the typical cropping rotations in the area greatly lagged adoption of no-till ahead of the row crops. Moreover, recurring droughts in the 2000s caused farm managers to take a second look at some of their more intensive crop rotations and farming practices, wondering if they should even step back to summerfallow wheat as a rotation. Through it all, Alan Schlegel has been conducting a tillage study at Tribune Kansas involving a wheat-milo-fallow crop rotation. Over the years of his study it has been learned that there likely are economic gains to a permanent no-till program, where even the fallow period is handled with herbicides rather than tillage. So, this study takes as a starting point permanent no-till.

Farm managers who are considering or have already adopted permanent no-till still have other questions. For example, will it work in areas besides near Tribune? Will it work for corn? Will it work for rotations that have less fallow time, thus in more intensive crop rotations? Such are broad questions that likely would benefit immensely from more and longer-term tillage studies in western Kansas. Yet, astute farm managers know that they must be “ahead of their neighbors” in technology adoption in order to capture and maintain farm profitability. So, they constantly wish to stretch research and understanding as far as they can to get this edge. In that process, they routinely ask the questions, What will the future bring? How much will it look like the past? How can I avoid the recency effect, where I put more weight on recent farming experiences than I probably should?

The work reported here is a formalized attempt to stretch the Tribune tillage study research. By simulating crop yields from long-term weather information, we had hoped that something striking would be learned, perhaps a holy grail of crop rotation in the area. Well, that did not quite happen. It was especially frustrating to see that a dynamic crop selection system based on soil water at planting (this rotation was called Opp) was not strikingly more profitable than a fixed cropping sequence. Though soil water at planting is an important determinant of crop yield, it may be less reliable as a crop selection guide. Granted, we did not explore the myriad possibilities for Opp, especially by location. But, we feared performing a data mining exercise that might look good in hindsight but be a poor predictor for the future. Moreover, we thought that a simple "one size fits all" framework for mapping water threshold values to crops would perform at least as well as the common fixed rotations in the area. So, perhaps farm managers can rest a little easier with their fixed rotations, not worrying so much about missing out on weather-induced opportunity.

In general, it is likely that the traditional western Kansas crop rotations of wheat-corn-fallow or wheat-milo-fallow will prevail as suitable permanent no-till crop rotations for at least the near future. But, even that should be worth knowing, especially for those who believe they might be greatly missing out on opportunities if they do not immediately push for more intensive rotations. Also, our study did reveal a few interesting and perhaps unexpected location-specific possibilities, for example, the weak showing of continuous wheat (WW) in Tribune and the strong showing of WW in Atwood. And finally, perhaps the most striking result, and this was across all locations, was the relatively strong showing of a wheat-fallow (WF) rotation. Perhaps it is premature to speak of the impending death of this rotation, which was a mainstay in western Kansas conventional farming practices for perhaps 5 or 6 decades.

Simulation-based research of the type presented here always is heavily laden with assumptions. So, it should be important to come back to some assumptions that may have been mentioned and others that have not. First, farm profitability is determined by many factors besides crop yields induced by water differences, for example, especially machinery management. What that means is that farm managers should still focus the bulk of their efforts on factors other than tweaking their crop rotations outside the norm in the area. It means that top notch farm managers using the least profitable crop rotations we studied will still be more profitable than the typical farm manager machinery-wise who otherwise astutely selects the most profitable crop rotation. But, those who already are successful at things like machinery management will marginally improve their profits even further by focusing on the harder-to-implement tasks like crop rotation selection. So, the top notch machinery manager who also does a good job with crop rotation will indeed be more profitable than the top notch machinery manager who ignores such things.

A second caveat for this work is that we expressly did not consider crops other than wheat, milo, and corn. We did not consider crops such as sunflowers and soybeans, which have been around in the area for some time but have not substantially held or increased land share for dryland farms in western Kansas, indicating they may have intrinsic recurring profitability problems. We did not consider other new-to-the-area crops either, for example, canola or peas, precisely because data do not exist to support our simulation efforts. That said, as western Kansas farms move to permanent no-till, such crops could have merit.

A third point of note is that we did not expressly consider the possibility, as suggested by Schlegel's 1991-2005 tillage study, that crop yields in permanent no-till improve over time, and perhaps disproportionately across crops. Clearly, this might have skewed our results inappropriately in favor of some crop over another. A related point is that our work reflects crop technology differences across the crops of wheat, milo, and corn that were observed in the 1991-2005 period, not in the future. This could be especially relevant for comparisons between corn and milo, since corn generally has seen considerably faster technology growth than milo, and likely will in the future. The implication is that, where our study might posit equal profits across corn and milo, a farm manager should lean towards corn in the future. Another related point has to do with recent growth in demand for feedgrains by the biofuel industry. If this continues, relative prices in the future might favor corn and milo over wheat more than that indicated by our futures-based crop prices. So, a farm manager who believes that should give the nod to corn and milo over wheat when the simulation work otherwise shows the crops to be about equal in profit.

A fifth caveat is that the continuous cropping rotations we considered made no attempt to consider problems such as crop diseases, insect infestations, or increased weed pressure that might plague such programs in real time application. Our interest was only water impacts on crop yield and whether one might want to consider "more" of such "stacked" rotations in his overall cropping plan. What this means is that the nod should go to the rotation with more crop diversity when two rotations might otherwise be considered equal in profitability.

A final caveat is that this work critically assumes that long-term historical weather is a better predictor of future weather than is short-term recent weather. We have not critically examined this most basic assumption underlying our work. Indeed, if we are heading for a multi-year future with increased global warming, or perhaps one of global cooling, then the value of our work is sharply diminished and we all truly will be "flying by the seat of our pants."

Appendix: More detailed description of underlying work

Description of data from Schlegel's 1991-2005 tillage study in Tribune, Kansas

Schlegel's research provided crop yield information for wheat and milo in a wheat-milo-fallow rotation, with each crop planted each year from 1991-2005. Though he provided information for each tillage regime, we considered only the permanent no-till regime in this analysis. Also, available soil water (ASW) was measured in one-foot increments to a depth of 8 feet at both planting and harvest time. However, we used ASW information to only the 6 foot depth. The data used directly from Schlegel's research are reported in table A1.

Table A1. Data from Schlegel's tillage study of wheat-milo-fallow near Tribune, Kansas, 1991-2005, no-till only.

	Wheat					Milo			
	ASW prev harv	ASW planting	Harvest yield	ASW harvest		ASW prev harv	ASW planting	Harvest yield	ASW harvest
year	inches	inches	bu/acre	inches		inches	inches	bu/acre	inches
1991	0.33	2.54	15	1.38		0.00	4.91	39	0.40
1992	1.77	4.06	21	1.82		1.38	7.98	27	1.41
1993	0.40	8.23	58	0.76		1.82	5.89	68	2.38
1994	1.41	9.74	46	3.41		0.76	7.64	57	3.29
1995	2.38	6.21	56	3.28		3.41	9.97	59	2.37
1996	3.29	9.37	26	6.29		3.28	3.97	119	3.12
1997	2.37	9.77	52	3.02		6.29	9.74	115	13.44
1998	3.12	9.06	64	0.72		3.02	12.33	131	2.88
1999	13.44	10.48	83	3.33		0.72	7.58	99	5.23
2000	2.88	11.57	44	1.25		3.33	8.68	51	2.10
2001	5.23	5.81	31	2.97		1.25	9.00	64	1.32
2002	2.10	9.27	0	4.45		2.97	2.92	0	1.58
2003	1.32	2.40	30	3.06		4.45	7.11	37	1.64
2004	1.58	6.18	4	4.31		3.06	4.59	118	3.44
2005	1.64	8.13	39	3.03		4.31	7.28	61	3.07
Avg.	2.88	7.52	37.93	2.87		2.67	7.31	69.67	3.18

Basic weather information

For weather data, we ultimately desire long-run information on a rainfall variable and a variable related to water loss. For the most part, although rainfall data generally are straightforward, water loss is not. In particular, estimates of water loss to the atmosphere are collected or computed in various ways. For example, free-surface, or pan, evaporation has long been a traditional measure of interest. More recently, however, it appears that the focus has turned towards reference evapotranspiration (ET) measures, designed to mimic water losses from standing crops rather than from an open pan. In this study, because it involves considerable crop residue in a semi-arid environment, we ignore water losses to deep percolation or field runoff.

Mathematical formulas have been designed to compute expected ET from various measures of weather. Although it is not immediately clear that one ET measure is better than another, what is clear is that a consistently defined measure of ET should be used in simulating crop yields across time. Accordingly, and especially since we wish to make inferences for locations other than Tribune, Kansas, we elected to use weather data provided by Mary Knapp, state climatologist at Kansas State University. Knapp compiles weather information from each of K-State's Experiment Stations. Recent measures comprising these data are available at the website for K-State's Weather Library, http://www.oznet.ksu.edu/wdl/. More historical measures should be obtained directly from Knapp. The main weather data set provided by Knapp covered Kansas locations associated with K-State's Experiment Stations, and as daily information from January 1, 1985 through December 31, 2005. More detail is provided later.

Mathematical models underlying the crop yield simulations

Fundamentally, ASW at planting, *ASWplant*, is considered to be a function of ASW at the preceding harvest (*ASWharv*), rainfall during the fallow period (*RAINfallow*), along with a measure of water loss to the atmosphere (*WLOSSfallow*) during the fallow period:

$$ASWplant = f\left(ASWharv, RAINfallow, WLOSSfallow\right). \qquad [1]$$

Crop yield (*Yield*) is considered to be a function of ASW at planting, rainfall during the growing period (*RAINgrow*), and water losses during the growing period (*WLOSSgrow*):

$$Yield = f\left(ASWplant, RAINgrow, WLOSSgrow\right). \qquad [2]$$

Finally, ASW at harvest (*ASWharv*) is considered to be a function of the same variables as those on the right-hand side of [2], along with the variable of crop yield itself:

$$ASWharv = f\left(ASWplant, RAINgrow, WLOSSgrow, Yield\right). \qquad [3]$$

Simple linear specifications were used to estimate operational versions of equations [1] through [3] using the data from table A1 along with the requisite weather data (described in more detail below). Moreover, we elected to model change in available soil water from harvest to planting (*chgASW*) rather than available soil water at planting itself. An estimate of *chgASW* can then be added to *ASWharv* to provide an estimate of *ASWplant*. The basic linear specifications of the equations to be estimated and used in simulations are as follows:

$$chgASW = \mathrm{A}_0 + \mathrm{A}_1 * RAINfallow + \mathrm{A}_2 * WLOSSfallow \text{, along with} \qquad [4]$$

$$ASWplant = ASWharv + chgASW; \qquad [4b]$$

$$Yield = B_0 + B_1 * ASWplant + B_2 * RAINgrow + B_3 * WLOSSgrow \text{ , and} \quad [5]$$

$$ASWharv = C_0 + C_1 * ASWplant + C_2 * RAINgrow + C_3 * WLOSSgrow + C_4 * Yield\ . \quad [6]$$

In [4] through [6], the A_0 through C_4 terms represent model parameters to be estimated from the data. Although not shown, there would be equations like [4]-[6] for each of wheat and milo. Moreover, although the time dimension is not shown in the equations, it must be carefully accounted for. For example, in a wheat-milo-fallow (WMF) rotation, *ASWplant* for the wheat crop will be observed in September in the year preceding wheat harvest. The *ASWharv* used to estimate that *ASWplant* is observed following milo harvest, which is one year ahead of wheat's *ASWplant* and two years ahead of wheat's *Yield*. Finally, in this case, the *ASWharv* of equation [6] is observed after wheat harvest. Also, the *ASWharv* in [4] for the wheat equations will be the same value as the *ASWharv* in [6] for the milo equations, only it is observed two years earlier.

In [4] we would expect A_1 to be positive and A_2 to be negative – since rain during the fallow period should increase ASW at planting, whereas moisture losses during the same time period ought to reduce ASW at planting. In [5], we clearly would expect B_1 and B_2 to be positive and B_3 to be negative. By "expect" we mean that it would be difficult to believe otherwise given that rain increases soil water and crop yield whereas moisture losses negatively impact soil water and crop yield. That said, in model estimation, we should require such positive and negative relationships to prevent unacceptable simulation models.

In [6], at first blush and all else held constant, it would seem that C_1 and C_2 ought to be positive but C_3 and C_4 negative (the latter because higher crop yield implies more water has been pulled from the system). But, "all else" is not held constant in this simultaneous equation. For example, *RAINgrow* impacts *Yield* positively (as explained around [5]). But, if *Yield* impacts *ASWharv* negatively, as presumed, it is impossible to definitively sign the net impact of *RAINgrow* on *ASWharv* (i.e., the C_2 term). Similar arguments can be made for other parameters in [6].

Data shown in table A1, along with the requisite weather data, allow for estimation of the six linear causal equations ([4]-[6] for wheat and [4]-[6] for milo) independently of each other. Typically, such equations would be estimated using ordinary least squares regression and with no numerical constraints placed upon the parameters. However, our goal is not merely to fit the existing data as best we might, but rather to be able to make meaningful (acceptable) predictions with other weather data. To better foster that goal, we elected to estimate the model equations "with no intercept." That is, A_0, B_0, and C_0 were constrained to equal 0 in model estimation. Table A2 reports the parameter estimates for the model estimations.

Table A2. Parameter estimates for models from Tribune data.

	Wheat models				Milo models		
causal variable	*chgASW* Eq. [4]	*Yield* Eq. [5]	*ASWharv* Eq. [6]		*chgASW* Eq. [4]	*Yield* Eq. [5]	*ASWharv* Eq. [6]
intercept	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
RAINfallow	0.4611				0.4813		
WLOSSfallow	-0.0264				-0.0165		
ASWplant		5.1682	0.2495			5.2160	0.2126
RAINgrow		5.5473	0.1806			7.5303	0.1515
WLOSSgrow		-1.0425	0.0257			-0.9683	-0.0436
Yield			-0.0455				0.0273
equation R^2	0.2713	0.8012	0.3313		0.5327	0.5533	0.3161

From the *chgASW* equations of table A2 we can see that we expect an additional inch of rainfall during the fallow period to end up as an additional 0.46 inch of soil water at planting for wheat (0.48 for milo), holding water loss during the fallow period constant. This indicates that our water loss variable is not a perfect measure of actual water loss – otherwise we would get 1 inch of additional ASW for each additional inch of rain. Meanwhile, an additional inch of water loss, as measured by the *WLOSS* variable, reduces soil water at planting by 0.03 inches for wheat and 0.02 inches for milo. But, we note that the water loss measure we use tends to run about 4 to 5 times as much as rainfall on an annual basis and so should not be considered as directly comparable to rainfall even though it is dimensioned in inches. According to the yield models, an additional inch of available soil water at planting, all else constant, results in 5.17 bu/acre increased wheat yield and 5.22 bu/acre increased milo yield. Meanwhile, an additional inch of rain during the growing season, all else constant, results in 5.55 bu/acre increased wheat yield and 7.53 bu/acre increased milo yield.

More detail on weather data

Among other variables, the daily 1985-2005 weather data provided by the state climatologist (referred to here as the *basedata*) involved these potentially relevant variables for locations of most Kansas Experiment Station fields (Tribune and Colby are included): *WIND* (average wind speed in miles per hour during the day), *tempH* (high air temperature for the day), *tempL* (low air temperature for the day), *RH* (average percent relative humidity during the day), *RAIN* (daily rainfall in inches), and a derived measure of expected evapotranspiration referred to as *ETNE* (daily ET in inches). The two variables we consider directly relevant for our crop simulation models are *RAIN* and *ETNE*. But, other variables are used in auxiliary models to backfill measures of interest going back to 1930, as well as to help derive measures for Atwood, a location not included in the *basedata*.

Because we desire coarser than daily but finer than monthly distinction in planting and harvest time across crops, we first aggregated the *basedata* to 24 half-month periods within a calendar year (days 1-15 in a month are associated with the first half of a month and the remainder are assigned to the last half). But, for use in models, half-month values will be summed across an entire fallow or crop growing period to become a single measure for some crop in some year. So, the half-month characterization is needed, not to pick up half-month weather impacts on crop yield or ASW, but rather only to ensure that the correct water cumulative time period is assigned to a crop in a cropping system. That is, the data set depicted in table A1 is not so rich that we can actually measure impacts at the half-month scale.

What about the period prior to 1985 for Tribune and Colby, and what about Atwood for the whole study period? First off, historical monthly data on precipitation were readily available from different sources. In this case, monthly precipitation values were merely divided by two to provide half-month values for our data prior to 1985 (all data in the case of Atwood). Unfortunately, historical measures of ET, at least those consistent with our *basedata*'s *ETNE* measure, were not readily available.

Regardless of the Experiment Station location in the *basedata*, it was determined that *ETNE* estimates could be reliably estimated from *WIND*, *tempH*, and *RH* measures (R^2 values for underlying models generally were higher than 0.90 at the half-month scale). So, the focus turned to acquiring historical measures of these variables. Monthly average *tempH* data were readily available from various sources (though, Atwood daily *tempH* data had to be purchased from a weather data provider and subsequently aggregated upwards). Since temperature is distinctively seasonal, half-month data points were created with a data smoothing process that resulted in an average value across the two half-month measures that identically equaled the acquired monthly measure.

Schlegel provided monthly Tribune wind information (total miles of air travel per month) for months of April-September over the entire 1930-2005 study period. However, it appeared that daily average wind speed computed from Schlegel's data were not consistent with the *basedata*'s measure of *WIND*. So Schlegel's April-September data were transformed to a *WIND*-consistent series using a monthly 1985-2005 regression model associating the two series. A separate model was used for each month and the average R^2 value across the six monthly models was 0.75. Monthly estimated values were then assigned to half-months. For the January-March and October-December periods in years 1930-1984, Tribune *WIND* for a given half-month was assumed to equal the 1985-2005 average *basedata* value for the same half-month. Colby half-month *WIND* prior to 1985 was taken from a half-month 1985-2005 regression model of Colby *WIND* on Tribune *WIND* ($R^2 = 0.45$), using 1930-1984 Tribune *WIND* as the independent variable in predicting (filling in) the missing data. Atwood *WIND* throughout the entire 1930-2005 period was assumed to equal Colby *WIND*.

For Tribune and Colby, backfilling *RH* measures for use in estimating *ETNE* was done using a half-month 1985-2005 regression model where *RH* is a function of *WIND* and *tempH*. Then, 1930-1984 *WIND* and *tempH* values were used to predict 1930-1984 *RH*. These two regression models had low R^2 values (0.15 for Tribune and 0.11) and so resultant 1930-1984 half-month *RH* values did not have as much variation as we might have hoped. Yet, we believe that the exercise was worthwhile. Atwood 1930-2005 *RH* measures were based on Atwood *WIND* and *tempH* measures, but using the Colby regression model described above.

Finally, for each of Tribune and Colby, a 1985-2005 half-month regression model was estimated where *ETNE* was considered to be a function of *WIND*, *tempH*, and *RH* (Tribune model R^2 = 0.94; Colby model R^2 = 0.93). Those models were used with 1930-1984 *WIND*, *tempH*, and *RH* values to provide *ETNE* measures for 1930-1984. Similarly, Atwood *ETNE* values were derived for the entire 1930-2005 period using Atwood values but the Colby regression model.

For backfilling *ETNE* into the 1930-1984 time period, we might have just considered the same-half-month 1985-2005 mean. This would have captured most of what is needed, namely, seasonal variation in *ETNE* across the calendar year. But, we believe that the additional effort expended with the various auxiliary models has provided some additional meaningful weather variation considered plausible for the 1930-1984 time period. Also, keep in mind that the main simulation model driver is *RAIN* and that variable required essentially no backfilling or regression estimates. So, our simulation models of soil water and crop yield likely will not be excessively smoothed over the 1930-1984 period by the auxiliary modeling process.

To provide the reader with some understanding of the underlying data, table A3 shows 1930-2005 means by calendar month for each of *RAIN* and *ETNE* by location.

Table A3. Mean monthly *RAIN* and *ETNE* by location, 1930-2005.

	RAIN			*ETNE*		
	Tribune	Colby	Atwood	Tribune	Colby	Atwood
JAN	0.37	0.36	0.53	2.38	2.13	2.22
FEB	0.41	0.45	0.61	3.38	3.00	3.21
MAR	0.95	1.14	1.39	5.27	4.77	4.81
APR	1.29	1.69	2.00	7.50	6.94	6.98
MAY	2.42	2.98	3.27	8.79	8.25	8.39
JUN	2.69	3.09	3.22	9.98	9.59	9.82
JUL	2.50	3.17	3.17	10.67	10.41	10.49
AUG	2.15	2.27	2.44	9.80	9.77	10.03
SEP	1.22	1.33	1.62	8.59	8.41	8.82
OCT	0.94	1.17	1.29	6.55	6.40	6.77
NOV	0.50	0.63	0.86	3.98	3.83	4.16
DEC	0.30	0.35	0.49	2.64	2.49	2.60
total	15.73	18.64	20.88	79.53	75.98	78.31

Note that, although our weather data begin in 1930, some of the crops we consider require a 2-year lag to adequately cover the pre-harvest period. So, fixing the time dimension to the year of harvest, the complete weather data we might use is referred to as 1932-2005 weather.

Miscellaneous simulation assumptions

Cap on available soil water

In simulating *ASWplant* and *ASWharv* it was assumed that ASW is capped at 12 inches, thus 2 inches per foot of soil in the top 6 feet of soil.

Cap on simulated crop yields
Based on experimenting with the simulation models during calibration (described later), simulated wheat yields were capped at 80, 85, and 90 bu/acre for Tribune, Colby, and Atwood, respectively. Simulated milo yields were capped at 125 bu/acre everywhere.

Water accumulation dates for the crops
As already noted, we consider the year to be broken into 24 half months. In the simulations, wheat is assumed to first begin to use water on September 15. It last uses water on June 15 the following year. So, water begins to accumulate for the following crop on June 15 as well. Milo begins to use water on June 1 and last uses water on September 15. Corn begins to use water on May 15 and last uses water August 31.

Starting ASW in simulations
In simulations, available soil water following one harvest impacts soil water at planting, which impacts yield, which impacts soil water following that harvest, and so on. Hence, in simulating thousands of crop yields over time, the soil water at which a simulation scenario begins is not particularly relevant to the analysis. Nonetheless, the beginning soil water does have to be assumed. So, all simulations were assumed to start at 3 inches of available soil water following the preceding crop's harvest.

Model calibration basics

As with most simulation work, calibration is required to make simulated results believable. For calibration, we developed target mean (1991-2005) crop yields for each of wheat, milo, and corn, and for each of the three locations. Then, working mathematical models were adjusted to get "close" to these targets in simulations involving 1991-2005 weather data and wheat-milo-fallow (WMF) and wheat-corn-fallow (WCF) cropping sequences. In developing targets we used USDA's National Agricultural Statistics Service (NASS) planted (not harvested) yields (i.e., production divided by planted acres) for the crops in Greeley, Thomas, and Rawlins counties of Kansas for years 1991-2005.

In developing target mean yields we assumed that no-till (NT) yields for crops in locations other than Tribune are related to NASS county yields in the same proportion as are Schlegel's NT yields. For example, the 1991-2005 mean NASS yield for total (summerfallow and continuous-cropped) non-irrigated wheat in Greeley County was 27.64 bu/acre. Schlegel's mean NT yield was 37.93, or 1.37 times as high. Multiplying Thomas County's mean NASS wheat yield of 30.93 times the 1.37 Schlegel adjustment factor would result in an expected NT yield in Colby of 42.46 (numbers slightly off due to rounding in this example). But, we also computed a similar adjustment, based on only NASS summerfallow wheat. For Colby, this resulted in a target of 42.64. Then, we averaged these two targets (42.46 and 42.64) to come up with our Colby NT wheat target of 42.55. Milo targets were developed in a similar fashion, using only NASS non-irrigated milo yields (6 of the 45 year-location milo yields were missing and filled in using crop reporting district yields). The Schlegel adjustment factor for milo was used against mean NASS non-irrigated corn yields to develop NT corn yield targets. Table A4 reports relevant NASS yields and associated NT yield targets for simulations.

Table A4. Mean (1991-2005) NASS yields and NT yield targets for simulations.

	NASS yields[a]			NT yield targets in WMF or WCF rotation		
	Greeley Co. Tribune	Thomas Co. Colby	Rawlins Co. Atwood	Tribune	Colby	Atwood
Wheat	27.99	31.47	34.32	37.93[b]	42.55	46.00
Milo	48.11	54.36	49.08	69.67[b]	78.72	71.06
Corn	46.85	52.26	53.48	67.83	75.67	77.44

[a] NASS yields shown for wheat are for wheat following fallow; milo and corn are total non-irrigated NASS yields.
[b] actual mean yields in Schlegel's study

Simulating corn yields from simulated milo yields

Because underlying yield simulation models were based on milo rather than corn (i.e., Schlegel's study did not consider corn), it is necessary to construct methods to get from milo simulations to corn simulations given we wish to consider corn in this study. Based on various simulation studies in the agronomy literature, and based on an understanding of non-irrigated crop production in western Kansas, it seems safe to say that corn will yield more than milo in high-yielding environments (here, in favorable years, weather-wise) but less than milo in low-yielding environments. Moreover, farmers in the area have now observed several years of droughts to weigh expected corn yields against milo yields in such situations. In particular, in the face of reduced or poorly-timed rainfall, corn yields will quickly drop near zero while milo yields may fall more slowly. This understanding has with it the implication of a "turning point" in crop yields, above where corn yields will exceed milo yields. Finally, it seems reasonable to assert that corn has a higher plateau yield than milo.

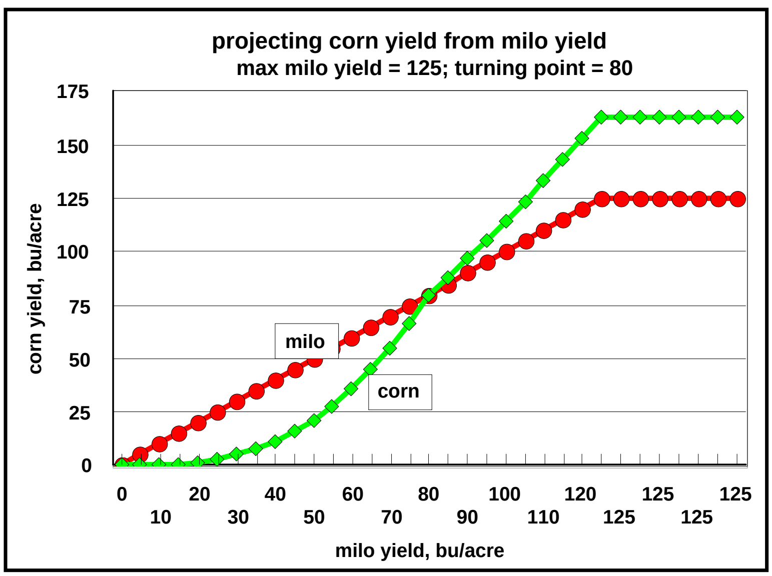

Figure A1

Without describing the underlying mathematics, figure A1 graphically depicts our simulation framework. The figure assumes a maximum milo yield of 125 bu/acre (implied corn maximum of 163), and a turning point of 80 bu/acre. In the example shown, a milo yield of 30 bu/acre would imply a corn yield of around only 5 bu/acre, which seems at least conversationally in line with what farms in western Kansas may have experienced in recent years with drought conditions. We used this framework in our corn yield simulations; weather determines milo yields via the yield models already discussed, and corn yields are simply computed from milo yields in this manner.

Based on recent droughts in western Kansas it may be tempting to posit considerably higher turning point yields than the 80 bu/acre shown in the figure. But, we should keep in mind the relationships between corn and milo NASS yields shown in table A4. In particular, despite recent droughts in the averages, 15-year average corn yields were higher than milo yields in the Atwood location and only marginally lower in the other two locations. So, we decided to use the framework described, only with location-specific turning point yields as determined in our simulation calibration. From the calibration we selected turning point yields of 79, 88, and 67 bu/acre for Tribune, Colby, and Atwood, respectively.

Random weather selection

In the simulations we first select the calendar year range (starting year to ending year) of historical weather data (rainfall and ETNE; ETNE determines water loss) to consider. Generally, although rainfall and ETNE have seasonal components, there is very little correlation across years or within years once the seasonal components are accounted for. In particular, the fact that last month saw below average rainfall is not a good indicator that this month will see below average rainfall or above average rainfall, and so on. So, for a particular half month of interest, say the first half of June, we draw from all first halves of June available in the selected calendar year range of data we select for our simulations. Moreover, it appears that historical rainfall and ETNE have generally been independent of each other as well. So, we also assume no dependencies between these two weather variables.

For a given simulation exercise, we begin by randomly selecting (simulating) a weather data set covering all possible years of the simulation. The years of the simulation, described in the next section, is not to be confused with the particular range of years of actual weather data underlying the random weather data. For example, say we wished to use an actual weather data set ranging from 1960 to 2000 and a 1,000-year simulation. For each half-month, of each of the 1,000 years, we would inject the actual rainfall amount from the same half-month only from a randomly-selected (sampling with replacement) year in the range 1960-2000. A similar procedure would be used to select the ETNE measure to fill in our 1,000-year weather data set. Then, for simulating crop yields and economic variables, etc. associated with the 1,000-year simulation exercise, we would scroll through the 1000 years, 1 year at a time, using that year's weather data (and the preceding year or two, depending on the cropping sequence being examined), to predict crop yields harvested in that year. Then, that year's crop yields would impact soil water at harvest, which impacts soil water at planting for the next crop, and so on.

Number of years in a simulation

The goal of our work is to derive reasonable expectations of crop yields and profit associated with various crop rotations or sequences, for example, wheat-milo-fallow (WMF). Given the description of random weather selection above, there is a nearly infinitesimal number of combinations of weather patterns that could be constructed from the data, hence a nearly infinitesimal number of values for expected crop yields and profits. Consequently, numerous outcomes of a simulation exercise must be examined for the resultant average values to be repeatable and thus provide reasonable expectations of the future given our agronomic and economic assumptions. We found that our simulation results generally were quite repeatable if we used 150,000 years as the size of our simulations. That is, our resultant measures of expected bu/acre crop yield, inches of available soil water, and $/acre profit each tended to be consistent at the first or second decimal place across alternative runs of the simulation model when we used at least 150,000 years.

Model calibrations

In an effort to keep our processes simple to ensure simulation believability, we considered only the following possible adjustments to simulation models: 1) a water adjustment factor unique only to location, 2) yield adjustment factors unique to crop and location, and milo-to-corn turning point yields by location as already described. Model calibration continued by considering various adjustment values and running a simulation using only 1991-2005 weather data for each set of adjustment values. In calibration, we principally considered yield targets for Tribune corn (to determine the milo-to-corn turning point yield there), along with wheat, milo, and corn targets for Colby and Atwood. We stopped calibrating when each of simulated mean yields was within 1 bu/acre of the target in table A4 (on average, the discrepancy was about 0.8 bu/acre).

In calibration, we also considered *ASWplant* and *ASWharv* values, using proportional adjustment factors that were multiplied by the *chgASW* parameters and *ASWharv* parameters shown in table A2. Hence, to get mean simulated *ASWplant* and *ASWharv* within 0.25 inch of the observed mean available soil water values in Schlegel's study, we used a water adjustment factor of 0.97 for Tribune. Not having a suitable target for such measures in Colby and Atwood, we believe that available soil water at planting should not be a lot different in Colby and Atwood than in Tribune. So, we selected water adjustment factors for these two locations of 0.78 and 0.65, respectively. These factors caused mean simulated *ASWplant* to be slightly higher for Colby and Atwood than in Tribune, but still within 0.25 inches of comparable simulated Tribune values. The substantial drops in predicted soil water from the Tribune-based equation for Colby and Atwood would imply that rainfall can be stored more efficiently in those soils than in Tribune. Alternatively or additionally, it could imply that evaporative losses are not as harmful for building soil water in those areas as compared to Tribune. These are merely conjectures but we did not wish to simulate large build-ups of soil water in Colby and Atwood that we practically considered to be indefensible. Of course, this points to the subjective nature of many simulation exercises, which might be considered an academic weakness of the technique.

Finally, as discussed earlier, to get mean simulated corn yields close to targeted yields shown in table A4, we selected milo-to-corn turning point yields of 79, 88, and 67 bu/acre for Tribune, Colby, and Atwood, respectively.

Economic assumptions

Crop prices

Crop prices used in simulations were based off of closing futures prices observed on December 12, 2006 for harvest time periods in 2007, 2008, and 2009. A 3-year average futures price was constructed and added to the 3-year historical average basis for Colby, Kansas. The result was an expected cash price expected to prevail at harvest over the next 3 years in Colby. Given the ongoing expansion of the ethanol industry, we would expect these high-by-historical-standards cash prices to prevail beyond 3 years, and thus consider them relevant for determining expected profit in the various crop rotations considered in this work. However, we do not distinguish prices by location; we assume the same prices for Tribune and Atwood as for Colby. The crop prices used in the simulations are $4.43/bu for wheat and $3.29/bu for corn. Based on recent harvest time relationships between corn and milo prices in Colby, we assume milo to be priced at 87% of corn, hence $2.86/bu.

Fertilizer rates and prices

Fertilizer prices are expectations in northwest Kansas for the next 3 years for liquid N (from 32% UAN) and liquid P (from 10-34-0, after accounting for the value of N it contains). We use $0.33/lb of N and $0.30/lb of P_2O_5. Fertilizer use is determined by simulated crop yields, using fertilizer removal values. We assume that wheat, milo, and corn remove 1.2000, 0.8064, and 0.7616 lb N per bu of yield, respectively, and adjust those numbers upwards by 15% to allow for N losses. We assume that wheat, milo, and corn remove 0.50, 0.40, and 0.33 lb P_2O_5, respectively.

Harvesting cost

We use Kansas Agricultural Statistics (KAS) 2005 custom rates for northwest Kansas, adjusted upwards by 5% to reflect expected increases from 2005 to 2007. These rates are a combination of a fixed $/acre rate, an added charge for high yield, and a trucking charge. The 2005 KAS wheat rates were $14.62/acre, plus $0.144/bu/acre above 20 bu/acre, plus $0.144/bu for trucking. Milo rates were $16.38/acre, plus $0.145/bu/acre above 34 bu/acre, plus $0.147/bu for trucking. Corn rates were $22.22/acre, plus $0.141/bu/acre above 55 bu/acre, plus $0.128/bu for trucking. We assume that crop yields under 5 bu/acre go unharvested.

Non-fertilizer costs

The cost of harvesting and the cost of fertilizer product depend on crop yield and so vary by each annual outcome of a simulation. In this work other costs generally do not vary by crop yield, but rather only by cropping sequence. In this category, referred to as non-fertilizer costs, we place the costs of herbicide and its application, fertilizer application, seed, and planting. Table A5 depicts values believed reasonable for northwest Kansas and taken from records at the Kastens Farm. More detailed crop descriptions are provided earlier in this paper. We assume a herbicide application charge of $4.35/acre, fertilizer application at $7.00/acre, and a planting cost of $12.50/acre.

Table A5. Cost of herbicide and application, fertilizer application, seed, and planting.

crop[a]	herbicide $/crop acre	no. of herbicide applications per crop acre @ $4.35 per applied acre	no. of fertilizer applications per crop acre @ $7.00 per applied acre	seed $/crop acre[b]	total non-fertilizer costs $/crop acre
WaF	19.95	5.25	1	7.00	69.29
WaM	13.30	3.5	1	7.00	55.03
WaC	13.30	3.5	1	7.00	55.03
WaW	10.60	3	1	7.00	50.15
WaS	0.00	0	1	10.50	30.00
MaW	28.34	3.75	0	5.00	62.15
MaM	25.53	2	0	5.00	51.73
MaC	25.53	2	0	5.00	51.73
CaW	26.44	2.75	0	25.00	75.90
CaM	19.79	1	0	21.05	57.69
CaC	19.79	1	0	21.05	57.69

[a] WaF is wheat after fallow, as in a wheat-fallow rotation, WaW is continuous wheat, WaM, WaC, MaW, CaW depict the typical crops in a wheat-milo-fallow or wheat-corn-fallow rotation. WaS is wheat after a spring crop, as in wheat planted immediately following corn harvest (into corn stalks). MaM, MaC, CaM, CaC represent milo-milo rotations, milo-corn, corn-milo, and corn-corn.

[b] All crops are assigned a planting charge of $12.50/acre (included in the totals in right column).

Land rent and government payments

This study assumes an annual land rent of $35.00/acre paid on all land committed to a crop rotation, including fallow land. We assume annual government payment receipts to be $12/acre, also assigned to all land.

Crop insurance

For simplicity, we assume actuarially fair crop insurance, where annual premium equals the expected indemnity, and a coverage of 65%. Thus, in a given simulation scenario, say one involving 1,000 yields of some crop, any yield less than 65% of the 1,000-yield average would receive an indemnity making up the difference to that 65%-of-average yield. The average of those indemnities is then assigned as an annual premium to each year the crop is raised.

Profit

For each year of a simulation scenario we compute $/acre crop sales (harvested crop yield times crop price) for the crop raised that year ($0 if the land is fallow or less than 5 bu/acre), and add to that number the government payment value plus any crop insurance indemnity paid. The result is a $/acre number for *revenue*. Note that *revenue* would be $12.00/acre in a fallow year (only the government payment). Annual $/acre *cost* is comprised of fertilizer cost, harvesting cost, non-fertilizer cost, crop insurance premiums, and land rent. Note that *cost* would be $35.00/acre in a fallow year (only the annual rent). Then annual $/acre *profit* is simply *revenue* less *cost*.

Risk
We compute two measures of risk, the first being standard deviation of annual profit. From a statistical standpoint, we can say that we would expect profit to fall within plus or minus one standard deviation value of its expected value about 2/3 of the time. Put another way, we can say that 1 year in 6 we would expect profit to be less than expected profit less one standard deviation.

Ideally, we would like to measure annual profit for a farm that has its acres proportionally divided between the crops (and fallow, if it is a part) in the crop rotation being considered. Then, we simply could compute the standard deviation across all observations of $/acre/year farm profit. However, our simulation exercise actually simulates essentially only one acre, so that it might be wheat this year, corn next year, and fallow the next (if considering a WCF rotation). So, we do the next best thing, which in this WCF case, is take a 3-year average of profit and call that an annual farm profit. We reason that a given crop's yield is impacted by more than one calendar year of weather (via water storage in the soil, or via a crop's growing period extending across two years, as in the case of wheat). Hence, we believe that our computed "annual" profit series is a reasonable one on which to base a standard deviation calculation. Moreover, we believe that geographical dispersion across a farm reduces risk because rain varies dramatically across space. So, our computed standard deviation (which likely would be lower than had we done what we said we would have liked to do ideally) might be a better characterization of farm level risk anyway.

The second measure of risk we consider is referred to as *worst6*. It is the lowest 6-consecutive-year average profit observed in an entire simulation. We used specifically 6 years as an arbitrary representation of multiple years of drought, similar to what many western Kansas farmers have experienced in the 2000s. Moreover, a number of our rotations are 2- or 3-year cropping sequences, meaningfully covered in a 6-year series.

Note that our risk measures are far from complete. First, they essentially consider only yield (basically, weather) risk, and not price risk. Also, they do not consider the possibility of more macro risk-mitigating occurrences such as government disaster programs. So, the risk measures we report should be used most meaningfully as relative comparisons across different crop rotations rather than as absolute measures of expected income variability across time.

Simulated mean crop yields associated with long-term (1946-2005) weather simulations

Table A6. Simulation yields using 1946-2005 weather data, Tribune

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	41.69	---	---	---	73.01	---	---	---	---	---
Rot2: WCF	---	---	42.91	---	---	---	---	---	69.32	---	---
Rot3: WCMF	---	38.47	---	---	---	---	---	62.74	68.91	---	---
Rot4: Opp	26.73	28.58	29.26	29.52	19.97	61.32	55.66	55.40	65.14	54.09	51.78
Rot5: WF	50.73	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	25.58	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	54.91	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	43.63
Rot9: CM	---	---	---	---	---	---	---	56.66	---	40.88	---

92.14% <cropping intensity of Rot4: Opp

50.18% <portion of crops in Rot4: Opp that are wheat

Table A7. Simulation yields using 1946-2005 weather data, Colby

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	46.80	---	---	---	72.03	---	---	---	---	---
Rot2: WCF	---	---	47.93	---	---	---	---	---	62.49	---	---
Rot3: WCMF	---	45.03	---	---	---	---	---	64.02	61.85	---	---
Rot4: Opp	42.69	37.58	38.37	37.20	28.32	64.51	59.25	59.40	61.88	53.50	51.10
Rot5: WF	54.47	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	31.19	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	59.22	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	45.18
Rot9: CM	---	---	---	---	---	---	---	60.70	---	42.66	---

89.55% <cropping intensity of Rot4: Opp

32.83% <portion of crops in Rot4: Opp that are wheat

Table A8. Simulation yields using 1946-2005 weather data, Atwood

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	45.61	---	---	---	60.35	---	---	---	---	---
Rot2: WCF	---	---	46.78	---	---	---	---	---	58.44	---	---
Rot3: WCMF	---	44.23	---	---	---	---	---	52.89	58.39	---	---
Rot4: Opp	32.35	39.85	40.19	38.53	30.76	55.28	50.36	50.79	59.44	49.36	49.38
Rot5: WF	53.80	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	33.24	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	49.41	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	41.51
Rot9: CM	---	---	---	---	---	---	---	50.75	---	39.55	---

86.26% <cropping intensity of Rot4: Opp

21.39% <portion of crops in Rot4: Opp that are wheat

Simulated mean crop yields associated with short-term (1991-2005) weather simulations

Table A9. Simulation yields using 1991-2005 weather data, Tribune

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	39.25	---	---	---	69.92	---	---	---	---	---
Rot2: WCF	---	---	40.27	---	---	---	---	---	67.73	---	---
Rot3: WCMF	---	36.27	---	---	---	---	---	60.30	67.60	---	---
Rot4: Opp	30.09	27.60	28.27	28.88	19.95	60.91	55.48	55.33	67.71	57.36	54.59
Rot5: WF	47.96	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	24.05	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	53.32	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	44.22
Rot9: CM	---	---	---	---	---	---	---	54.71	---	41.85	---

88.22% <cropping intensity of Rot4: Opp

46.98% <portion of crops in Rot4: Opp that are wheat

Table A10. Simulation yields using 1991-2005 weather data, Colby

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	42.62	---	---	---	78.86	---	---	---	---	---
Rot2: WCF	---	---	43.65	---	---	---	---	---	76.32	---	---
Rot3: WCMF	---	40.70	---	---	---	---	---	70.25	76.16	---	---
Rot4: Opp	34.30	32.84	33.29	33.13	24.32	70.45	66.15	66.35	75.51	68.53	65.53
Rot5: WF	50.28	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	27.89	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	65.71	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	58.21
Rot9: CM	---	---	---	---	---	---	---	66.95	---	56.18	---

88.43% <cropping intensity of Rot4: Opp

44.62% <portion of crops in Rot4: Opp that are wheat

Table A11. Simulation yields using 1991-2005 weather data, Atwood

	WaF yield	WaM yield	WaC yield	WaW yield	WaS yield	MaW yield	MaM yield	MaC yield	CaW yield	CaM yield	CaC yield
Rot1: WMF	---	45.85	---	---	---	71.38	---	---	---	---	---
Rot2: WCF	---	---	46.78	---	---	---	---	---	78.21	---	---
Rot3: WCMF	---	44.28	---	---	---	---	---	63.23	78.16	---	---
Rot4: Opp	41.64	39.22	39.50	36.65	28.69	64.66	60.17	60.36	76.08	65.98	65.60
Rot5: WF	54.01	---	---	---	---	---	---	---	---	---	---
Rot6: WW	---	---	---	32.64	---	---	---	---	---	---	---
Rot7: MM	---	---	---	---	---	---	60.08	---	---	---	---
Rot8: CC	---	---	---	---	---	---	---	---	---	---	59.37
Rot9: CM	---	---	---	---	---	---	---	60.96	---	57.46	---

89.86% <cropping intensity of Rot4: Opp

27.53% <portion of crops in Rot4: Opp that are wheat