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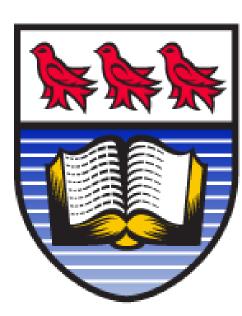
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Baojing Sun¹, Peter Bell² and G. Cornelis van Kooten² ¹College of Economics & Management, Northwest A&F University, China ²Department of Economics, University of Victoria, Contact author: B. Sun <u>baojings@uvic.ca</u>

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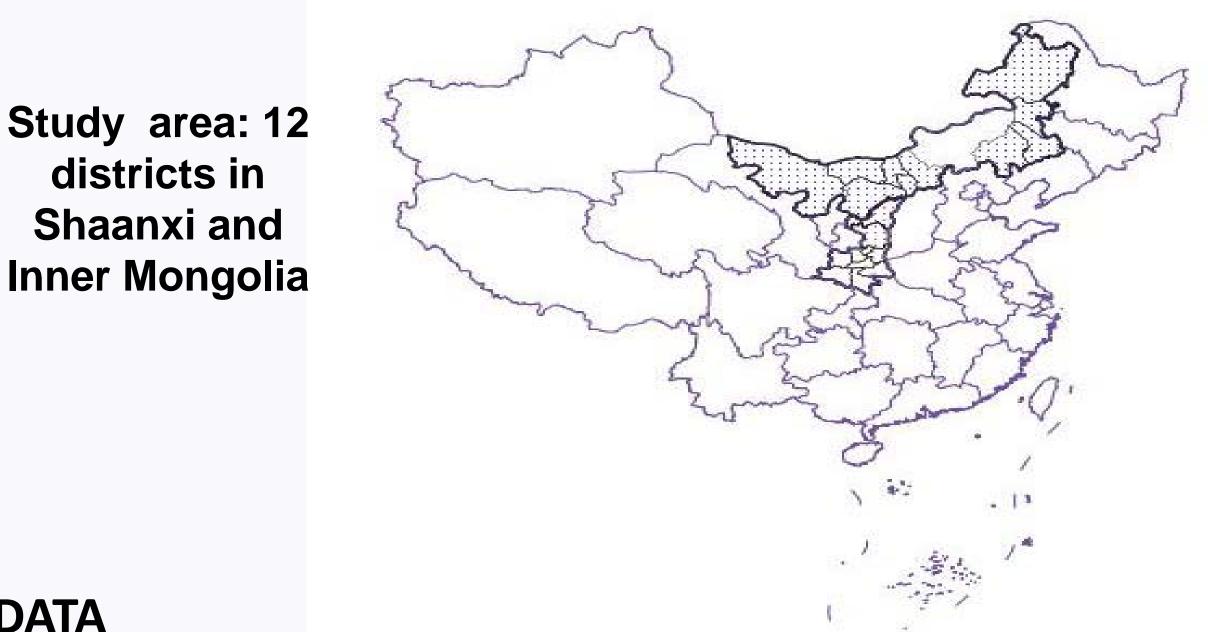
University of Victoria

INTRODUCTION

- Farmers in China face various weather risks, but have few options to offset them. Weather-indexed insurance is a financial weather derivative that has promise. Compared with traditional crop insurance, it links crop yields with weather records and avoids moral hazard.
- Studies show farmers in China are interested in weatherindexed insurance[1], but little research focuses on constructing weather-indexed insurance in China. Crop yield and weather data are a major obstacle.
- \succ This study estimates the effects of weather on crop yields, simulates yields using the estimated model, and constructs weather-index insurance according to relationship between weather records and crop yields.

STUDY AREA

>China's main corn production area, including ten districts of Inner Mongolia and two districts of Shaanxi Province in Northern China.



DATA

- >Weather records are from Ecological Environment Database of the Loess Plateau. Daily average temperature and monthly total precipitation from May to September for 11 to 13 years. Daily average temperature is used to calculate growing degree days (gdd).
- Corn yields are from Statistic Year Books of Inner Mongolia covering 1989-1999, and Shaanxi Province 1989-2001.

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Potential for Weather-Indexed Insurance in Northern China

Baojing Sun^{##}, PhD Candidate; Peter Bell[#], PhD Candidate; and G. Cornelis van Kooten[#], Professor;

[‡] College of Economics & Management, Northwest A&F University, China; [#]Department of Economics, University of Victoria, Canada

METHODS

Flexible fractional polynomial (FP) method is used to capture nonlinear relation between growing degree days and corn yields.

 $W(G, p, time, D) = y_{i,t} = \beta_0 + F(G) + \alpha_i z_{i,i,t} + D_i + \varepsilon_{i,t}, [2] [3];$ (1)Where *F*(*G*) is FP for growing degree days(*G*), *z* are other factors *i* (precipitation, technology, fertilizers) that affect crop growth in region *j* during *t*; α , β_0 are parameters to be estimated; *D* are time-invariant, district fixed-effects; and $\epsilon \sim N(0,\sigma)$ are iid.

- Monte Carlo methods are utilized to predict average yields ('Results').
- Probability Distribution Function of corn yields is employed to construct weather-index insurance pricing function [4]. $V(.) = (\tilde{y} - \overline{y}) \times \text{pr} \times p(\tilde{y}) = [W(.) - \overline{y}) \times \text{pr} \times p(W(.))$ (2) where \tilde{y} is estimated crop yield from the estimated model; \bar{y} is the average yield predicted by Monte Carlo methods; pr is adjusted crop price at time t; and $p(\tilde{y})$ is the probability of the estimated yield.

RESULTS and CONCLUSIONS

- >Coefficients of gdd for the first 3 models are not significant; coefficients for #4 and #5 are significant at 1% level. Deviance differences of the two models are significant under 1% and 10% levels, and they explain 80% and 82% variation in corn yields, respectively. Among models, the FP models #4 and #5 best explain corn yields.
- >In #4, precipitation in July, August and September, and time (representing technology), have significant effects on corn yields. Results for #5 are similar regarding precipitation, July precip is insignificant. Remaining variables in #4 and #5 also explain crop yield variation.
- > Predicted yields from models #4 and #5 match actual average district yields quite closely (Fig 2). Predicted yields from model 4 fit better than those from #5.
- > Model 4 could be used to construct a weather-indexed insurance price function. In #4, time and July and August precipitation positively affect corn yields, but September precipitation lowers it (because crops are ripe at that time and dry weather aids harvests).
- >The relation between gdd and corn yield is illustrated in Fig 3.

	#1	#2	#3	#4	#5
	(linear)	(linear, quad)	(Degree 1)	(Degree 2)	(Degree 3)
G ^{-0.5}				60408.94***	
G ^{-0.5} × (InG)				33287.7***	
G ¹	-2.19	3288.286			
G ²		-1493.91			
G ³			-193.0588		6039.994***
$G^3 \times InG$					-12611.59***
G³×(InG)²					6789.672***
P ₇	1419.79	2007.405**	1883.549**	1665.632*	1423.573
P ₈	1464.12^{*}	1516.562*	1524.749**	1731.731**	1735.878**
P ₈ ²	-669.36*	-701.9397*	-696.5165*	-837.6941**	-850.5945**
P ₉	-2315.02**	-2284.589**	-2314.334**	-2144.388**	-1986.002**
time	2600.48***	2441.459***	2437.684***	2543.325***	2681.286***
constant	6392.88***	6213.294***	6203.659***	6438.776***	6756.987***
R ²	0.7762	0.7952	0.7878	0.8028	0.8236
Deviance	2223.65	2208.53	2215.38	2201.18	2183.19
Res.SD	950.38		918.66	875.86	823.50
Dev.dif.	51.00		42.73	28.53	10.54
P(*)	0.000		0.000	0.001	0.079
Powers(G)	1	1,2	3	-0.5,-0.5	3,3,3

12000 10000 8000 6000 4000 2000

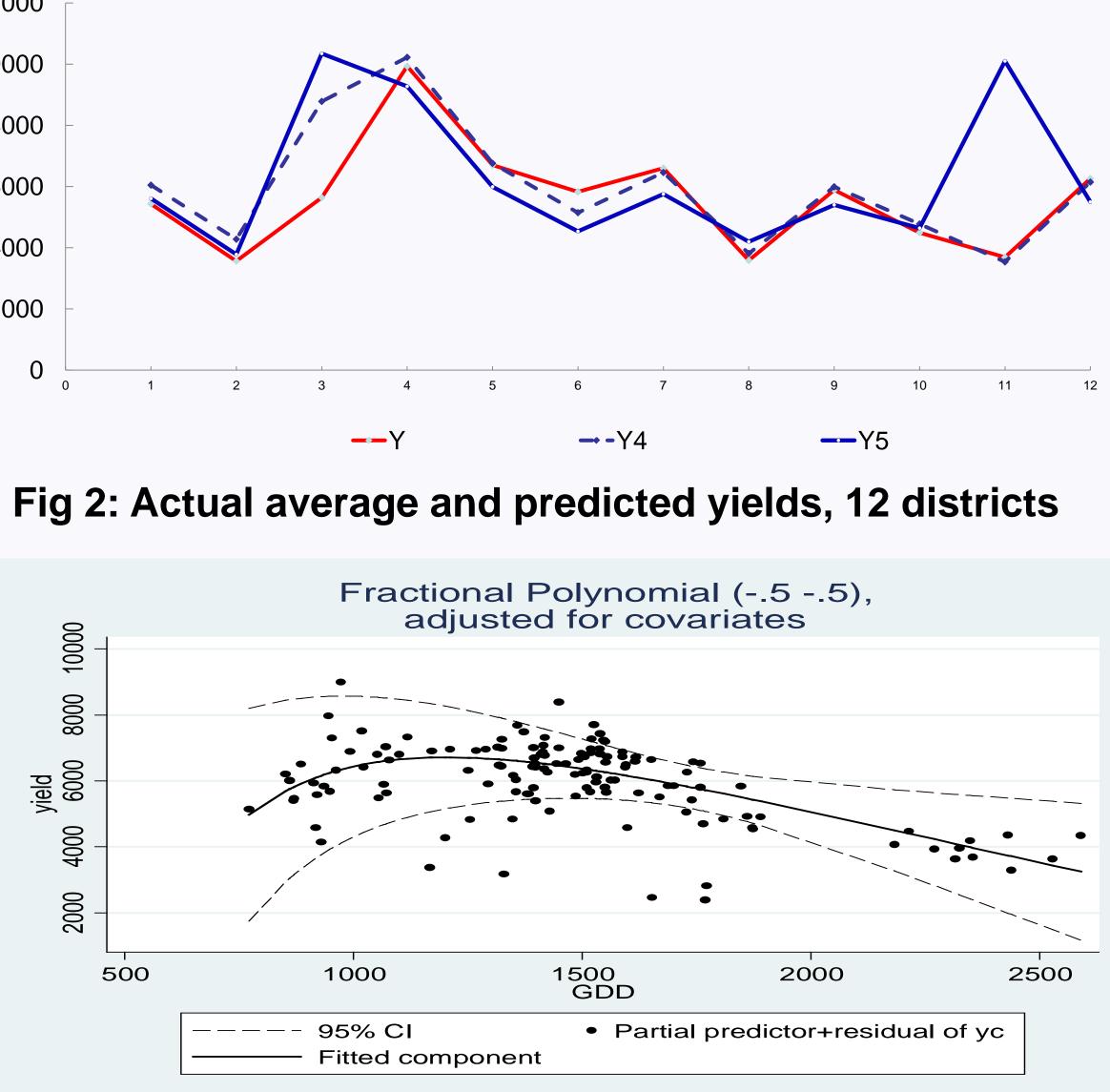


Fig 3:Relationship between gdd and corn yields

Table: Estimated Model (not all variables shown)

Note: G and p_7 , $p_8 \& p_9$ are standardized forms of gdd and precipitation.