Geographical Diversification in Agriculture

An Applied Case to Western U.S. Wheat Growers

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Abstract

Yield correlations between 380 different counties are calculated for non-irrigated wheat. Using this data, a function is estimated that shows the relationship between correlation and changes in geographic and climate data. In addition movement variables are included added to the specification to capture the impact of moving from one production region to another. A negative relationship was found between changes in latitude, longitude, precipitation, elevation, and temperature. Correlations and longitude and precipitation showed downward sloping concave relationship, whereas correlations and latitude showed downward sloping convex relationships. Changes in latitude and longitude are found to have greatest impact on correlation with elasticities of -1.54 and -1.

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Agriculture is inherently susceptible to all types of risk. Risks associated with agriculture include production risks, market or price risk, and costs risk (Boehlje and Lins, 1998, Escalante and Barry, 2001, Featherstone, et al., 2005, Hardaker, et al., 1997, Harwood, et al., 1999, Just and Pope, 2002, Moschini and Hennessy, 2001, Turvey and Diver, 1987). Mishra and Lence (2005 p.131) defined risk as "… as the uncertainty faced by a firm (be it an individual, agribusiness, or lender) that affects its welfare." They classify risk management strategies into two categories, within-firm and risk-sharing strategies. Within-firm strategies include enterprise diversification, reducing leverage, gathering additional information about future scenarios, and increases in liquidity. Risk-sharing strategies consist of insurance, futures and options, use of contracts, and off-farm income.

Risk management strategies utilized by producers varies by size and composition of the agricultural entity (Mishra and Lence, 2005). An industry that was once composed mainly of family farms has now been segmented into three areas, large-industrial companies, commercial-scale family operations, and the traditional small family farm (Featherstone, et al., 2005). Large-industrialized companies are diversifying risk through vertical integration and multi-national operations (Boehlje and Lins, 1998, Handy and MacDonald, 1989). Commercial-scale family operations utilize risk management tools such as hedging, insurance, and crop diversification (Mishra and El-Osta, 2002). Small scale family farms are diversifying by depending on off-farm income (Harwood, et al., 1999).

Another risk management strategy employed by commercial-scale farms is diversifying their portfolio geographically. Producers are locating operations geographically separated within a state or crossing state lines to locate their farms closer to processing plants and to reduce yield risk (Davis, et al., 1997). A limited number of studies have addressed farm level effects of geographic diversification on either the international level or at a state level (Davis, et al., 1997, Kreuger, et al., 1999, 1994). Additional studies are necessary concerning geographical diversification, including examining geographical diversification on an intra-national level. Two problems faced by producers considering geographical diversification are what location(s) "best" diversify their risk and what are the additional costs associated with geographical diversification?

The primary objective is to provide information on factors that influence the reduction in yield risks associated with geographical diversification. To obtain this objective, a wheat correlation function based on changes in latitude, longitude, elevation, and climate variables between each location is estimated. Effects for the various factors are summarized graphically and by calculating elasticities. This research extends current literature on geographical diversification by taking a more detailed look at the main factors impacting yield correlations.

Literature Review

Geographical diversification is not a new method of risk management. The banking industry and real estate investors have used this tool extensively in the past to manage portfolio risk. Liang and Rhoades (1988) using the changes in banking regulations that were taking place in the late 80's as motivation, studied the impact of geographical diversification in the banking industry. Many banks had begun to expand beyond state borders because of changes in regulations which allowed banks to expand into different regions. The authors also hypothesized that geographical diversification will reduce insolvency risk, but, in turn, may increase operating risk through increased management costs and issues surrounding the acquisition of a new firm. To test this hypothesis, they examined 5,500 banks over the period of 1976 to 1985 examine the effect of geographic diversification on overall diversification. Results suggest that geographic diversification reduces insolvency risk, but caution must be taken because of the potential increase in operating risk which could offset any potential gains from geographic diversification. In another banking study, the impact of geographic diversification was specifically applied to small banks that were acquired by larger banks (Rose and Wolken, 1990). Mergers appeared to provide no long run advantages for the small banks. In the short run, mergers, however, provided some opportunities for entry into new markets.

Ehling and Ramos (2006) examined the differences between sector diversification and geographic diversification using industries within the Eurozone. They argued that with the implementation of the Euro, gains associated with geographic diversification are diminished. Using a mean-variance efficiency test (Basak, et al., 2002) the authors test whether companies are better off by sector or geographical diversification. Results depend on the constraints imposed on the model. If short-selling constraints are imposed, then geographic diversification outperforms sector diversification. The two strategies are statistically equivalent if the problem is unconstrained. Kim and Mathur(2007) suggest geographical diversification increases operating costs but also increases return on equity and return on assets when compared to industrially diversified firms. These results suggest that there are some possible gains from geographic diversification.

Within an agricultural setting, results of studies on geographical diversification are conflicting. Kreuger et al. (1999) show that a grape grower could increase profits by producing in the U.S. and Chile. Nartea and Barry (1994)address the question is geographical diversification a legitimate risk management strategy for individual grain growers in central Illinois. Costs included in their model are increased transportation costs, monitoring costs, and losses due to poor machinery coordination. These costs are compared to increases in returns. Nartea and Barry conclude that there are no realizable gains from diversifying geographically in central Illinois. Davis et al. (1997) found an inverse relationship between Georgia peach orchards yields correlations and distance apart. Using farm level data gathered from peach growers, they estimated the volatility in yields that could be reduced by spatially dispersing the orchards. They concluded that correlation between yields is reduced by 2.28% for every additional mile orchards are separated.

Model Specification and Data

To address the objective of this study, a wheat yield correlation function is estimated

$$\rho_{ij} = f(Lat_{ij}, Long_{ij}, Ele_{ij}, Prec_{ij}, Temp_{ij}, Mvmt) + \varepsilon_{it} \qquad (1)$$

where ρ_{ij} is the county yield correlation between county i and county j, ε_{ij} is the error term, Mvmt are a set of 0-1 qualitative variables representing the two USDA regions the counties i and j reside in, and the remaining variables are differences in absolute value between the two counties i and j in latitude (Lat) in degrees, longitude (Long) in degrees, elevation (Ele) in feet, annual precipitation (Prec) in inches, and annual temperature (Temp) in Fahrenheit.

Dependent Variable

Before obtaining county yield correlations, historical county level yield data is detrended. A simple linear trend model is used

$$Y_{itn} = \alpha_{in} + \beta_{in} t + \varepsilon_{itn}$$

where Y_{it} is county wheat yield from county n in year t, α and β are coefficients to be estimated, t represents the year with t = 1, 2, …., T, and ε_{itn} is the error term. The significance of the coefficient β_{in} is used to determine whether a trend is present in the county data. Approximately 50% of the counties show a significant trend in their yield data (Table 1). To be consistent, all yields are detrended. Detrended county level yields (the residuals from the trend equation) are used to calculate the standard Pearson correlation coefficient. Two specifications of equation (1) are estimated a linear and a quadratic form. In addition, the models are estimated with and without the Mvmt dummy variables.

County level wheat yields from 1976 to 2001 for non irrigated wheat (both spring and fall) are used to estimate the yield correlation function. The criterion used to select a county was as follows. First the county had to be one of the following states, Washington, Oregon, Idaho, Montana, Utah, Colorado, North and South Dakota, Texas, Kansas, Oklahoma, and Nebraska. The analysis is limited to western and plains states. Unfortunately, many Oklahoma counties could not be included because of large gaps of missing data. Second, the county must have more than 10,000 acres of harvested wheat based on 2006 total harvested county acreage (Figure 1). Three hundred and eighty counties met these two criteria (Table 2).

To illustrate how the correlations vary between counties, an example is presented in Figures 2. The color coding on this map represent the magnitude of the correlation between county yields. In figure 2, the base county is Dallam County, Texas. As expected yields from counties close to Dallam are positively correlated with Dallam's county yields. Numerous counties located in Montana, Idaho, Washington, and Oregon are negatively correlated with Dallam County.

Independent Variables

To provide a consistent location across the counties for geographical and climate data, the county seats are used to represent each county. Latitude, longitude, and elevation for each of county seats are obtained from Lat-Long.com (2008). Thirty year average annual temperature and precipitation from weather stations located at or near the county seats from the Natural Resource and Conservation Service (2008) are used to represent climate variables.

Summary statistics for the geographical and climate data are given in Table 3. As expected, there is a large degree of diversity between the counties. The county with the largest precipitation level is Linn County, Oregon at 57 inches per year; Grant County, Washington has the smallest annual precipitation with 7.7 inches per year. Cavalier County, North Dakota has the lowest average temperature at 36^{o}F. The county with the highest average temperature is Milan, Texas at 68^{o}F. Elevation ranges from 150 feet in Washington County, Oregon to 7,066 feet in San Juan County, Utah. The maximum distance between any two counties, based on latitude, is 19.35 degrees between Guadalupe County, Texas and Divide County, North Dakota. In miles, the distance is 1,188 miles. The maximum difference, based on longitude, is 28.608 degrees or 1,350 miles between Polk County, Oregon and Bourbon County, Kansas.

The last variables in the model are indicator variables to capture the location of the counties given by USDA regions. To avoid the complexity of modeling movement between each state interaction, growing regions provided by the Economic Research Service of the USDA are used (Figure 4). Four regions comprise the study area. Region 1 consists of Oregon and Washington. Region 2 is made up of Idaho, Montana, Utah, and Colorado. Region 3 consists of North Dakota, South Dakota, Nebraska, and Kansas. Region 4 consists of Oklahoma and Texas. $Mvmt_{bh}$ indicates the two counties are located in regions b and h. A total of nine variables were used in the model to capture the effects of movement from one specific region to another. To avoid perfect collinearity $Mvmt_{11}$ is dropped from the estimations.

Results

Results for both the linear and quadratic specification with and without movement variables are provided in Tables 5-8. For ease of discussion and space issues, the following discussion focuses on the quadratic specification because this specification provides a better fit. Results from both with and without movement variable models are discussed.

W*ithout Movement Variables*

Using the quadratic specification, all variables are significant (at the 5% level) except for the linear and squared terms associated with changes in elevation and the squared term associated with latitude. As expected, the coefficients for the linear terms are negative except for elevation, which is insignificant at any reasonable alpha level (Table 8). The coefficients of the squared term for the longitude and temperature variables are positive, whereas, the coefficients for the squared terms of latitude, elevation, and precipitation are negative. These results provide support for the hypothesis that there is generally an inverse relationship between yield correlations and geographic variables in the relevant range. In other words, correlation between yields is reduced as changes in both spatial and climate variables increases. The negative squared term is indicative of a convex shape, while those with a positive squared term have a concave shape (Figures 4- 7). Elasticities associated with percentage changes in yield correlations for each of the geographical variables are calculated (Table 9).

The elasticity of latitude and longitude are -1.29 and -1.44 when the movement variables are not included in the model. These elasticities can be interpreted as a 1% change in either variable leads to a 1.29% and 1.44% decrease in the correlation between wheat yields. A 1% change in elevation leads to a 0.302% increase in correlation and a 1% change in precipitation leads to a 0.30% decrease in correlation. A 1% change in temperature leads to a decrease in correlation of 0.17%.

With Movement Variables

There are some notable differences between the specifications of the models with and without movement variables. In the model with movement specification, all linear terms are negative. This differs from the model without movement specification in that the sign associated with elevation changed. All squared terms are positive except for the coefficient associated with precipitation squared. Further, the three coefficients that are insignificant in the without specification become significant: squared term associated with latitude and the linear and squared terms associated with elevation.

The variables $Mvmt_{14}$, $Mvmt_{22}$, $Mvmt_{23}$, $Mvmt_{33,}$ $Mvmt_{34}$, and $Mvmt_{44}$ are statistically significant (Table 7). All the variables have a negative coefficient except for $Mvmt_{34}$. The negative coefficients estimated in the model range from -0.059 for $Mvmt_{44}$ to -0.093 for $Mvmt_{22}$. The one variable with a positive coefficient, $Mvmt_{34}$, represents the movement from the upper Midwest region to Oklahoma or Texas. The estimated increase in yield correlations when moving from the upper Midwest region to the Southern region is 0.046.

Inclusion of movement variables had an impact on the elasticities. Elasticities associated with latitude and longitude changes are -1.54 and -1.20. A 1% change in elevation leads to a 0.23% increase in the correlation, whereas, a 1% change in precipitation leads to a 0.30% decrease in correlation. Finally, a 1% change in temperature leads to a decrease in correlation of 0.012%.

Graphical Analysis

To further examine the inter-relationship between the spatial/climate data and correlations three dimensional graphs are presented. The relationship between latitude, longitude, and correlation are illustrated in Figure 4. The curvature of the plot represents the interaction between latitude and longitude and correlation. The graph also emphasizes the importance of latitude movements. The lowest correlation on the graph is represented by the maximum amount of change in latitude and only a small change in longitude.

Interrelationship between correlation, latitude and precipitation are shown in Figure 5. The drop off that occurs in the far corner is caused by large differences in latitude and small changes in precipitation. This once again illustrates the importance of latitude as a determining factor in determining reductions in yields correlations. Figure 6 is similar to Figure 5. Here the relationship between correlation, precipitation, and longitude is illustrated. The largest negative correlations occur when there is a moderate change in longitude and precipitation, approximately a change of ten degrees of longitude and ten inches of precipitation. This graph also illustrates that there is more of a relationship between precipitation and longitude than precipitation and latitude. Moving east and west is much more sensitive to changes in rainfall than moving north and south. The last graph shows the interrelationship between temperature and latitude (Figure 7). The lowest correlation is found where the changes in latitude are the greatest and the changes in temperature are at a minimum.

Conclusions

The issue of geographical diversification has not been extensively. Geographical diversification provides an opportunity to examine several interesting risk management issues. This study illustrates the expected result that yield correlations vary geographically.

Quantification of the relationships between yield correlations and spatial variables allows the next step of geographical diversification to be undertaken, namely examining how geographical diversification will impact risk and profitability of agricultural enterprises. Elasticity estimates suggest on a percentage basis, changes in latitude and longitude have the greatest effect on correlation. Negative relationships are also found between yield correlations changes in either precipitation or temperature.

The objective of this research is to establish a foundation for both researchers and producers to better understand the impacts of geographical diversification. An extension of this research will be used to develop an interactive tool for growers to specify spatial data so that they may see the changes in yield correlations that are possible by moving operations. This will also include an extension into different crops such as cotton and sorghum.

References

Basak, G., R. Jagannathan, and G. Sun. "A direct test for the mean variance efficiency of a portfolio." *Journal of Economic Dynamics and Control* 26, no. 7-8(2002): 1195-1215.

Boehlje, M. D., and D. A. Lins. " Risks and Risk Management in an Industrialized Agriculture." *Agricultural Finance Review* 58(1998).

Davis, S. B., et al. "Reducing Yield Variation in Peach Orchards by Geographic Scattering." *American Journal of Agricultural Economics* 79, no. 4(1997): 1119-1126.

Ehling, P., and S. B. Ramos. "Geographic versus industry diversification: Constraints matter." *Journal of Empirical Finance* 13, no. 4-5(2006): 396-416.

Escalante, C. L., and P. J. Barry. "Risk Balancing in an Integrated Farm Risk Management Plan." *Journal of Agricultural and Applied Economics* 33, no. 3(2001): 413-429.

Featherstone, A. M., et al. "Farm Financial Structure." *Agricultural Finance Review*, no. Fall(2005): 97-117.

Handy, C., and J. M. MacDonald. "Multinational Structures and Strategies of U.S. Food Firms." *American Journal of Agricultural Economics* 71, no. 5(1989): 1246-1254.

Hardaker, J. B., et al. *Coping with Risk in Agriculture*. 2 ed. Cambridge: CABI, 1997.

Harwood, J., et al. (1999) Managing Risk in Farming: Concepts, Research and Analysis, United States Department of Agriculture Economic Research Service.

Just, R. E., and R. D. Pope. *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture*. Natural Resource management and Policy. Edited by A. Dinar, and D. Zilberman. Boston: Kluwer Academic, 2002.

Kim, Y. S., and I. Mathur (2007) The Impact of Geographic Diversification on Firm Performance.

Kreuger, A., et al. "Profitability of Geographic Diversification Strategy." *Journal of Food Distribution Research*, no. March(1999): 112-123.

Lat-Long (2008) Latitude and Longitude of Populated Places. Internet Site: www.lat-long.com (Accessed February 2008)

Liang, N., and S. A. Rhoades. "Geographic diversification and risk in banking." *Journal of Economics and Business* 40, no. 4(1988): 271-284.

Mishra, A., and H. El-Osta (2002) Risk Management Through Enterprise Diversification: A Farm-Level Analysis. Long Beach, CA.

Mishra, A., and S. H. Lence. "Risk Management by Farmers, Agribusinesses, and Lenders." *Agricultural Finance Review*, no. Fall 2005(2005): 131-148.

Moschini, G., and D. A. Hennessy (2001) Uncertainty, Risk Aversion and Risk Management for Agricultural Producers, ed. B. L. Gardner, and G. C. Rausser, vol. 1A. New York, Elsevier, pp. 87-144.

Nartea, G. V., and P. J. Barry. "Risk Efficiency and Cost Effects of Geographic Diversification." *Review of Agricultural Economics* 16, no. No. 3(1994): 341-351.

Rose, J. T., and J. D. Wolken. "Geographic Diversification in Banking, Market Share Changes, and Viability of Small Independent Banks." *Journal of Financial Services Research* 4(1990): 5-20.

Turvey, C. G., and H. C. Diver. "Systematic and nonsystematic risks in agriculture." *Canadian journal of agricultural economics = Revue Canadienne d'economie rurale* 35, no. 2(1987): 387-401.

U.S. Department of Agriculture--Economic Research Service. "*Off Farm Income Supports Many Farm Households*."Agricultural Income and Finance: Situations and Outlook Report, Resource Economics Division, Economics Research Service, AIS-74, February 2000b, pp. 37-39.

U.S. Department of Agriculture-- Economic Research Service. Internet Site: "Commodity Costs and Returns Estimates.". http://www.ers.usda.gov/Data/CostsAndReturns/ (Accessed March 18, 2008)

U.S. Department of Agriculture-- National Agriculture Statistics Service/State Facts/County Facts. Internet Site: www.nass.usda.gov/QuickStats/Create_County_All.jsp (Accessed March 18, 2008)

U.S. Department of Agriculture-- Natural Resource and Conservation Service. Internet Site: www.wcc.nrcs.usda.gov/climate/wetlands.html (Accessed March 18, 2008)

Table 1 . Trend Regression Results

State	Total Counties	Number of Counties w/Trend	Percent with Trend
Washington	8	3	38
Oregon	11	9	82
Idaho	10	10	100
Montana	32	22	69
Utah	4	0	0
Colorado	18	17	94
Nebraska	37	29	78
South Dakota	37	25	68
North Dakota	45	45	100
Kansas	104	5	5
Texas	66	12	18
Oklahoma	8	1	13
Total	380	178	47

Significance at the 0.05% level is used for trend determination.

Table 2. Summary Number of Counties Used in the Analysis by State

State	Number of Counties	Average County Acreage Planted	Average Yield
Washington	8	135,327	47.89
Oregon	11	64271	50.04
Idaho	10	36971	44.57
Montana	32	136289	24.21
Utah	4	16,137	31.79
Colorado	18	97,613	24.62
Nebraska	37	47,744	31.93
South Dakota	37	49,072	31.21
North Dakota	45	206,452	24.67
Kansas	104	149,666	33.00
Texas	66	56,087	24.88
Oklahoma	8	82,102	28.60

Source: USDA-NASS

Table 3. Geographical Data Summary Statistics

Variable	Mean	Std. Dev	Minimum	Maximum
Correlation	0.165	0.293	-0.742	0.968
Latitude	40.805	4.900335	29.569	48.914
Longitude	-101.824	5.979359	-123.316	-94.708
Elevation	2215.611	1204.852	150	7066
Temperature	51.397	6.981969	36.5	68.2
Precipitation	23.29634	8.632145	7.7	57.43

Source: www.lat-long.com and USDA-NRCS

Table 3. Variables Descriptive Statistics

Change in	Mean	Standard Deviation	Minimum	Maximum
Elevation	1330.228	1064.822	0	6916
Latitude	5.609707	4.069151	0	19.345
Longitude	5.911457	6.04654	0	28.608
Precipitation	9.499926	7.666816	0	49.73
Temperature	7.958991	5.843862	0	31.7
Correlation	0.164671	0.292902	-0.74202	0.968473

Number of observations 72,010

Table 4. Linear Regression Results without Movement Variables

Variable	Coefficient	t-value	p-value
Latitude	-0.0080	-8.48	0.00
Longitude	-0.0056	-9.22	0.00
Elevation	-1.7E-05	-23.45	0.00
Precipitation	-0.0047	-36.31	0.00
Temperature	-0.0012	-10.86	0.00
Intercept	0.4462	237.32	0.00

$R^2 = 0.358$

Table 5. Linear Regression Results with Movement Variables

Variable	Coefficient	t-value	p-value
Latitude	-0.0321	-72.2100	0.0000
Longitude	-0.0146	-41.3200	0.0000
Elevation	-1.36E-07	-0.1400	0.8880
Precipitation	-0.0070	-48.7500	0.0000
Temperature	-0.0013	-4.3300	0.0000
$Mvmt_{12}$	-0.0532	-2.4100	0.0160
$Mvmt_{13}$	0.0169	0.7700	0.4410
$Mvmt_{14}$	0.2920	12.7600	0.0000
$Mvmt_{22}$	-0.0626	-2.9000	0.0040
$Mvmt_{23}$	-0.0632	-3.0300	0.0020
$Mvmt_{24}$	0.1147	5.4300	0.0000
$Mvmt_{33}$	-0.0144	-0.7000	0.4860
$Mvmt_{34}$	0.0829	3.9900	0.0000
$Mvmt_{44}$	0.0575	2.7400	0.0060
Intercept	0.4928	23.8300	0.0000

$R^2 = 0.401$

Table 6. Quadratic Estimation Results with Movement Terms

Variable	Coefficient	t-value	p-value
Latitude	-0.0807	-69.210	0.000
Longitude	-0.0526	-69.940	0.000
Elevation	0.0000	-2.980	0.003
Precipitation	-0.0177	-41.560	0.000
Temperature	-0.0080	-10.500	0.000
$Latitude^2$	0.0003	2.400	0.016
$Longitude^2$	0.0010	30.470	0.000
$Elevation^2$	0.0000	4.750	0.000
$Precipitation^2$	-0.0002	-12.000	0.000
$Temperature^2$	0.0004	6.990	0.000
Latitude*Longitude	0.0037	63.010	0.000
Latitude*Elevation	0.0000	3.440	0.001
Latitude*Precipitation	0.0005	8.870	0.000
Latitude*Temperature	0.0009	7.340	0.000
Longitude*Elevation	0.0000	-8.340	0.000
Longitude*Precipitation	0.0005	19.600	0.000
Longitude*Temperature	-0.0008	-20.000	0.000
Elevation*Precipitation	0.0000	17.270	0.000
Elevation*Temperature	0.0000	6.820	0.000
Precipitation*Temperature	0.0005	13.840	0.000
$Mvmt_{12}$	-0.0246	-1.070	0.283
$Mvmt_{13}$	-0.0303	-1.330	0.183
$Mvmt_{14}$	-0.0826	-3.570	0.000
$Mvmt_{22}$	-0.0926	-4.160	0.000
$Mvmt_{23}$	-0.0661	-3.050	0.002
$Mvmt_{24}$	-0.0259	-1.190	0.235
$Mvmt_{33}$	-0.0648	-3.000	0.003
$Mvmt_{34}$	0.0463	2.140	0.033
$Mvmt_{44}$	-0.0592	-2.710	0.007
Intercept	0.8092	37.290	0.000
R^2 =0.541			

Table 7. Quadratic Estimation Results without Movement Terms

Variable	Coef.	t-value	p-value
Latitude	-0.0725	-64.450	0.000
Longitude	-0.0560	-86.930	0.000
Elevation	0.0000	-0.040	0.965
Precipitation	-0.0171	-41.480	0.000
Temperature	-0.0101	-13.190	0.000
$Latitude^2$	-0.0001	-0.680	0.494
$Longitude^2$	0.0012	45.120	0.000
$Elevation^2$	-3.37E-10	-0.650	0.514
$Precipitation^2$	-0.0002	-11.920	0.000
$Temperature^2$	0.0006	11.460	0.000
Latitude*Longitude	0.0032	60.720	0.000
Latitude*Elevation	1.28E-06	4.000	0.000
Latitude*Precipitation	0.0007	13.290	0.000
Latitude*Temperature	0.0009	7.840	0.000
Longitude*Elevation	-2.31E-06	-12.130	0.000
Longitude*Precipitation	0.0005	16.020	0.000
Longitude*Temperature	-0.0007	-17.670	0.000
Elevation*Precipitation	3.22E-06	24.240	0.000
Elevation*Temperature	1.78E-06	8.370	0.000
Precipitation*Temperature	0.0002	5.620	0.000
Intercept	0.7485	259.310	0.000

$R^2 = 0.523$

Table 8. Model Elasticities (estimated at mean)

Variable	Elasticity	[95% Confidence Interval]	
	Linear Model without Movements		
Latitude	-0.8515	-0.8804	-0.8224
Longitude	-0.5210	-0.5343	-0.5079
Elevation	-0.0184	-0.0332	-0.0037
Precipitation	-0.4100	-0.4258	-0.3943
Temperature	-0.0362	-0.0647	-0.0076
	Linear Model with Movements		
Latitude	-1.0950	-1.1247	-1.0653
Longitude	-0.5252	-0.5502	-0.5004
Elevation	-0.0011	-0.0165	0.0143
Precipitation	-0.4020	-0.4182	-0.3859
Temperature	-0.0739	-0.0900	-0.0339
	Quadratic Model without Movements		
Latitude	-1.28516	-2.469147	1.729996
Longitude	-1.43687	-2.471537	0.0481144
Elevation	0.301937	-0.4322145	1.272039
Precipitation	-0.27772	-1.007364	1.130389
Temperature	-0.17055	-1.136739	0.6497111
	Quadratic Model with Movements		
Latitude	-1.54282	-3.25365	0.168021
Longitude	-1.19889	-2.11627	-0.28151
Elevation	0.227003	-0.15196	0.605968
Precipitation	-0.29719	-1.06653	0.472159
Temperature	-0.01183	-0.62638	0.602714

Figure 1. U.S. Wheat Acreage

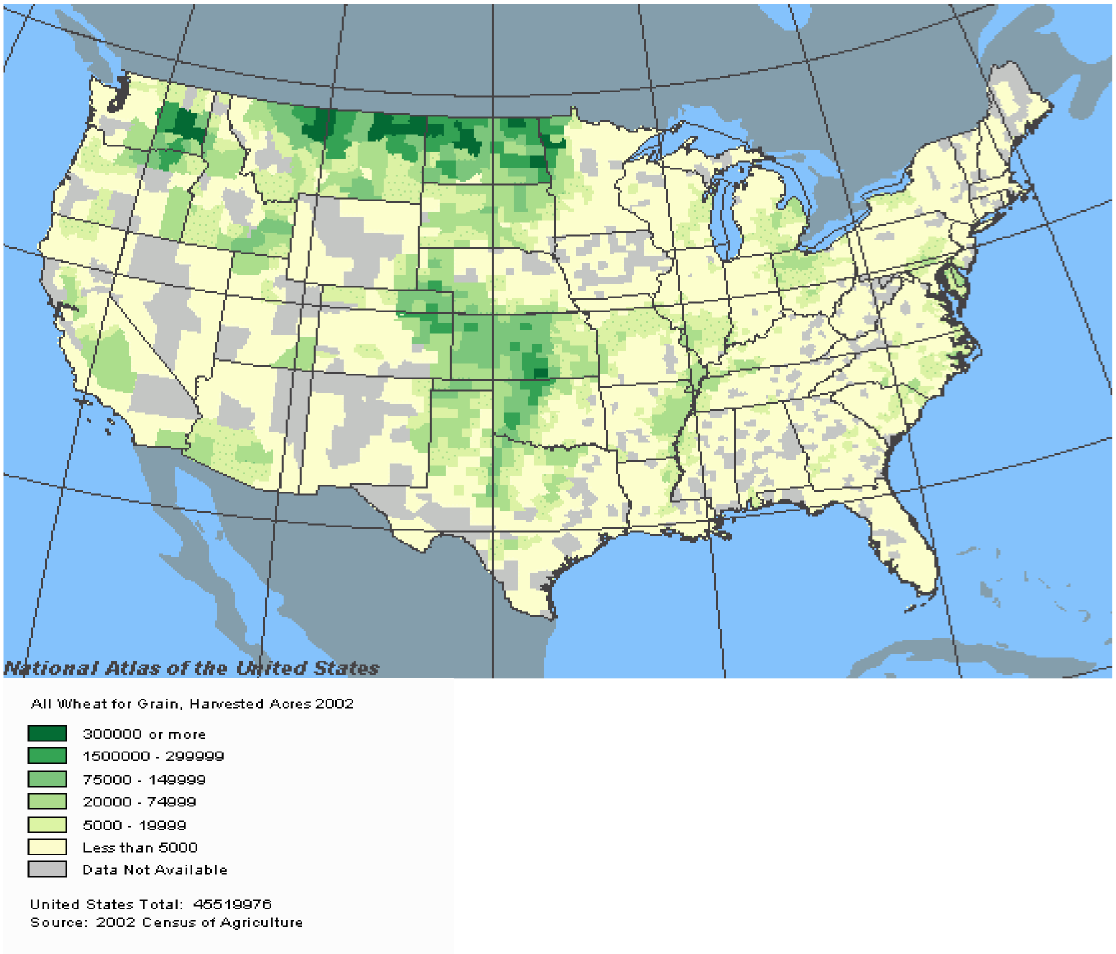


Figure 2. Wheat Yield Correlations, Base County Dallam County, TX

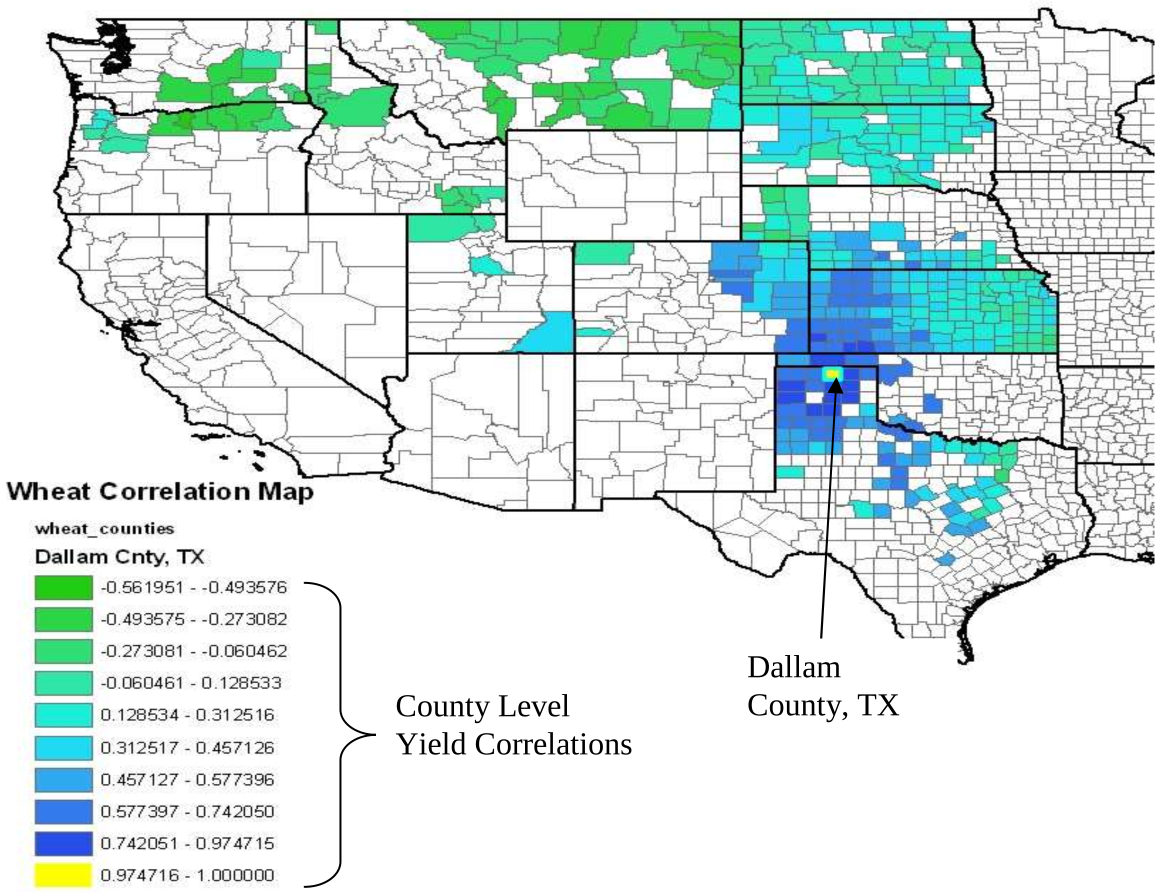
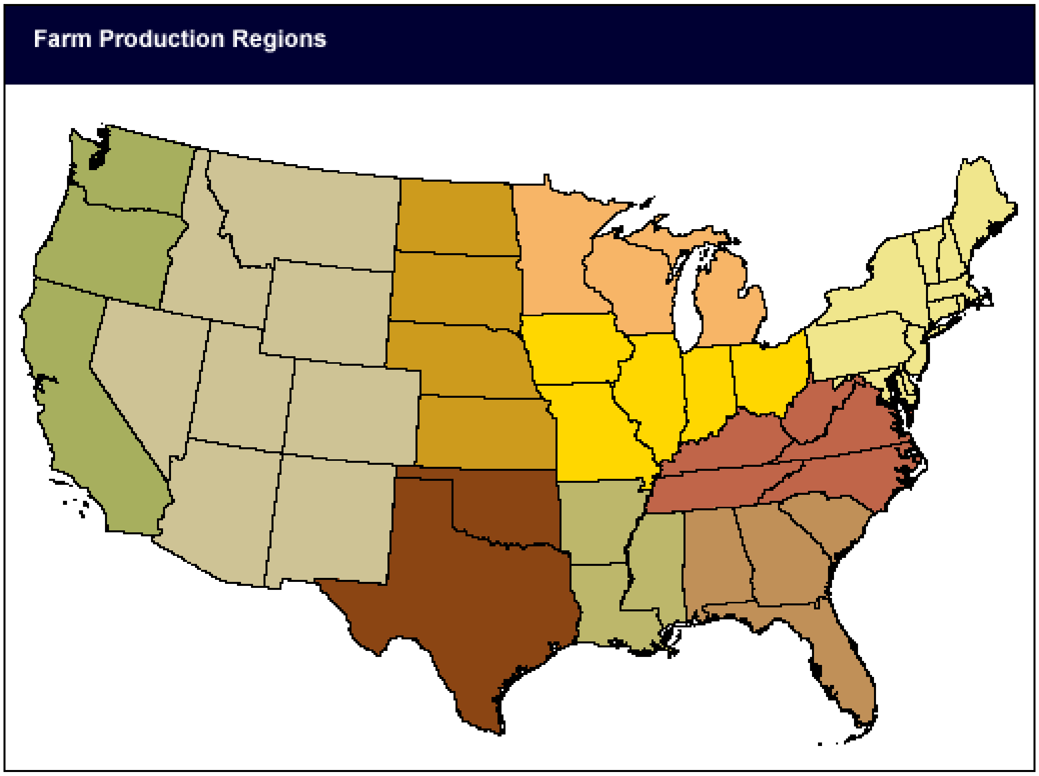


Figure 3. USDA Farm Production Regions



Source: Economic Research Service, USDA

Figure 4. Wheat yield Correlations as a Function of Latitude (x) and Longitude (y)

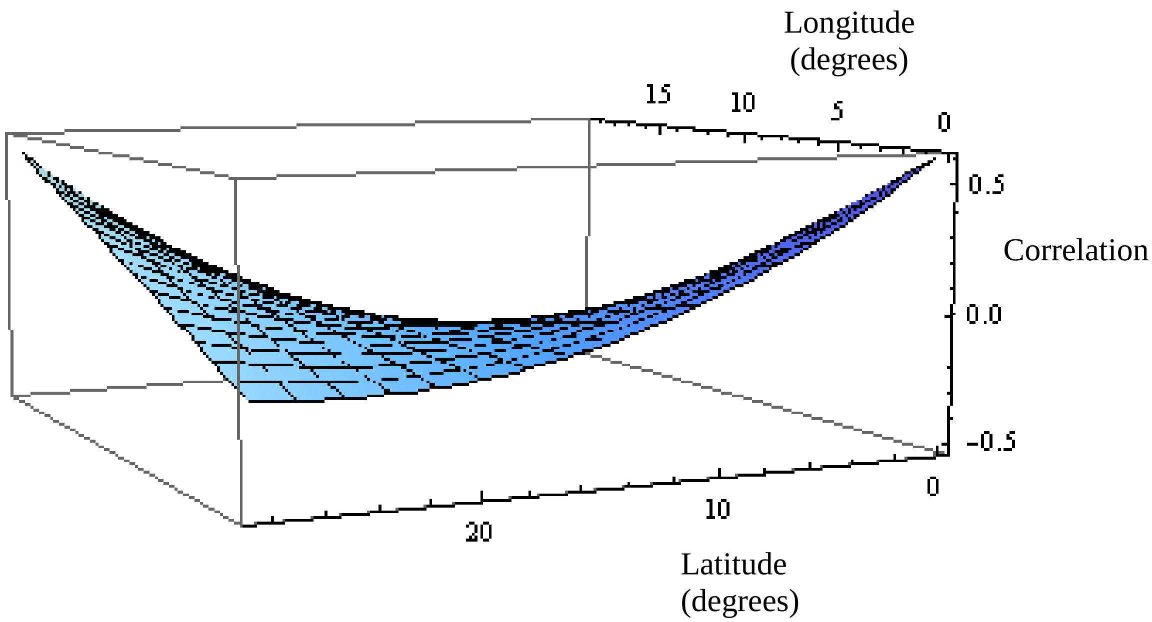


Figure 5. Correlation as a Function of Latitude (x) and Precipitation (y)

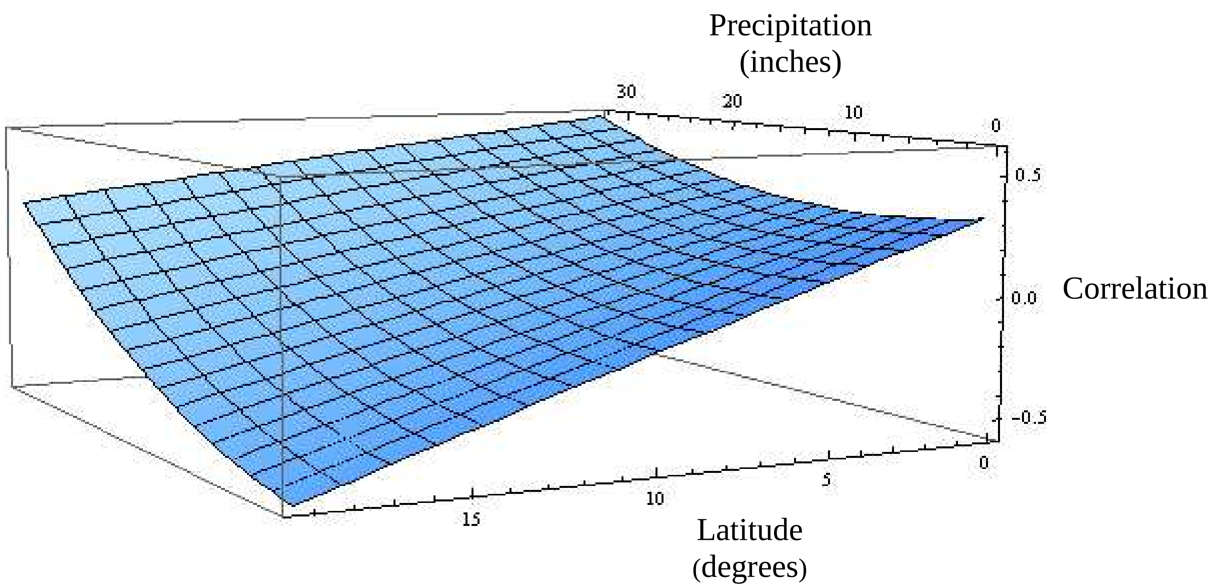


Figure 6. Correlation as a Function of Longitude (x) and Precipitation (y)

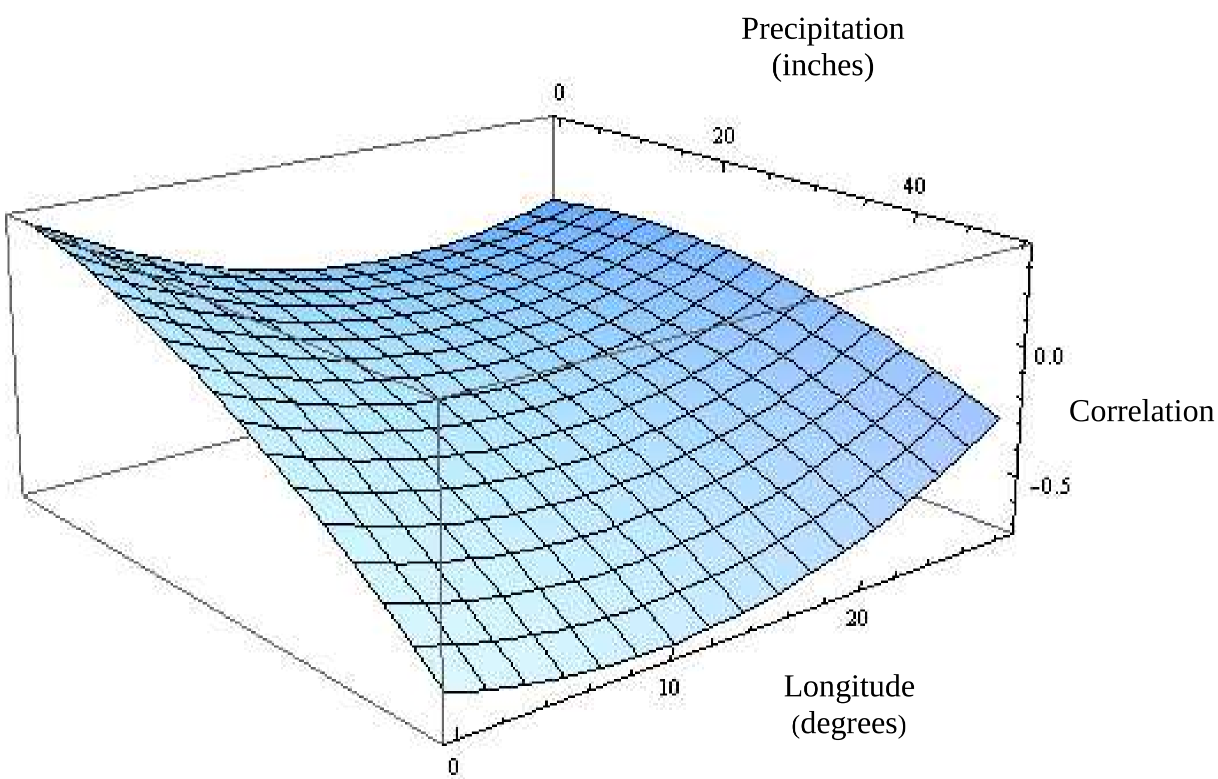


Figure 7. Correlation as a Function of Latitude (y) and Temperature (x)