Title of paper: Prediction of Weather Event Associated Crop Yield Losses in Kansas

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Key Words: crop insurance, computer simulation, EPIC, hail damage, risk, yield loss.

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Reliable long term crop yield data are valuable information for crop insurance policy-formulation and individual farm management. In the crop insurance program, determination of a predetermined crop yield quantity, i.e., unit guarantee, is a key information to establish levels of crop insurance policy guarantee. In practice, production data are obtained by calculating a producer's mean self reported actual production history (APH) with four or more years of self-certified APH as the basis for coverage. If four or more years of certified records are not available, transitional yields (County T-yields) are substituted for years missing production data. In some instances, use of T-yields instead of APH data reduces yield guarantees over time for insurance purposes by as much as 50 percent.

Yield risk varies regionally, and depends on soil type, climate, use of irrigation, and other variables. Weather factors (e.g., hail, drought, flooding, and cold temperature) are poorly predicted because they are stochastic by nature. Importantly, weather factors detrimentally influence annual crop yield variation. For example, in Kansas the annual indemnity payment made by insurance companies for weather-related yield loss reached more than 1.18 billion dollars over fourteen years (1991 – 2004). The distribution of damage payments demonstrates the importance of weather in crop loss: (1) 67% attributed to drought, (2) 14% to too cold, (3) 11% to hail, and (4) 8% to flooding (table 1). It is important to note that indemnity payments varied considerably by crop, cause of loss, and geographical regions in the state. Therefore, it is important to predict how the weather factors affect crop yield.

Regression analyses have been done, and deterministic "simulations" conducted. However, computer simulation has not been applied to the research objective of providing data that are actuarially useful when only 4 or 5 years of history are available.

Computer simulation models, ranging from statistical to deterministic, are used in common practice in various disciplines such as scheduling in manufacturing (Koh, Souza, and Ho; Dogan, McClain, and Wicklund), statistical parameter estimation (Takahashi, Hiraki, and Soshiroda), and medicine and biology (Azgomi and Movaghar). Computer simulation is also used in forestry, and to predict crop production associated with climate variation and some specific weather factors (Gassman et al.). Choice of the appropriate simulation model is critical to the success of modeling any phenomenon. Numerous environmental models exist, and some have integrated NASA satellite data to estimate the cost of crop damage from hail and wind storms (Bentley, Mote, and Thebpanya). Even satellite-imagery estimates of crop damage caused by the extreme weather have its own limitations because it cannot assess damage severity. Damage severity analysis is very important from the viewpoint of economics. Research indicates that crops have a recovery ability, dependent upon the crop's stage of development, and weather during the remainder of the growing season. For example, in corn production seedlings remain below ground two to three weeks after the plant germinates (5-leaf). If the pre-emergent seedling is not damaged, corn will recover and perform better than replanted corn. In contrast, corn in the silking and tasseling stage can result in severe yield losses when damaged by hail (Cogdill and Kringler).

Crop models are generally designed to operate at the field level, and they rely on detailed field-scale inputs, such as the soil type/series, plant genotype and weather, to predict yield and other crop variables at that scale. Climate prediction models have a much coarser resolution, typically from tens (in regional models) to hundreds of square kilometers (Priya and Shibasaki).

For agricultural computer simulation analysis, EPIC is a continuous, field scale agricultural management/water quality model (Michels, Potter, and Williams; Gassman et al.; Williams et al.). The EPIC model is broad-based and can be used to model major biophysical processes, including weather, hydrology, erosion, nutrient (nitrogen and phosphorus) cycling, pesticide fate, soil temperature, crop growth, tillage, plant environmental influences and economic inputs and outputs. EPIC input data are generally available (i.e., crops, soil types/series, tillage, fertilizer, pesticides, weather). Daily weather may be input or simulated by EPIC using its built-in stochastic weather generator. EPIC is capable of simulating the long-term effects of cropping systems on soil erosion and productivity in specific environments. EPIC simulated yields of maize, wheat, rice, sunflower, barley and soybeans were compared to 227 measured yields reported by independent research groups around the world. Mean simulated yields were within 7% of mean measured yields for these crops. Measured and simulated means were not significantly different ($P > 0.05$), and EPIC accurately simulated maize responses to irrigation at locations in the western U.S. and to nitrogen fertilizer in Hawaii (Williams).

The EPIC crop growth component is capable of forecasting yield reduction because of environmental stresses caused by water (too wet or too dry) and temperature (too hot or too cold). However, the EPIC model previously had no hail damage function integrated. Hail damage is, nonetheless, an important source of crop damage in crop insurance and agricultural practice and policy-formulation. Hence, a hail damage component was developed, added to the EPIC simulation, and reported here.

The present investigation was aimed to: (1) develop and integrate a hail damage function into EPIC, and (2) test the EPIC model's accuracy to simulate weather-related crop yield losses for each of nine districts in Kansas with hail damage included, in addition to hydrologic and temperature damage functions.

METHODS AND MATERIALS

The present investigation describes data sources, model development, calibration, and validation for the integration of hail into the EPIC simulation model. The model forecasts were tested against insured, observed yields in Kansas for 1998 to 2004.

Data Sources

Data inputs to the EPIC simulation model include soil, weather, hail probability, hail-caused yield loss (damage function), location of crop production, and crop yield. These data were assembled from various sources.

Soil. Data on soil types were obtained from the Kansas Agricultural Experiment Station, Kansas State University, and were used to identify dominant soil types in each county. Soil type data originated from the county soil survey, and the type that accounted for the highest percentage was considered the dominant soil type in the county. Direct data matching between crop type and soil type was not available. Therefore it was assumed that the dominant soil type was used to grow the dominant crop in a county. For example, if the soil survey data indicates that 80% soil in Graham County is kuma silt loam and if corn is the dominant crop in the county, then the kuma silt loam soil will automatically be recognized as the dominant soil for corn production in this county. The county level soil type data was further aggregated into district level soil data for crop yield simulation. Actual soil data were synthesized from the STATSGO soil database as compiled by the United States Department of Agriculture Natural Resource Conservation Service (NRCS) (USDA). All variables used to describe a soil's physical and chemical properties were included in each soil file except for the hydrologic soil group number. The hydrologic soil group number was extracted from the USDA Soil Conservation Service National Engineering Handbook, Hydrology, Section 4, Chapter 7 (USDA).

Crop Type. Crop type data was obtained published from Kansas agricultural statistics (Kansas Agricultural Statistics, Staff Paper no. 95-10). Data provided the annual county crop production information during 1995-2002 by crop, identifying the dominant crops in each county. Combined with dominant soil type data for each county, dominant soil type was matched with dominant crop data, as previously described. This provided realistic model inputs for the simulations.

Weather Data. The weather data was gathered from Earthinfo's weather database (EARTHINFO, Inc., NCDC). Daily weather variables (1960 to 2003) included: precipitation, maximum and minimum temperature, relative humidity, solar radiation, and wind speed were obtained for each weather station in Kansas. Missing daily weather records were simulated by the EPIC weather generator through interpolation.

Crop Yield Data. Yield data were extracted from the USDA Risk Management Agency (RMA) database for 1984 to 2003. Average annual corn, soybean, sorghum, and wheat yields were calculated for the period 1984-2003 for each county and aggregated to the district level. Years with zero acreage of a particular crop were excluded from the mean yield calculation.

Hail Data. Daily hail data from January 1, 1955 to June 20, 2004 were assembled from the National Climatic Data Center, NOAA Satellites and Information, National Environmental

Satellites, Data, and Information Service (NCDC). County based daily hail events were recorded by the local weather stations and some field observers. County level daily hail data were aggregated to district level for probability distribution analysis. Observed data showed that hail only occurred from day 45 to day 340 and peaked during the period day 140 to 160, i.e., in the late April and early June each year (figure 1).

Hail Damage. Crop yield hail damage data were synthesized from the USDA RMA database for the period 1991-2004. The raw data included hail insurance policy level information such as policy number, planting dates, cropping practices (irrigated and dryland), insured acres, claimed acres, etc., in each county. District hail damaged acres were aggregated up to the District level from the county data. Hail-caused crop yield damage was defined as a percentage term: (claimed hail damage acres/insured acres of each crop/year) in a district. Hail-caused crop yield loss ranges from 0.5% to 21% with the majority of hail damage comprising less than 5% of the total for a District. On average, hail caused about 5 percent yield loss in Kansas, but the severity of hail damage varied from crop to crop, and from district to district (table 2).

The EPIC Hail Model

Correct estimation of crop yield damage caused by hail is very complex because of variation in hailstone size, number of hailstones per unit area, and associated winds. Hail risk is a combination of these factors plus the frequency of hail at a point or over an area (Bentley, Thomas, and Thebpanya). Hail can result in no damage or a total loss, or any proportion in between. Statistics on hailstorms that are relevant to agricultural production are difficult to obtain, primarily because of shortcomings in observational systems. As a result, the historical hail damage assessment was primarily based on crop hail insurance records. An additional confounder is that not all farmers have crop insurance coverage. Hail insurance is estimated to cover 25 to 30 percent of all crop losses caused by hail (Changnon). Records of hail as a cause of loss are limited to crops that are growing and susceptible to loss. As noted earlier, vulnerability to hail damage changes during the growing cycle and varies between crops (Cogdill and Kringler). In addition, crop-hail losses for a state or the nation change with time because of coverage (liability) differences and crop value. Cyclical temporal variation in hail occurrence is pronounced (figure 1).

The EPIC hail model simulates hailstorm occurrence and hail damage to crops. The model is stochastic and independent of the EPIC weather simulation model. Hail storm occurrence is simulated using daily probability distributions derived from various observers within a District ((NCDC), NOAA Satellites and Information, National Environmental Satellites, Data, and Information Service). Kansas Districts are large, generally comprised of several counties. In contrast, hailstorms tend to be isolated, normally covering a small fraction of the District. Thus, the probability of hail occurrence on a particular field within a district is usually much less than the probability of hail occurrence within the district. We developed a stochastic approach for adjusting the district probabilities to probabilities for a particular field within the district using the equation:

$$HPCA = HDPB * (-\ln(FX)) \quad (1)$$

where HPCA is the hail probability conversion factor for adjusting district probabilities to field site probabilities, HDPB is the mean fraction of the district area covered by an individual hail storm, and FX is a uniform random number. Hailstorm occurrence is simulated when

$$RN < HPCA*HLPB_j \quad (2)$$

where RN is a uniformly distributed random number, and $HLPB_j$ is the district hail probability for day j. When a simulated hailstorm occurs crop damage is simulated using hail damage functions for irrigated and dry land winter wheat, corn, grain sorghum, and soybeans by District. Damage statistics include the mean and standard deviation. The damage function was assumed to be normally distributed and hail damage was simulated with the equation:

$$CHDM = HLDM_k + SND * HLDS_k \quad (3)$$

where CHDM is the proportion of crop damage caused by the hail storm, HLDM and HLDS are the mean and standard deviation of the hail damage distribution for crop k, and SND is the standard normal deviate drawn randomly from a normal distribution. Crop yield is adjusted with the hail damage fraction using the equation:

$$YLD = YLD_o * (1.0 - CHDM) \quad (4)$$

where YLD is the crop yield as affected by hail damage and YLD_o is the crop yield with no hail damage.

Model Calibration

The EPIC model was calibrated on three parameters: (1) crop yield, (2) hail damage severity, and (3) the damage distribution associated with different factors including hail, too wet, too cold, and too dry. Calibration of yield and hail damage was evaluated using a goodness of fit and two-sample mean tests (assuming equal sample sizes) were performed to evaluate whether there was statistically significant difference between observed and simulated results. For instance, if both R^2 and two sample mean tests revealed there was no statistically significant difference between observed and simulated outcomes, we would conclude that the EPIC-hail model was validated and is calibrated for use in long run crop productivity and hail damage forecasts for each investigated crop. In addition, prior to the two-sample mean test, a two-sample equal-variance test (F-test) was performed to determine an appropriate two-sample t test procedure to be used in each test. EPIC was calibrated using exactly same length of period (20 years) because only 20 years (1984-2003) of crop yield data were available from the USDA RMA database. Non-hail yield damage was validated by checking the simulated damage ratio against observed damage ratio of each investigated weather factor. The damage ratio associated with each weather factor was defined as percent of yield loss attributed to each factor with respect to the total yield loss of each crop.

To simplify the analysis, four simulations (one for each crop) were performed in each District using one soil and one weather station (located nearest the center of the district). The choice of weather station is not particularly important because precipitation and temperature are very similar for all stations within a district. However, there is substantial variation in rainfall among Districts as one proceeds from east to west.

Crop management files (operation schedules) were generalized to formulate District level simulations. These operation schedules were developed to represent normal farming practices for each of the four crops within each District. They include planting and harvest dates, tillage type, planting depth, and dates of cultivation. Of course these operation schedules vary among farmers and across individual years, but data are not available for these parameters. In addition, it is likely that they would have little effect on long term crop yields if they were quantified. Separate operation schedules were developed for irrigated and dryland crops. Irrigation and fertilizer were applied automatically by the model's algorithms to meet crop needs. These were "fixed" parameters. Specific model parameter validation procedures for those variables allowed to vary were done for crop yield, hail damage, and non-hail weather damage.

Crop Yields. Simulated and observed crop yields were compared. The EPIC parameters are well established for the crops in the simulation because they are the four crops most commonly simulated with this model. Thus, the initial yield estimates compared fairly well with observed yields. The initial estimates were refined primarily by adjusting plant populations and potential heat units to maturity. Other less important adjustments were made in winter wheat dormancy, potential evapotrans-piration, and amounts of fertilizer and irrigation applied.

Hail Damage. The stochastic hail model is based on the probability of hail occurrence and associated damage functions (normal distribution assumed). Thus, there is very little to adjust except for HDPB (the mean fraction of the district area covered by an individual hail storm). Little variation among Districts in the value of HDPB was obtained during the calibration process. The direct relation between hail damage and crop yield complicated the validation of these variables. Also, the stochastic nature of the hail model prevents annual damage comparisons to observed data; only long-term means are comparable. Further complications were encountered in the statistical analyses. A small error in magnitude can translate to a large percent difference in simulated and observed yields because most hail-induced yield loss was less than 5%. Appropriately, the two-sample equal mean tests were omitted in this instance in favor of goodness of fit tests. In general, if R^2 attained 0.50 or above, the validation result with respect to the hail damage would be considered acceptable.

Non-hail Weather Damage. The EPIC crop model constrains daily potential growth using the minimum of water, nutrients, temperature, aeration, and salinity stress factors. The factors range from 0-1 (0 means no growth and 1 means no constraint). The stress factors considered in the present analysis are water, temperature, and aeration. The water stress factor translates to the too dry condition and aeration to the too wet condition. Temperature had to be separated to obtain the necessary too cold and too hot conditions because the temperature stress factor is a composite of cold and heat stresses. The too hot condition was combined with the too dry condition for comparison to the too hot observed data.

Results

Crop Yields. Comparisons of observed and simulated yields for each of the four crops produced high R^2 values (0.995 for corn; 0.989, soybeans; 0.975, grain sorghum; 0.931, wheat. Furthermore, the two-sample mean tests indicated no statistically significant difference between observed and simulated yields for each crop simulated in each District (table 3). The test could not be performed for dryland wheat in Districts 20 and 30, and irrigated and dryland wheat in Districts 70, 80, and 90 because there was no observed data. Where observed data were available, both R^2 and t-tests showed that EPIC was validated with respect to crop yields.

Hail Damage. Hail damage was measured as a percentage of yield loss for each simulated crop. Comparison of average annual observed and simulated hail damage yield losses for all four crops and all nine Districts produced an R^2 of 0.652. The same comparisons for individual crops resulted in R^2 values of 0.497 for wheat, 0.704 for soybeans, 0.603 for corn, and 0.308 for grain sorghum. The main reason that the R^2 values are low relative to those of crop yield is that the hail damage model is stochastic. Only long-term observed and simulated means can be compared because the model is stochastic. It is not logical to compare annual values from a stochastic model to observed values. Also, the longer the term (i.e., number of years) analyzed, the closer simulated and observed mean values agreement. The relatively short term (20 years) data available for this study is not ideal for these comparisons, especially considering the infrequent nature of hail events. Within these constraints, the model performed well especially considering the relatively small magnitude of the differences in observed and simulated means of hail damage.

Non-hail Damage. Non-hail damage includes yield losses attributed to too hot and dry (or drought), too wet (flooding), and too cold (frost). The fraction of the total damage attributed to each component is shown in table 4. Observed and simulated damage distributions are similar. Hot/dry weather (or drought) caused the greatest damage loss for each crop (more than 90% in corn, soybeans, and grain sorghum). The remaining 10% damage loss was attributed to the combination of hail, too wet and too cold. One noticeable difference between observed and simulated result was for too wet damage; simulated results consistently under-estimate observed damage due to “too wet” conditions. This was probably because the dominant soils used in this study are located on upland areas rather than floodplains where wet conditions are more prevalent.

Discussion and Summary

A hail damage model was developed as an integrated component of EPIC. The model was used to estimate weather-caused crop yield losses for four crops growing in nine Districts for the state of Kansas. Multiple data elements were synthesized, including weather (hot, dry cold), hail event distribution, soil, crop management, and historical crop yields. The most important data element was the district hail event distribution. Other weather-factor related yield damage assessments were based on the pre-existing EPIC components (water, temperature, and aeration stresses), in addition to hail. The EPIC-hail model simulates (1) hail storm occurrence and then (2) hail damage to crops. The model is stochastic and independent of the EPIC weather simulation model. Hailstorm occurrence was simulated using daily probability distributions derived from various data sources within a district. Hailstorm events tend to be isolated, and normally cover a small fraction of the district. Thus, the probability of hail occurrence on a particular field within a District is usually much less than the probability of hail occurrence within the District because they are additive probabilities. In the present investigation, a stochastic approach for adjusting the District probabilities to probabilities for a particular field within the District using a series of mathematical and statistical distribution formulas was developed. When a hail storm occurs, crop damage is simulated using hail damage functions for irrigated and dry land winter wheat, corn, grain sorghum, and soybeans by district. The damage statistics include the mean and standard deviation, assuming that the damage function was normally distributed.

EPIC was able to simulate crop yields that compare closely with observed yields ($R^{2 >}$ 0.95 and no statistically significant difference between observed and simulated crop yields across the districts ($p<0.05$) by correlation and two-sample equal mean test analyses. The hail damage model test indicated that EPIC was able to predict hail-induced yield losses reasonably well ($R^{2 >}$ 0.60). The main reason that the R^2 values are low relative to those of crop yield is that the hail damage model is stochastic and totally independent of the daily weather input. Also, the relatively short term (20 years) data available for this study is much less than ideal for these comparisons, especially considering the rarity of hail occurrence. Given these constraints, the model performed reasonably well especially considering the relatively small magnitude of the differences in observed and simulated means. In addition, observed and simulated damage (too hot or dry, too cold, too wet) distributions are similar. Importantly, too hot or too dry conditions are the dominant crop damage factors in all nine Districts in Kansas. Hail accounts for less than 8% of the total yield damage in Kansas.

Therefore, simulation results on hail and other weather factor damage functions could be improved by: (1) using more accurate hail data collection (area covered by the hail storm and the crop damage within that area), and (2) focusing the simulation scale to a county or sub-county level would provide more specific weather, soil, and management data.

References

Azgomi, M.A. and A. Movaghar. “A Modeling Tool for Hierarchical Stochastic Activity Networks.” Simulation Practice and Theory, vol 16, 6 (Sept. 1995) 505-524.

Bentley, M.L, L.M. Thomas, and P. Thebpanya. “Using Landsat to Identify Thunderstorm Damage in Agricultural Regions.” American Meterological Society 363-377, 2002.

Cogdill, B. and J. Kringler. “Hail Damage in Crops.” North Dakota State University Extension Service, 2004.

Dogan, C.A., T.F. McClain, and S.A. Wicklund. “Simulation Modeling and Analysis of A Hardwood Sawmill.” Simulation Practice and Theory 5 (1997) 387-403.

Gassman, P.W., T. Campbell, C. Izaurralde, A.M. Thomson, and J.D. Atwood. “Regional Estimation of Soil Carbon and Other Environmental Indicators Using EPIC and I_EPIC.” Center for Agricultural and Rural Development. Technical Report 03-TR 46, April 2003.

Harwood, J., R. Heifner, K. Coble, J. Perry, and A. Somwaru. A managing Risk in Farming: Concepts, Research, and Analysis. U.S. Department of Agriculture, Economic Research Service Agricultural Economic report No. 774, March 1999.

Kansas Agricultural Statistics. “Incorporating Abandoned Acreage into the Income Capitalization Method for Valuation of Agricultural Land.” Kansas State University, Staff Paper no. 95-10, 2002.

Koh, K., R.D. Souza, and N. Ho. “Database Driven Simulation/Simulation-based Scheduling of A Job-Shop.” Simulation Practice and Theory 4 (1996) 31-45.

Lobell, D.B. and G.P. Asner. “Climate and Management Contributions to Recent Trends in U.S. Agricultrual Yields.” BREVIA, Science, 299:1032, 2003.

Michels, K., K.N. Potter, and J.R. Williams. "Calibration of EPIC for the Simulation of Wind Erosion Damage to Pearl Millet in West Africa." Web-publication at http://www.weru.ksu.edu/symposium/proceedings/michels.pdf.

National Climatic Data Center, NOAA Satellites and Information, National Environmental Satellites, Data, and Information Service (NCDC, 2004). Available at http://www.crh.noaa.gov.

Priya, S. and R. Shibasaki. "GIS-Based Regional Spatial Crop Yield Modeling." Web-publication at http://www.gisdevelopment.net/aars/acrs/1999, P. 1-5, 1999.

Stanley Changnon. " Trends in Hail in the United States." Chief Emeritus & Principal Scientist Illinois State Water Survey, Mahomet, IL, *changnon@uiuc.edu*. Internet Web Publication at sciencepolicy.colorado.edu/ socasp/weather1/changnon.html, 2000.

Takahashi, K., S. Hiraki, and S. Soshiroda. "Estimating A Percentile from Autocorrelated Simulation Outputs." Simulation Practice and Theory 3 (1995) 45-62.

The United States Department of Agriculture (USDA). Soil Conservation Service National Engineering Handbook. Hydrology, Section 4, Chapter 7, P68-96, 1972.

Williams, J.R. and R. C. Izaurralde. "The APEX Model." Texas A&M Blackland Research Center at Temple. BRC Report No.2005-02, April 2005.

Williams, J.R. "EPIC: The Erosion-Productivity Impact Calculator." Pp. 676-681 In: J.K. Clema (ed) Proc. 1989 Summer Computer Simulation Conf., July 24-27, 1989, Austin, TX.

Williams, J.R., Jones, C.A., Kiniry, J.R., and Spanel, D. A. "The EPIC Crop Growth Model." Trans. ASAE 32(2):497-511, 1989.

Table 1 Observed crop yield losses attributed to different weather factors

Crop	Hail	Too Hot	Too Wet	Too Cold	Sum
			Percent		
Corn	10	81	6	3	100
Soybeans	4	85	10	1	100
Sorghum	2	87	8	3	100
Wheat	18	45	9	28	100
			1,000 Dollars		
Corn	2,388	19,343	1,433	716	23,881
Soybeans	674	14,313	1,684	168	16,839
Sorghum	490	21,328	1,961	735	24,515
Wheat	9,503	23,757	4,751	14,782	52,793
Sum	13,055	78,741	9,829	16,402	118,027
Percent	11	67	8	14	100

Table 2. District based % hail damages (claimed acres/total planted acres in each district*100)

	Wheat		Corn		Sorgum		Soybean	
District #	Irrigated	non-irri.	Irrigated	Non-irri	Irrigated	Non-irri.	Irrigated	Non-irri.
10	5.56	5	3.73	1.81	4.81	1.18	7.88	5.05
20	5.8	6	3.41	2.36	3	1.08	6.1	4.85
30	3.39	3	1.6	2.04	2.39	0.82	4.48	7.97
40	9.18	4	1.08	1.06	0.94	0.37	1.26	0.86
50	3.16	6	2.95	1.22	0.53	0.37	2.5	1.03
60	2.54	4	1.54	2.17	1.29	0.53	2.73	1.87
70	2.5	1	3.27	0.28	--	0.45	0.78	0.63
80	20.89	2	0.36	0.21	--	0.12	2.47	0.32
90	20.85	1	1.5	0.44	--	0.11	6.13	0.26

Table 3 Comparison between observed and simulated annual average crop yields (1984 - 2003)

District	Observed Mean	Simulated Mean	Significant difference	Observed Mean	Simulated Mean	Significant Difference
		Irrigated			Dryland	
			Corn			
District 10	8.68	8.56	no *	3.92	3.75	No *
District 20	8.3	8.46	no *	3.09	3.8	No *
District 30	9.11	8.86	no *	2.25	3.32	No *
District 40	7.92	7.98	no *	4.51	4.39	No *
District 50	7.85	8.5	no *	3.8	3.92	No *
District 60	9.13	8.88	no *	3.37	3.51	No *
District 70	7.66	7.75	no *	5.75	5.62	No *
District 80	7.96	8.1	no *	5.12	4.93	No *
District 90	5.73	6.52	no *	5.4	5.4	No *
			Soybeans			
District 10	2.95	2.85	no *	1.24	1.47	No *
District 20	2.45	2.4	no *	n.a.	n.a.	No *
District 30	2.97	2.91	no *	n.a.	n.a.	No *
District 40	2.77	2.7	no *	1.74	1.59	No *
District 50	2.92	2.86	no *	1.6	1.6	No *
District 60	3.11	3	no *	1.69	1.77	No *
District 70	2.89	2.79	no *	2.03	1.87	No *
District 80	2.99	2.91	no *	1.73	1.67	No *
District 90	2.01	2.23	no *	1.62	1.64	No *
			Sorghum			
District 10	5.11	5.44	no *	3.37	3.65	No *
District 20	5.34	5.33	no *	3.25	2.96	No *
District 30	5.27	5.66	no *	2.83	2.96	No *
District 40	5.52	5.54	no *	3.9	3.98	No *
District 50	5.33	5.35	no *	3.4	3.43	No *
District 60	5.28	5.3	no *	3.2	3.18	No *
District 70	5.1	5.41	no *	4.5	4.4	No *
District 80	5.1	5.51	no *	4.11	3.94	No *
District 90	4.59	4.72	no *	4.26	4.17	No *
			Wheat			
District 10	2.87	2.93	no *	n.a.	n.a.	No *
District 20	2.83	2.9	no *	n.a.	n.a.	No *
District 30	30.2	2.9	no *	2.38	2.11	No *
District 40	2.48	2.56	no *	2.38	2.38	No *
District 50	2.51	2.56	no *	2.25	2.34	No *
District 60	2.72	2.87	no *	2.08	2.31	No *
District 70	n.a.	n.a.	---	2.39	2.22	---
District 80	n.a.	n.a.	---	2.28	2.44	---
District 90	n.a.	n.a.	---	2.13	2.22	---

Significance of t-test where $*p<0.05$; n.a. not applicable due to missing observed historical data.

Table 4. Comparison between observed and simulated yield damages attributed to different weather factors

Damage Types	Corn	Soybeans	Sorghum	Wheat
		Observed (%)		
Hail	10	4	2	18
Too Hot	81	85	87	45
Too Wet	6	10	8	9
Too Cold	3	1	3	28
		Simulated (%)		
Hail	7	4	8	22
Too Hot	90	94	92	70
Too Wet	0	1	0	1
Too Cold	3	0	0	7

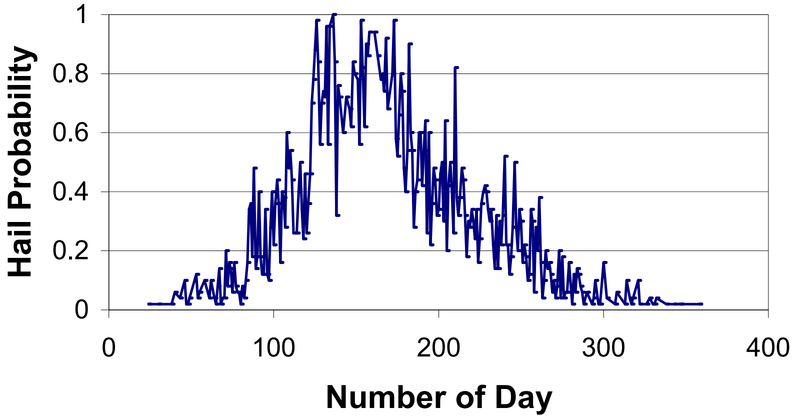

Figure 1. Hail event distribution in Kansas State, 1955 - 2004