



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Systemic Risk in Wheat Yields

Ashley Hungerford, North Carolina State University
aemabee@ncsu.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Copyright 2014 by Ashley Hungerford. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Systemic Risk in Wheat Yields *

Ashley Hungerford

May 19, 2014

Abstract

In 2011 and 2012 severe droughts caused extensive damage in crops throughout the Midwest. These conditions combined with concerns for climate change have led to a growing focus on risk management in agriculture. The increasing emphasis on risk management is reflected in the 2014 Farm Bill, which replaces direct payments with shallow loss programs. For this paper we turn our attention to winter wheat production in Kansas and explore the ratings of the crop insurance policies as well as predicted payouts from the new Agricultural Risk Coverage program established under the 2014 Farm Bill. Using spatial models we simulate yields of non-irrigated winter wheat and irrigated winter wheat to estimate crop insurance premium rates as well as payouts from the Agricultural Risk Coverage program.

Introduction

In 2011 and 2012 severe droughts caused extensive crop damage throughout the Midwest. During 2011 stories flooded news networks of cattle ranchers being unable to feed their herds due to the shortage of feed. The following year proved to be disastrous as well. The loss cost ratio (LCR)¹ for corn in 2012 was 2.82, which translates to \$12.7 billion of indemnity payments paid to producers (Summary of Business, 2014). These recent events combined with concerns for climate change have led to a growing focus on risk management in agriculture.

*Do not cite without author's permission.

¹This ratio is indemnity payments divided by premiums.

The increasing emphasis on risk management is reflected in the 2014 Farm Bill, which replaces direct payments with shallow loss programs.

For this paper we turn our attention to winter wheat production in Kansas. Historically, the majority of winter wheat production in Kansas has been produced without irrigation, also known as dryland production. Although dryland wheat production is typically more cost-effective than irrigated production, if a drought strikes Kansas irrigation could not be used as a means of mitigating damages. Currently, irrigated wheat and dryland wheat have different benchmark yields for crop insurance guarantees, but these benchmarks do not account for differences in the variances or correlations of yields caused by the different practices. If differences in variances and correlations are not properly accounted for in insurance ratings, premiums will be inaccurate due to incorrect probabilities and expected loss estimates.

Using spatial models for winter wheat yields in Kansas, we investigate the ratings of the crop insurance policies as well as expected payouts from the Agricultural Risk Program established under the 2014 Farm Bill. We model irrigated winter wheat and dryland wheat separately since these practices have different benchmarks. The data is censored because some counties during certain years did not plant winter wheat. For this reason we use a Bayesian version of a tobit model. This model allows us to estimate the probability of an observation being censored. Also we look for changes in the spatial relationship among county yields since yields tend to be more spatially correlated during times of drought or other natural disasters.

Risk Management in Agriculture

The Federal Crop Insurance Corporation (FCIC) underwrites crop insurance policies, which are then sold by private firms, called Approved Insurance Providers (AIPs), to producers. These policies insure producers against any form of natural disaster that affect crop production. Policy guarantees are typically based on revenue or yield. Common coverage levels are 65% and 75% although some crops/areas may be insured at 85% coverage. The Standard Reinsurance Agreement developed by the Risk Management Agency (RMA) of the United States Department of Agriculture (USDA) determines the share of losses paid by the AIPs and the share losses paid by the FCIC. For a list of policies underwritten by the FCIC refer to Table 1. The most popular of these policies is Revenue Protection, which makes up over 80% of all crop insurance policies.

The current methodology for rating COMBO² policies is outline by Coble et al. (2010). COMBO insurance ratings begin with the calculation of the unloaded target rate, which is a function of loss cost ratios (LCRs) for the county of interest and its neighboring counties. The loss cost ratio for a county is ratio of the indemnity payments paid to producers over the premiums collected for the given county. This rate is the anchor rate for insurance policies within the county. The rate is referred to as "unloaded" because it is calculated without the highest 10% of losses for the counties. These large losses are accounted for in the catastrophic loading. The unloaded target rate is a weighted average of the historical LCRs of the county and its neighbors, weights are calculated with the Bühlmann method, which is defined as

$$R = ZX + (1 - Z)\mu \tag{1}$$

where

$$Z = \frac{P}{P + K}$$

²COMBO is an umbrella term for yield-based and revenue-based policies.

and

1. R: county unloaded target rate
2. Z: Bühlmann credibility factor
3. X: sample mean of the county of interest
4. μ : the mean of the adjusted LCR of the county group
5. P: exposure units
6. $K = \nu/\alpha$
 - (a) ν is the sample variance of the adjusted LCR for the county of interest.
 - (b) α is the sample variance of the adjusted LCR for the county group.

Once the unloaded target rate has been established, COMBO policies are rated with the Iman Conover (1982) procedure. The Iman Conover procedure generates correlated random draws of yields for a given county and price deviates. These correlated random draws of yield and price deviates are then used to establish then premium rate for 65% coverage. The premium rate is the expected loss divided by liability, which can be defined as $E(Y|\hat{Y})/(\lambda\hat{Y}) - 1$, where Y is the realized yield, \hat{Y} is the predicted yield, and λ is the coverage level (Goodwin and Ker, 1998).

Disaster assistance for farmers was first established in 1938. For many years crop insurance was offered for only a few crops and remained rather experimental. However, modern day crop insurance was established by the Federal Crop Insurance Act of 1980. The legislation created the Federal Crop Insurance Corporation under the jurisdiction of the Risk Management Agency. Also the Federal Crop Insurance Act of 1980 permitted 30% of premiums to be subsidized for 65% coverage policies (History of Crop Insurance Program, 2014). The federal crop insurance program floundered through the 1980s and was on the brink of extinction in the early 1990s, the program was revitalized by the Federal Crop Insurance Reform Act of 1994 (Glauber, 2004) . This new legislation permitted premium subsidies for higher coverage levels, created catastrophic (CAT) coverage, and made program participation mandatory. However, the

mandatory participation requirement was repealed in 1996. The 2000 Farm Bill has allowed for private entities to carry out research and create new insurance products through a partnership with RMA (History of Crop Insurance Program, 2014). The most recent agriculture legislation, 2014 Farm Bill, made notably changes involving RMA.

One characteristic that sets crop insurance apart from other non-life insurance is the potential for systemic risk. Systemic risk is the risk of losses occurring simultaneously and dependently, such as in the event of a natural disaster. Natural disasters require insurance firms to possess very large reserves of capital or reinsurance. Jaffe and Russell (1976) conjectured that large reserves of capital would cause a firm to be susceptible to hostile takeovers. Miranda and Glauber (1997) as well as Goodwin (2001) present arguments for the importance of incorporating the potential of systemic risk into crop insurance portfolios. In 2012 crop insurance indemnity payments over all crops totaled \$17.4 billion, which amounted to a loss cost ratio of 1.57 (Summary of Business, 2013). With nearly \$116 billion in liabilities for 281 million acres, not including livestock, the Federal Crop Insurance Corporation claims that private firms would not be able to fully bear the risk of a catastrophe such as the 2012 drought. Therefore, according to the FCIC, the Standard Reinsurance Agreement (SRA), which allows private insurers to share risk with the FCIC, is necessary.

In the last decade there has been reoccurring concern about crop insurance policies being inconsistently rated for different regions and crops. Babcock et. al (2004) criticized the assumption of constant relative risk, in other words when the loss cost ratio remains constant over time. Woodard et. al (2011) demonstrated that the using the loss cost ratio to determine crop insurance premiums is only unbiased when the assumption of constant relative risk is not violated. They found there was an upward bias in estimates when this

assumption was violate.

Title I and Title XI of the 2014 Farm Bill focuses on risk management strategies and has eliminated direct payments, counter-cyclical payments, and the Average Crop Revenue Election (ACRE) program. These programs are replaced by the Price Loss Coverage (PLC) program and the Agriculture Risk Coverage (ARC) program. Farmers can choose to enroll into one of these two programs. The PLC program pays out the difference between the market price and the reference price³ multiplied by 85% of the base acres. The ARC program guarantees can either be based on individual producer revenues or county revenues. Pay outs occur if the producers' revenue drops below 86% of the benchmark revenue. Then producers are paid the different between the actual revenue per an acre and the guarantee multiplied by 85% of the base acres. The benchmark revenue is generated from the 5-year Olympic average of yields and the 5-year Olympic average⁴ of the national price. Benchmark revenues for irrigated and dryland crops are calculated separately. The 2014 Farm Bill's shift towards these new programs in place of direct payments and countercyclical payments is a cause to further examine the risk associated with yields (Agricultural Act, 2014).

Data

Yields for winter wheat measured in bushels per an acre were collected from the National Agricultural Statistical Services over the sample period 1970 - 2013. These yields are aggregated at the county level and grouped by irrigation practices: dryland (non-irrigated) and irrigated. All 105 counties of Kansas produced dryland winter wheat during the sample period, and 67 counties of

³The reference price for wheat is \$5.50 per bushel.

⁴Olympic average eliminates the highest and lowest values then averages the remaining values.

Kansas produced irrigated wheat. There are years during the sample period without production for both dryland wheat and irrigated wheat; therefore, our modeling needs to account for this censoring. Figure 1 shows the number of acres planted for both dryland winter wheat and irrigated winter wheat in Kansas. Here we see the majority of winter wheat is produced without irrigation, which is true for winter wheat production throughout the United States. Figure 3 shows a slightly increase in mean yield of winter wheat for the entire state over the sample period; however, when the yields are dis-aggregated into counties, the trend is not significant in parametric or non-parametric regression.

Since 80% of the crop insurance policies are revenue based, we need prices to simulate premiums. Wheat futures contract prices were collected from the CBOT and cash prices for Kansas wheat were collected from the National Agricultural Statistical Service. The futures contract were priced in September and expired in July of the following year. The cash prices were the averages for transactions in July. We use the September quotes because the projected price for winter wheat is announced on September 30. Related to the price announcement, September is the month when winter wheat is planted in Kansas. Also we use the July expiration date and cash prices from July because most of the winter wheat in Kansas is harvested from late June to mid July.

Methodology

Model for Censored County Yields

Because the dryland and irrigated yield data have years without production, we utilize a Tobit-like Bayesian model. Tobit models (Tobin, 1958) assume the

data have a latent variable y^* driving the observation y , such that

$$y_{it} = \begin{cases} B_{it}(\beta_0 + \sum_{j=1}^P \beta_j x_{j,it} + \epsilon_{it}) & \text{if } y_{it}^* > c \\ B_{it} & \text{if } y_{it}^* \leq c \end{cases}, \quad (2)$$

for County $i = 1, \dots, N$ during Year $t = 1, \dots, T$. c is a constant threshold, and $\epsilon_{it} \stackrel{i.i.d}{\sim} N(0, \sigma^2)$. $B_{it} = I(c > 0)$, where $I(\cdot)$ is the indicator function. If a response variable has the form described in Equation 2, it is called a censored variable. Censoring may be a result from sampling methods or the nature of the data. For example if an individual is below the age of 65, single, and makes less than \$10,000, he does not have to file a tax return; therefore, his income could appear to be \$0 to somebody investigating tax return data. Equation 2 and the example above show right-handed censoring because values below a particular threshold are censored. When values of above a certain threshold are censored, this is called left-handed censoring. An example of left-handed censoring could be caused by instrument that cannot exceed a particular threshold, such as physician's scale, which typically has a weight limit of approximately 400 pounds.

The likelihood function for the tobit model is

$$\prod_{i=1}^N \prod_{t=1}^T \left(\frac{1}{\sigma} \phi \left(\frac{y_{it} - x_{it}\beta}{\sigma} \right) \right)^M \left(1 - \Phi \left(\frac{x_{it}\beta}{\sigma} \right) \right)^{M-1}, \quad (3)$$

where $M = 1$ if $y_{it} = y_{it}^*$ and 0 otherwise, $\phi(\cdot)$ is standard normal probability density function, and $\Phi(\cdot)$ is standard normal cumulative density function.

The difference between a typical tobit model and our model is the estimation of a logit link as well as the estimation of the normal regression truncated at zero. The logit link is used to predict whether or not the observation y_{it} will be censored, while the truncated normal regression predicts the values of the

yields when the observation y_{it} is not censored.

The variable $B_{it} \sim Ber(P_{it})$; therefore, B_{it} can be modeled using a logit link function. For the logit link function, we surmise that the year, location, and the September futures contract price may affect whether the observation is censored or not. The form of the logit link is

$$\text{logit}(P_{it}) = \alpha_{i,0} + \sum_j^B \alpha_j x_{jt} \quad (4)$$

for County $i = 1, \dots, N$ and Year $t = 1, \dots, T$. $(\alpha_{1,0}, \dots, \alpha_{N,0}) \sim \text{CAR}(\mu, \tau)$ for its prior distribution. $\text{CAR}(\mu, \tau)$ is the abbreviation for the Conditional Autoregressive model, which is a spatial distribution. The mean (or intercept in our model) of one county is dependent or *conditional* on the means (intercepts) of other counties and is conditioned on "surrounding" counties. "Surrounding" can be defined by distance or contiguity. In this model, we choose contiguity over distance since the counties greatly vary in size and shape.

The prior distribution of the coefficients on the September futures contract prices and the years are both normal distributed. Using the notation of $N(\mu, \sigma^2)$, the prior distributions of the covariates can be written as $\alpha_j \sim N(0, 100)$.

The normal regression truncated at zero has the form

$$y_{it} = \beta_{i,0} + \beta_{i,1} z_{it} \quad (5)$$

for County $i = 1, \dots, N$ and Year $t = 1, \dots, T$. $(\beta_{1,0}, \dots, \beta_{N,0}) \sim \text{CAR}(\mu, \tau)$ for its prior distribution. The same prior distribution is used for $(\beta_{1,1}, \dots, \beta_{N,1})$.

The covariate z_{it} is a binary covariate defined as

$$z_{it} = \begin{cases} 0 & \text{if } y_{it} > \theta m_i \\ 1 & \text{if } y_{it} \leq \theta m_i \end{cases}, \quad (6)$$

where m_i is the median yield for County $i = 1, \dots, N$. The purpose of the covariate z_{it} is to capture changes in spatial dependencies that occur at lower yields. As Goodwin (2001) demonstrated, yields across space during droughts or other natural disasters have stronger dependencies compared to yields during normal years. The prior distribution of θ is a truncated normal distribution $N(1, \frac{1}{9}, 0, 2)$. Note the notation of the truncated normal is $N(\mu, \sigma^2, a, b)$, where μ is the mean, σ^2 is the variance, a is the lower limit, and b is the upper limit.

This model for censored county yields is used to simulated yields for the risk management application of this paper. Note that we do not employ the same simulation technique used in classical statistical statistics instead we use posterior predictive sampling. In classical statistics one typically uses the maximum likelihood estimates in the sampling distribution to make random draws from the sampling distribution. Posterior predictive sampling differs from the sampling in classical statistics. Posterior predictive sampling is a two part process. Since Bayesian methods treat parameters as random variables, the first part of posterior predictive sampling is drawing parameters from the posterior distribution. The sample of parameters drawn from the posterior distribution are then used in the sampling distribution to draw random samples of observations.

Prices

For the simulated revenues used in the premium ratings, we need to generate prices that are correlated with the yields. After obtaining a posterior predictive sample of county yields from the model described above, these yields are

averaged to compute the state yield average. This state yield average is then regressed against log difference of the September futures contract prices and the July cash price. Prices are then generated from $p_t = w_{t-1} \exp(r_t)$, where p_t is the cash price for Year t , w_{t-1} is futures contract price, and $r_t \sim N(\omega_0 + \omega_1 y_t, \sigma_r^2)$. Note y_t is the state yield for Year t . The use of log-normal distributions for price differentials is common in crop insurance ratings.

Computations are performed using the software R, and the Bayesian models are implemented using the software package R2OpenBUGS.

Risk Management Application

In non-life insurance applications, there are several measures of interest: 1.) the probability of a loss, 2.) the expected loss, i.e. the actuarially-fair premium, and 3.) the premium rate. These values can be found through the Monte Carlo integration. As shown by Goodwin and Ker (1998), the probability of a loss is defined as $P(y < C \cdot Y^*) = \frac{1}{M} \sum_{i=1}^M I(\tilde{y}_i < C \cdot Y^*)$, where C is the coverage level, Y is the expected yield or revenue, \tilde{y}_i is the i^{th} simulated yield or revenue, M is the number of replications, and I is an indicator function. The expected loss is defined as the $E(L) = P(y < C \cdot Y^*) \times E(C \cdot Y^* - y | (C \cdot Y^* - y) > 0)$, where L is the difference between the guarantee and the actual yield or revenue. Finally, the premium rate can be determined by dividing the expected loss by the liability, which is $C \cdot Y^*$.

We simulate prices and yields to rate Group Risk Income Protection policies with the Harvest Price Option (GRIP-HPO) as well as estimate payouts for the new Agricultural Risk Coverage program based on county yields. The rate for the GRIP policy with the Harvest Price Option is referred to as the "HP Rate". We estimate the "HP" rate because the majority of revenue plans purchased include the Harvest-Price Option. The summary of Harvest Price Option and

the GRIP policy are included in Table 1. The Group Risk Income Protection policy is rated similarly to the methods discussed by Coble et al. (2010), which described in detail the rating of COMBO insurance plans⁵. The rate for the Group Risk Income Protection with the Harvest Price Option is defined as

$$\text{HP Rate} = \frac{\sum_{i=1}^{10000} \max(0, C \cdot Y \cdot \min(2 \cdot P, \max(P, \tilde{p})) - \max(0, (y_i \cdot \tilde{\sigma}_y + \tilde{\mu}_y) \cdot \min(2 \cdot P, \tilde{p})))}{10000 \cdot Y \cdot C \cdot P}, \quad (7)$$

where Y is the actual production history (APH) yield, P is the September futures contract price of wheat in 2013, C is the coverage level, \tilde{y}_i is the simulated yield and \tilde{p} is the simulated price. Note that for the Harvest Price Option if the harvest price exceeds twice the September price, $2 \cdot (\text{September price})$ is used in place of the harvest price. We estimate the 65%, 75%, and 85% coverage levels.

For the simulations of the Agricultural Risk Coverage program, we simulate county yields and prices for 2009 to 2013. Then the Olympic averages for each county and the prices are calculated. This process is repeated 10000 times to create distributions for the Olympic averages of county yields and the price. Unlike with the GRIP plan, there is only one coverage level, which is 86%. Using the simulated Olympic averages of yields and prices, we determine the probability of a payout from the program and the expected payout for each county in 2014.

Results

To help determine the best fitting models for dryland and irrigated wheat yields, the Deviance Information Criterion (DIC) is calculated for each model version.

⁵COMBO insurance is the umbrella term used to describe yield and revenue based crop insurance policies.

DIC is a Bayesian measure similar to AIC. Like AIC lower measures of DIC indicate a better fit, and the measure penalizes additional parameters. Table 2 shows the DIC for the dryland and irrigated wheat models, where the covariates of the logit link differ. For the logit links of both dryland wheat and irrigated wheat, the covariates Year and September price affect censoring. The location of the county does not seem to affect the censoring of dryland yields, but the location of the county does affect the censoring of irrigated yields. Figure 6 shows the prior and posterior distributions for the parameter θ of dryland wheat and irrigated wheat. The median of the parameter θ is 1.167 for dryland wheat and 1.039 for irrigated wheat. For dryland wheat the DIC for the model is 28070 when the covariate z_{it} is included and 32280 when the covariate z_{it} is not present. For irrigated wheat the DIC for the model is 16090 when the covariate z_{it} is included and 17820 when the covariate z_{it} is not present. Therefore we find that within our framework county yields are best described using not only spatial intercepts, but also including a secondary spatial covariate for yields for under θm_i . Due to the short length of the time series of yields, identification of more spatial covariates is not feasible.

The posterior distributions of the parameters in the logit links of dryland and irrigated wheat differ substantially. Figure 4 shows the prior and posterior distributions for the parameters in the logit link functions of dryland wheat and irrigated wheat. For dryland wheat the intercept α_0 is constant across counties and has a median of 1.808. The medians of the posterior distributions for the coefficients of Year and September price are -0.003 and -0.001. These coefficients indicate a decrease in the probability of censoring as years go by or if the September price increases. For irrigated wheat, the medians of the posterior distributions of the coefficients for Year and September price are approximates 0.019 and 0.039, respectively. Therefore, the odd of irrigated yields being cen-

sored increases by 0.04 for every year that goes by, and the odds of censoring increases by 0.019 for every dollar the September price increases. Also according to the spatial intercepts of the logit link for irrigated wheat found in Figure 5, counties in northeastern Kansas are the most likely to be censored.

The truncated normal regression for both dryland and irrigated wheat contain spatial intercepts with a CAR prior distribution, the secondary spatial covariate with a CAR prior distribution. For the spatial intercepts and the secondary spatial covariates, we show maps of the 2.5%, 50%, and 97.5% percentiles of the posterior distributions. The maps for spatial intercepts for dryland wheat and irrigated wheat, shown in Figure 7 and Figure 9, do not indicate distinct patterns across the state of Kansas. This is also true for the secondary spatial covariate as seen in Figure 8 and Figure 10.

To evaluate the fit of our models, we use the Chi-Squared discrepancies, which are a method posterior predictive checking described by Gelman et al. (2004). The Chi-Squared discrepancy is defined as

$$\sum_{i=1}^N \sum_{t=1}^T \frac{(y_{i,t} - E(Y_{i,t}|\boldsymbol{\theta}_{i,t}))^2}{Var(Y_{i,t}|\boldsymbol{\theta}_{i,t})}, \quad (8)$$

where $y_{i,t}$ is the observed yield for County i during Year t . $E(C_{i,t}|\boldsymbol{\theta}_{i,t})$ and $Var(C_{i,t}|\boldsymbol{\theta}_{i,t})$ are calculated from the simulated yields. The Chi-Squared discrepancy with the lowest value gives the best fitting model. For comparison we not only simulate yields from the best fitting models for dryland wheat and irrigated wheat, but we also simulate yields from the models where the truncated normal regressions has spatial intercepts with independent normally distributed prior distributions and no secondary spatial covariate. Figure 11 and Figure 12 show the simulated yields for the best fitting models. For the simulated dryland yields, central Kansas has relatively high yields and eastern Kansas has lower yields compared to the rest of the state. However, there are

no distinct patterns for irrigated wheat. Also visible inspection indicates the simulated yields are reasonable when compared to observed yields seen in Figure 3. Table 3 shows the Chi-Squared discrepancies. The best fitting model for dryland wheat has a Chi-Squared discrepancy of 3886.0, where the model with independent intercepts has a Chi-Squared discrepancy of 4054.4. Also we see the best-fitting model for irrigated wheat has a Chi-Squared discrepancy of 2795.1, where the model with independent intercepts has a Chi-Squared discrepancy of 3983.4. These Chi-Squared discrepancies show the improvement in fit caused by including the CAR prior distribution for the spatial intercepts and the secondary spatial covariates.

Next we generate revenues for the year 2014 to determine premium rates of the GRIP-HPO policies. Again we simulate from the best fitting models for dryland and irrigated wheat as well as the models with independent intercepts. The policies have revenue guarantees of 65%, 75%, and 85%. Before estimating the premium ratings, we look at the probability of a loss occurring for these guarantees. Figure 13 and Figure 14 show the probabilities for the different guarantees for dryland wheat and irrigated wheat. The probabilities of the best fitting model of dryland wheat have very distinct patterns. This model indicates higher probabilities of loss in northwestern Kansas and south central Kansas compared to the rest of the state. The probability of a loss is lower in eastern Kansas. The median probabilities of a loss across all counties are 0.207, 0.328, and 0.449 for the 65%, 75%, and 85% guarantees, respectively. Similar patterns emerge for the dryland wheat model with independent intercepts although this model has consistently higher probabilities. For the model with independent spatial intercepts, the median probabilities of a loss across all counties are 0.241, 0.357, and 0.480 for the 65%, 75%, and 85% guarantees, respectively. Figure 17 and Figure 18 show the premium rates for the dryland wheat for the best

fitting model and the model with independent intercepts. The premium rates are higher for the model with independent intercepts compared to the best fitting model. The median premium rates across all counties for the best fitting model are 0.038, 0.069, and 0.107 for the 65%, 75%, and 85% guarantees, while the median premium rates across all counties for the model with independent intercepts are 0.051, 0.084, and 0.123.

The probabilities of a loss and the premium rates for irrigated wheat differ from the probabilities and premium rates of dryland wheat. Figure 15 and Figure 16 show the probabilities of a loss for the 65%, 75%, and 85% guarantees for the best fitting model and the model with independent intercepts. Again we see the probabilities of a loss generated from the model with independent intercepts are higher than the probabilities of loss generated by the best fitting model. The median probabilities of a loss for the best fitting model across all counties are 0.158, 0.292, and 0.439 for the 65%, 75%, and 85% guarantees, while the median probabilities of the model with independent intercepts are 0.2109, 0.3483, and 0.4959. Also the premiums rates for irrigated wheat, seen in Figure 19 and Figure 20, show the model with independent intercepts has slightly lower premium rates than the best-fitting model. The median premium rates across all counties for the best fitting model are 0.023, 0.05, and 0.088 for the 65%, 75%, and 85% guarantees, while the median premium rates across all counties for the model with independent intercepts are 0.022, 0.048, and 0.084.

The final component of our analysis is the application of our models to the new Agricultural Risk Coverage program. We simulated yields and prices from 2009 to 2013 and then take the Olympic average of the simulated prices and the Olympic average for the simulated yields of each county. All of this analysis is conducted using the best fitting model and simulate 10,000 replications of prices and yields. The 2.5%, 50%, and 97.5% percentiles for the simulated Olympic

averages of the yields are shown in Figure 23 and Figure 24 for dryland and irrigated wheat, respectively. The distribution of Olympic averages for prices is shown in Figure 21. The mean Olympic average price is \$6.48 with a 95% confidence interval from \$5.25 to \$8.11. The expected median payout across all counties for the ARC program is \$17.65 per an acre for dryland wheat, and the expected median payout across all counties is \$21.32 per an acre for irrigated wheat as seen in Figure 25. It is worth noting the the probability of a pay out from the ARC program is silently lower than the probability of a payout from a crop insurance policy with an 85% guarantee. The probability of a payout across all counties is 0.412 for dryland wheat and 0.314 for irrigated wheat.

Discussion

Our analysis shows that the best fit for county yields allows the spatial dependencies among the counties to change with the value of the yields. When compared to a model that assumes no correlation between yields, we see the dryland wheat premium ratings for different coverage levels are more consistent. Therefore, by including spatial dependencies in crop insurance ratings, the premium rates better reflect intuition. Although the target rate used by RMA is a weighted average of a county's yields and the yields of its neighboring counties, this average is only a point estimate and does not does fully describe the dependencies among the distributions of the county yields. Therefore, RMA may want to consider a model that better accounts for spatial dependencies.

According to a study conducted by Ifft et al. (2012), the total for direct payments from 2004 to 2008 was equal to 6.8% of crop revenues. One of the major concerns of the 2014 Farm Bill is how the Agricultural Risk Coverage program and Price Loss Coverage program will compare to direct payments

and the other programs being eliminated. The best fitting models predict the average revenue for an acre of Kansas winter wheat in 2014 will be \$ 213.78 and \$276.56 for dryland and irrigated winter wheat. The expected median payout per an acre of winter wheat from the ARC program is \$17.65 and \$21.32 for dryland and irrigated winter wheat. If we multiply these values by 0.85 (because ARC payouts are applied to 85% of base acres), the ratios of the payouts of the ARC program to the expected revenue are 7.02% for irrigated winter wheat and 6.55% for dryland wheat. Therefore, our analysis concludes the payouts from the ARC program will be very similar to direct payments.

Concluding Remarks

This paper found that not only do spatial dependencies exists among county yields, but the spatial relationships are dependent on the value of the yields. Including these spatial dependencies, the forecasting ability of the models for both dryland and irrigated are improved. This improved forecast translates into more accurate premiums ratings for crop insurance policies. We also determine that based on the best fitting models presented in this paper, the ARC program expected payouts will be very similar to amounts paid out for direct payments.

Title I and Title XI of the 2014 Farm Bill have prioritized risk management in United States agriculture for the next several years. Since the majority of crop insurance policies have guarantees based on the production of individual producers instead of county level production, we plan to apply the models used in this paper to yields of individual producers. Also we plan to further compare expected payouts of these new programs to direct payments, county-cyclical payments, and the ACRE program.

Tables and Figures

Actual Production History (APH)	insures on a percentage of the predicted yield, typically 50% to 75%. The policy holder also selects a percentage of the predicted price set by RMA, which is typically between 55% and 100%
Actual Revenue History (APH)	similar to APH but it insures historical revenue instead of historical yields. Each crop has unique provisions
Adjusted Gross Revenue (AGR)	insure the a percentage of the revenue entire farm instead of each individual crop.
Area Risk Protection Insurance (ARPI)	provides coverage based on the production of an entire county. ARPI replaces GRP and GRIP described below.
Group Risk Plan (GRP)	insures using an index based on county yields. Coverage levels up to 90% are offered.
Group Risk Income Protection (GRIP)	similar to GRP but insures based on index of county revenue not yield.
Group Risk Income Protection-Harvest Price Option (GRIP-HPO)	allows for the producer to choose between the revenue calculated with expected price at the time of harvest and producer chosen coverage level percentage.
Revenue Protection (RP)	insures individual produce against both yield losses from natural causes as well as revenue losses from changes the projected harvest price. Producers choose a percentage of their yield to insure typically 50% to 75%. Indemnity payments are then based on the greater of the yield multiplied by the harvest price or the projected price.
Revenue Protection With Harvest Price Exclusion	insures the revenue of the producer using the predicted price.
Yield Protection	is similar to APH policies; however, the projected price is determined by futures contracts not RMA.
Catastrophic Risk Protection Endorsement (CAT Coverage)	pays 55 percent of the projected price on yield losses exceeding 50 percent. There is \$300 fee for each crop insured with CAT Coverage; however, the Federal Government pays the premium.

Table 1: Descriptions of policies offered by RMA

Model	Logit	Dryland	Irrigated
One	Year September price	27930	18070
Two	Constant Intercept Year September price	27850	17570
Three	Constant Intercept September price	28080	17680
Four	Constant Intercept Year	28270	17680
Five	Spatial Intercept (CAR) Year September price	27850	16440

Table 2: DIC for the entire model. Here the logit link is varied, while the truncated normal distribution has the spatial intercept, the spatial covariate with the optimal threshold, and the September price.

	Dryland	Irrigated
Best- Fitting	3886.0	2795.1
Independent	4054.4	3983.4

Table 3: Chi-Squared Discrepancies. "Best-fitting" show the Chi-Square discrepancy of the model that has spatial intercepts with the CAR distribution prior, the optimal threshold covariate in the truncated normal regression, and the September price covariate. "Independent" has different intercepts for each county with independent priors and the September price covariate. These two models have the same logit link.

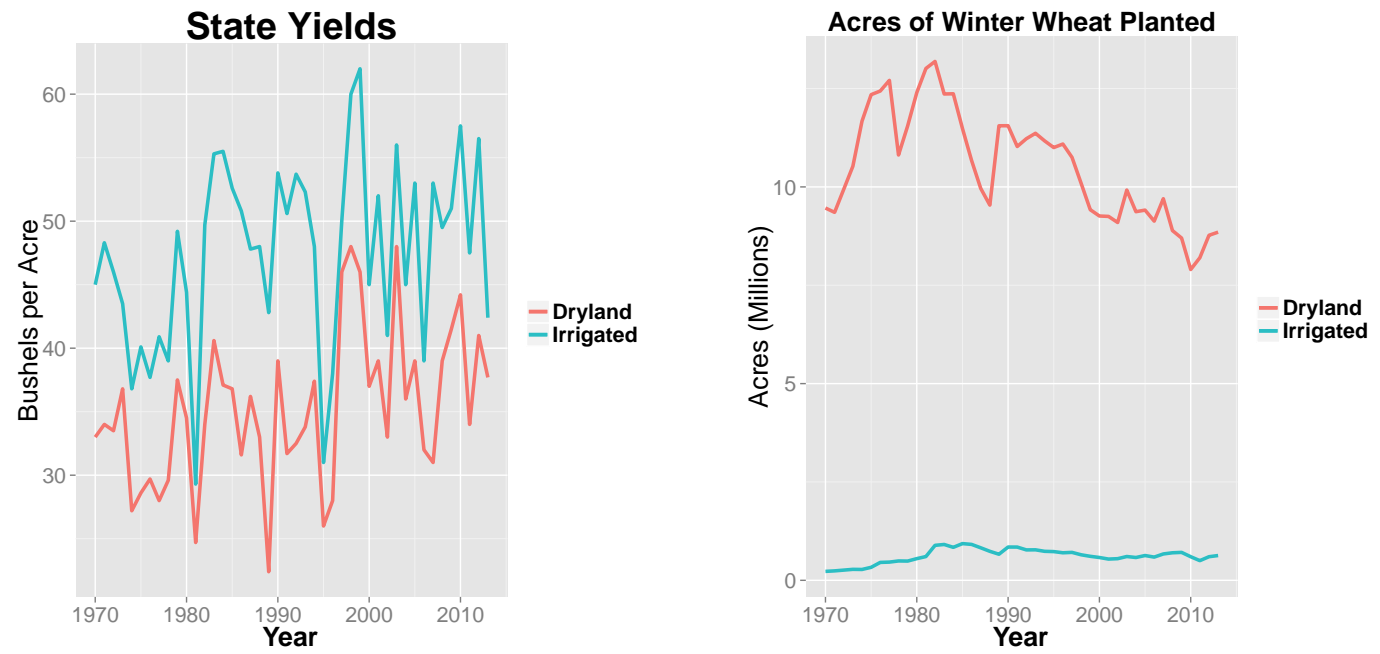


Figure 1: Figures for the entire state of Kansas including the average yield and number of acres planted.

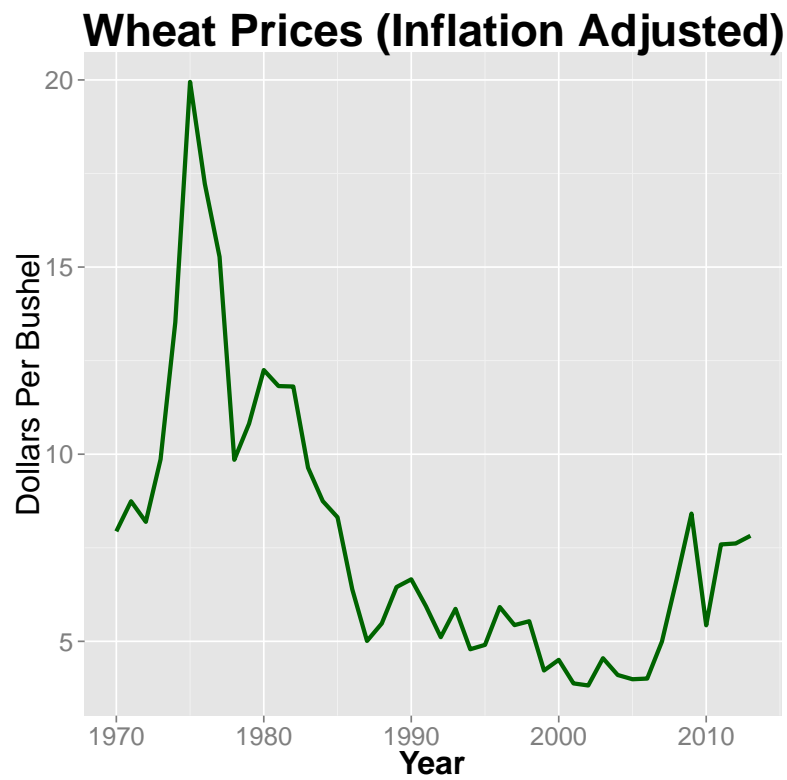


Figure 2: Wheat price for a per bushel (adjusted to 2013 price)

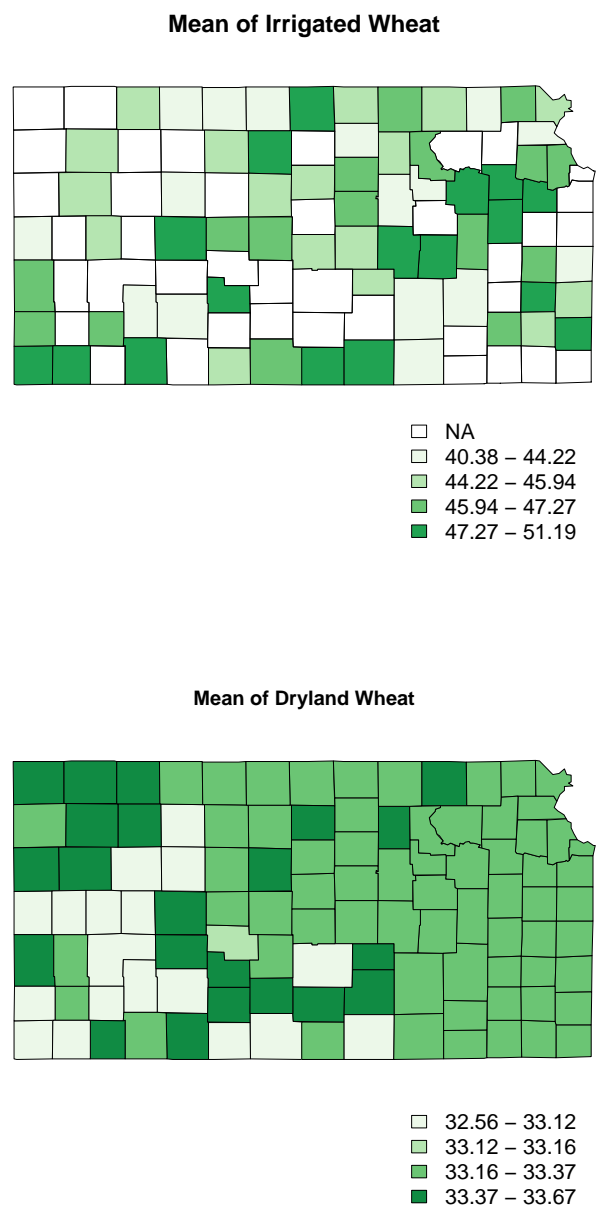


Figure 3: Average yield (bushels per acre). Sample period: 1970-2013

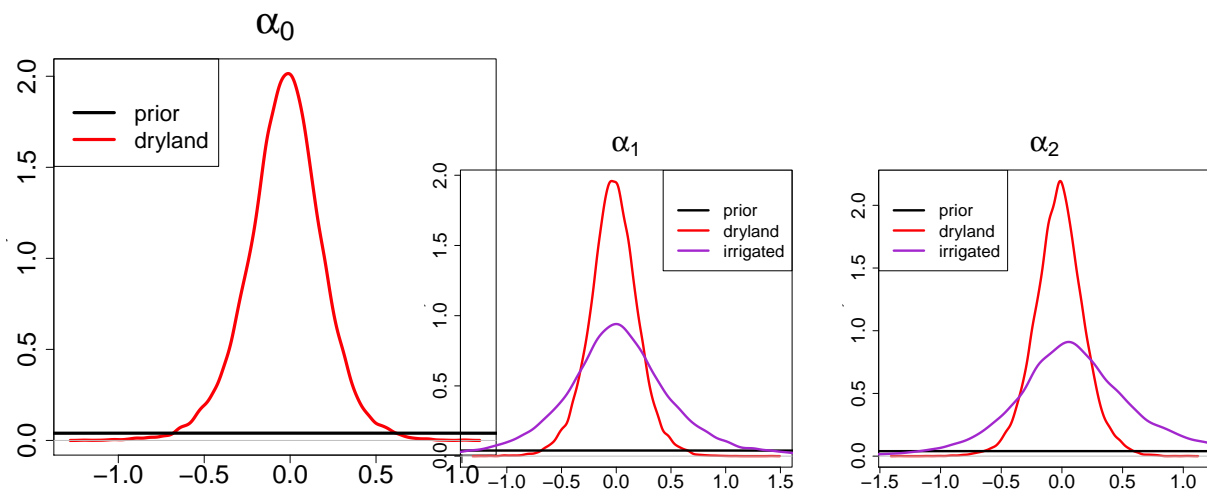


Figure 4: Prior and posterior distributions of the dryland and irrigated wheat logit link functions. Note there is no α_0 posterior distribution for irrigated wheat because the intercepts for the best-fit irrigated wheat logit link function are spatially-varying.

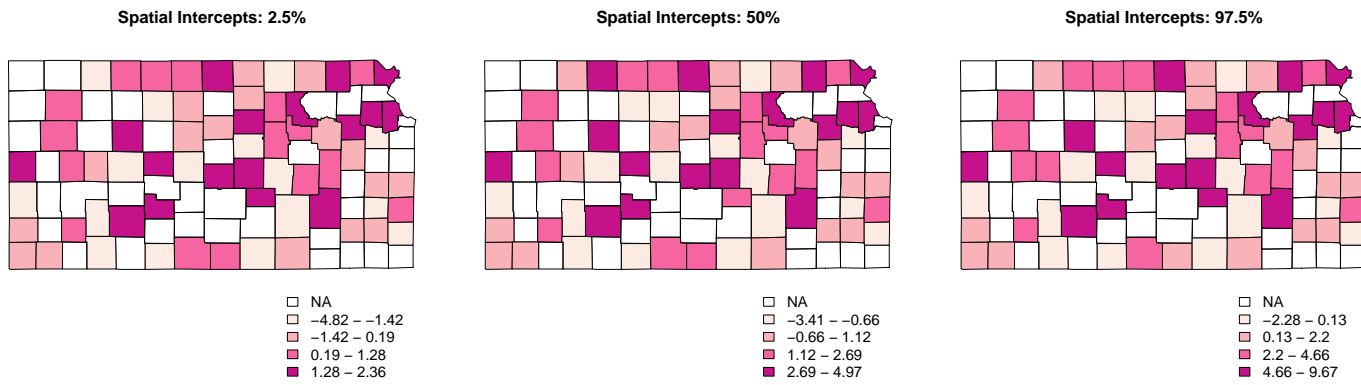
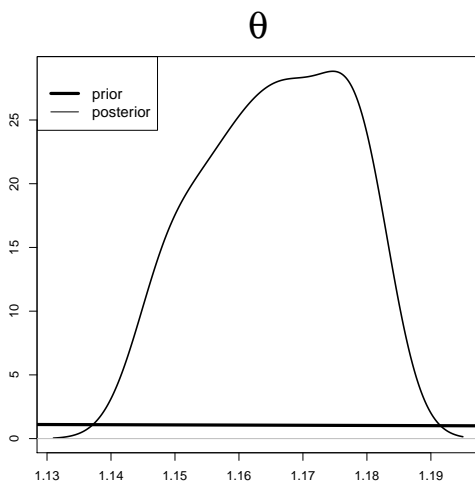
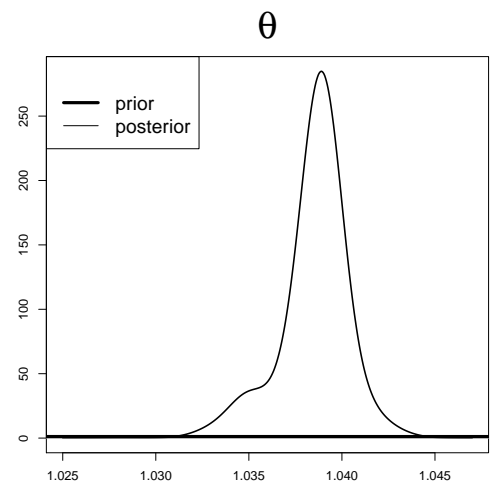


Figure 5: Posterior percentiles for the spatial intercepts of the irrigated wheat logit link.



(a) Dryland Wheat



(b) Irrigated Wheat

Figure 6: Prior and posterior distributions for the parameter θ of the dryland wheat and irrigated wheat

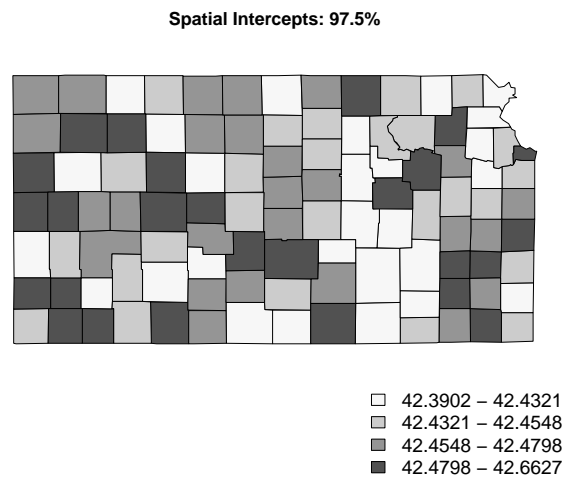
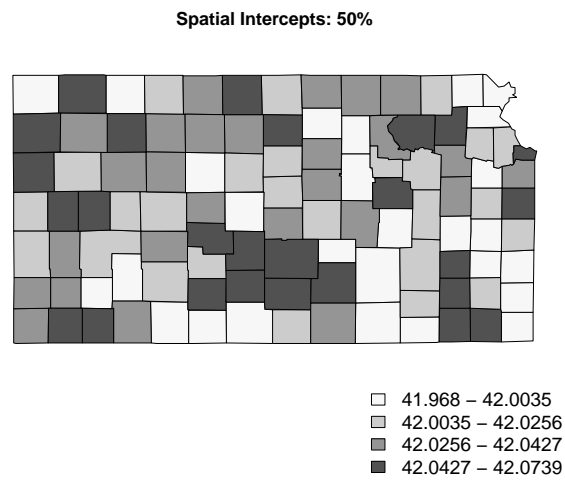
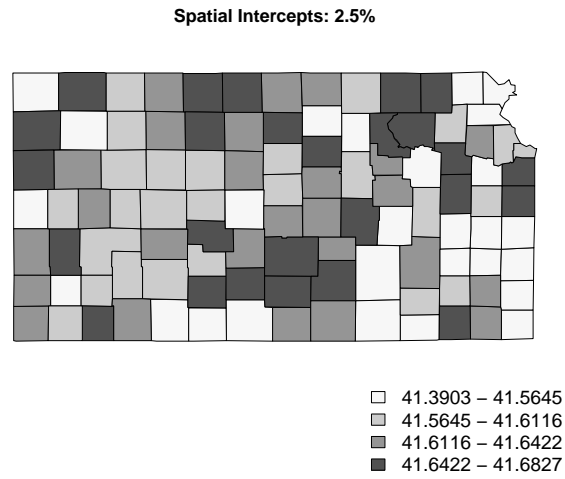


Figure 7: Posterior percentiles for the spatial intercepts of the dryland wheat truncated normal regression

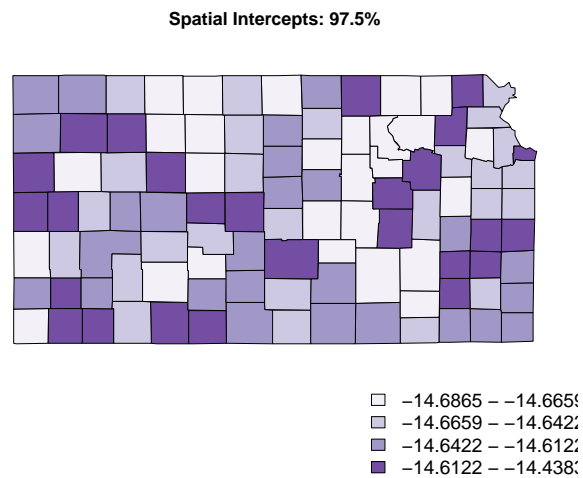
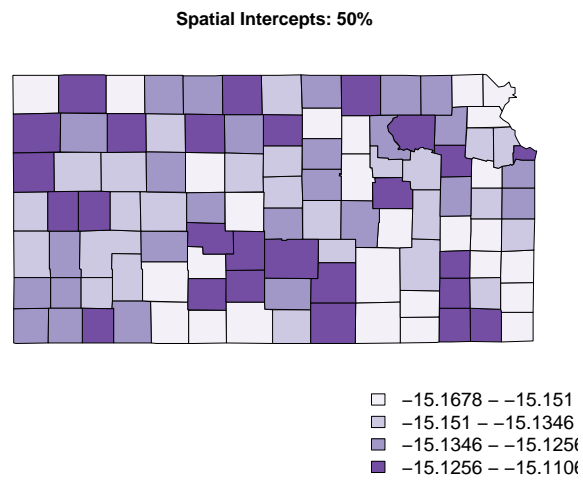
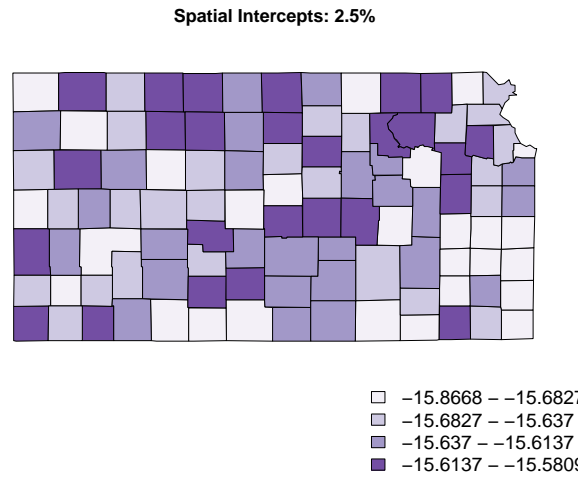
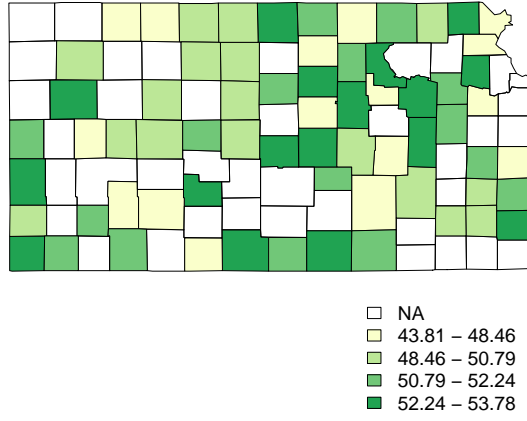
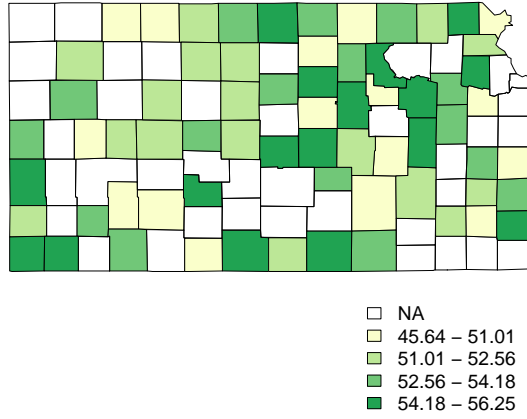


Figure 8: Posterior percentiles for the secondary spatial covariate of the dryland wheat truncated normal regression

Spatial Intercepts: 2.5%



Spatial Intercepts: 50%



Spatial Intercepts: 97.5%

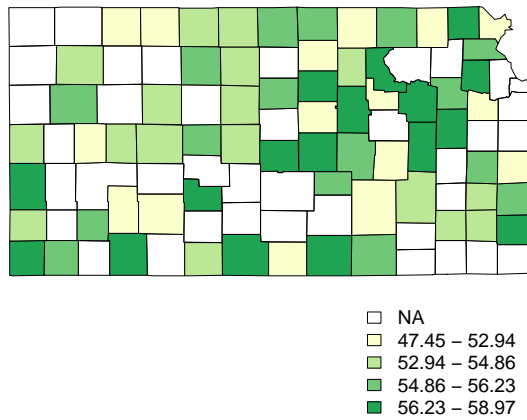
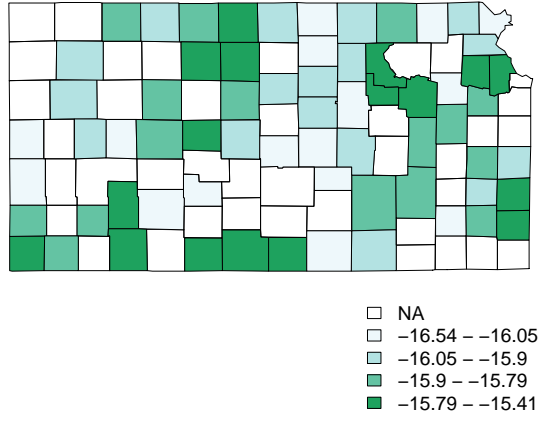
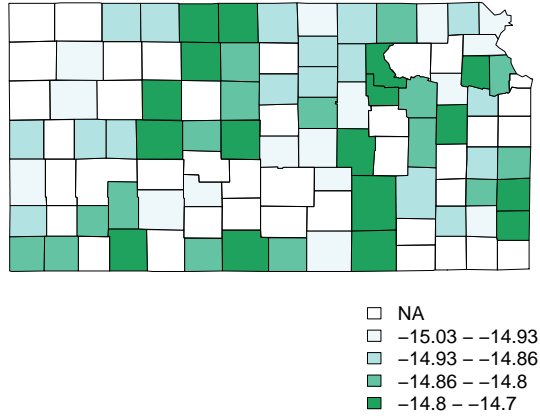


Figure 9: Posterior percentiles for the spatial intercepts of the irrigated wheat truncated normal regression

Spatial Intercepts: 2.5%



Spatial Intercepts: 50%



Spatial Intercepts: 97.5%

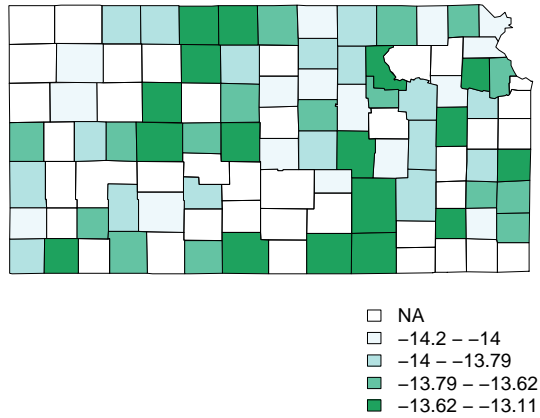
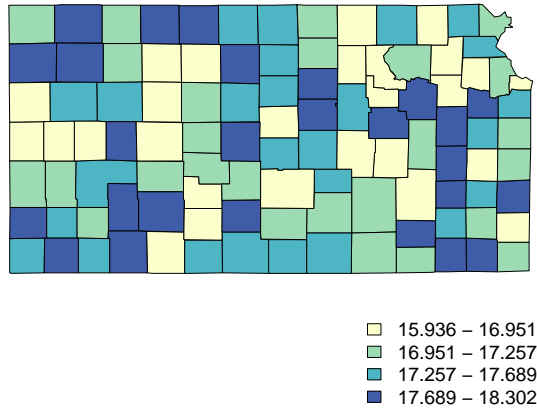
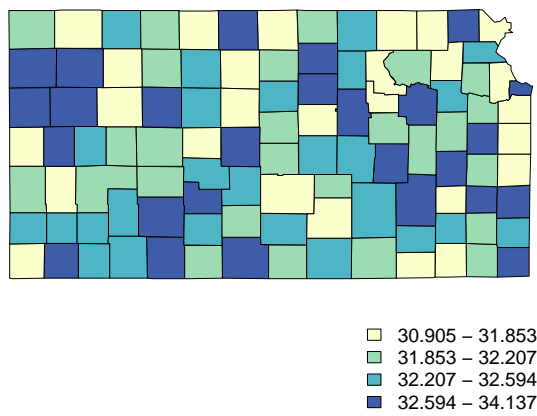


Figure 10: Posterior percentiles for the secondary spatial covariate of the irrigated wheat truncated normal regression

Simulated Yields: 2.5%



Simulated Yields: 50%



Simulated Yields: 50%

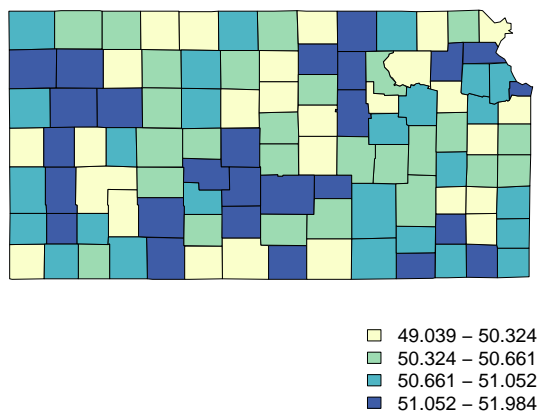
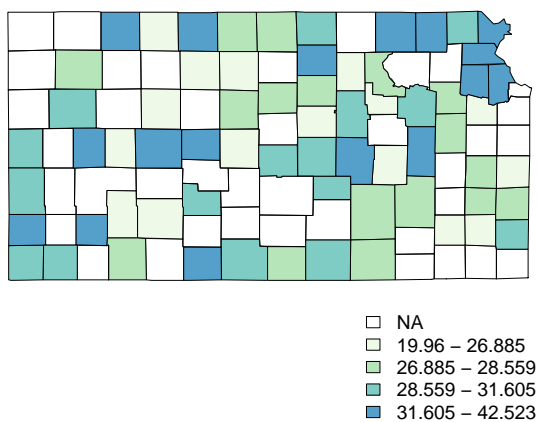
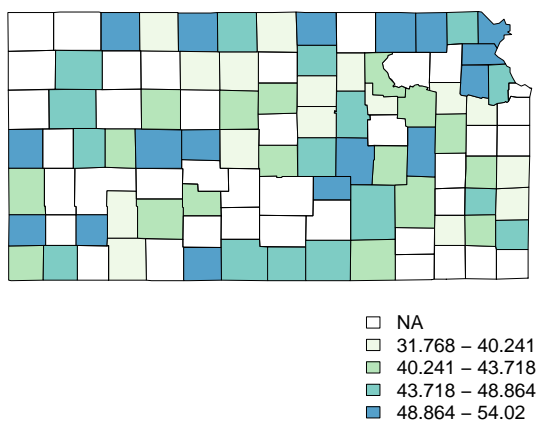


Figure 11: Percentiles for the simulated dryland yields

Simulated Yields: 2.5%



Simulated Yields: 50%



Simulated Yields: 50%

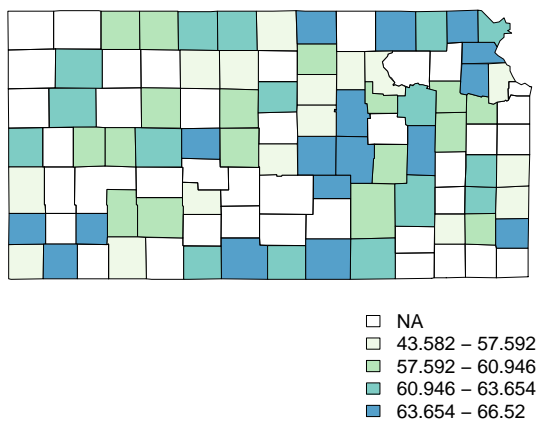


Figure 12: Percentiles for the simulated irrigated yields

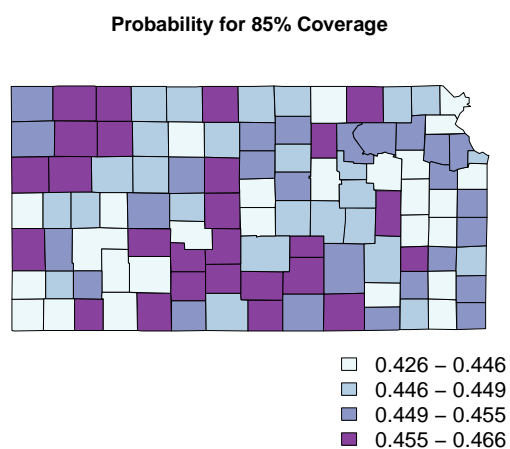
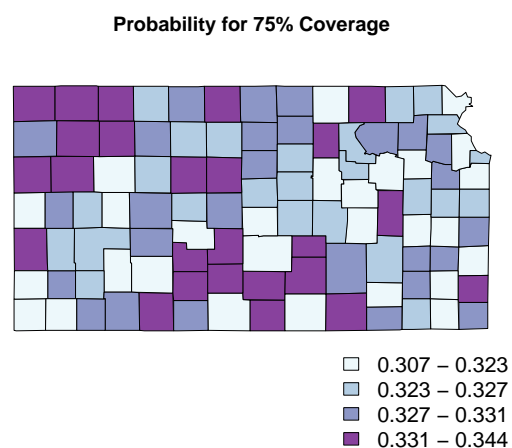
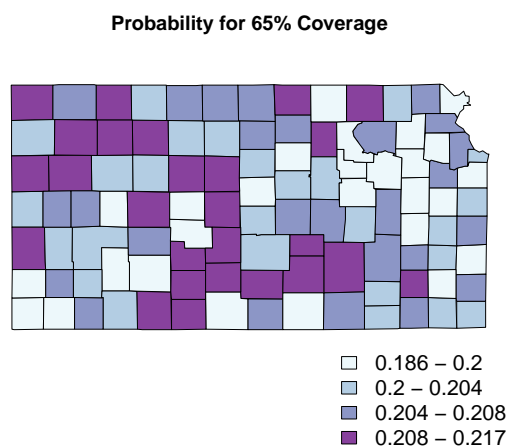


Figure 13: Probability for the three coverage levels of dryland wheat of the best fitting model.

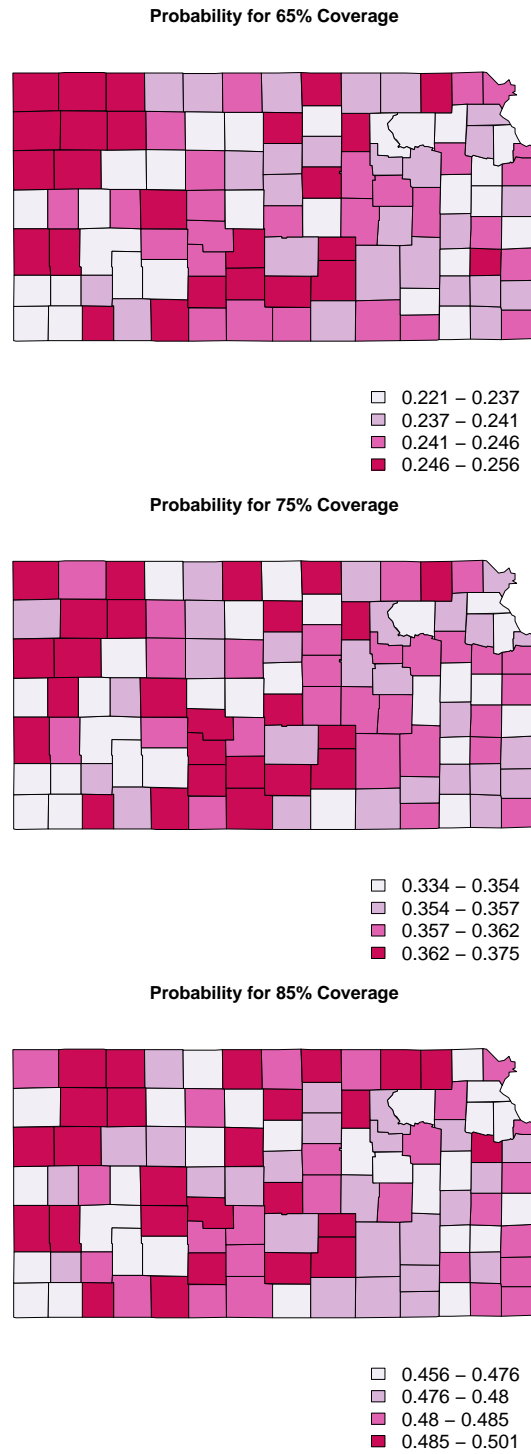


Figure 14: Probability for the three coverage levels of dryland wheat of the model with independent counties.

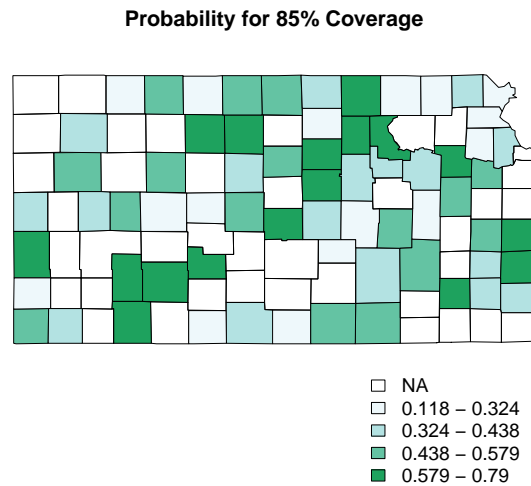
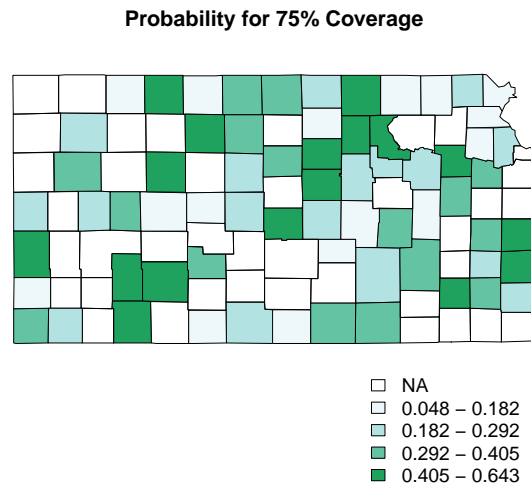
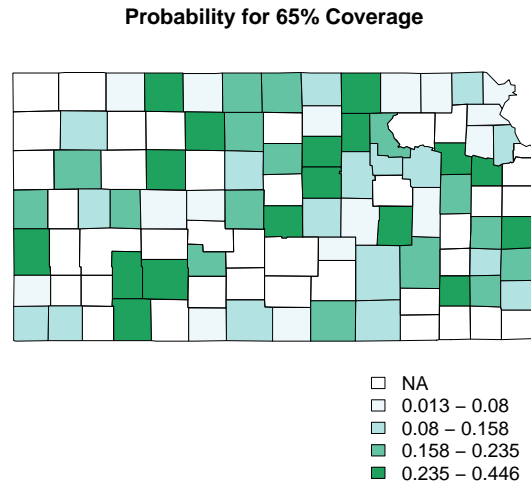


Figure 15: Probability for the three coverage levels of irrigated wheat of the best fitting model.

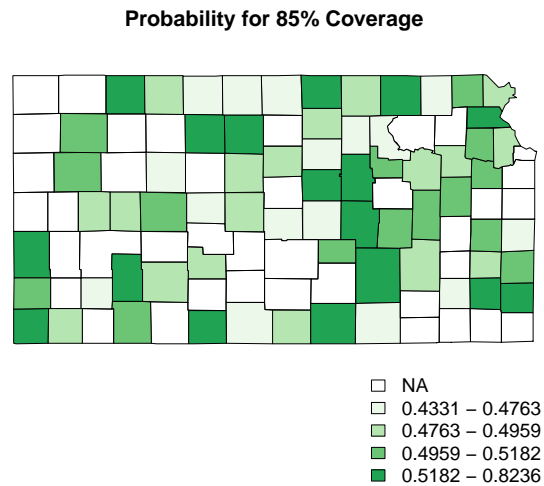
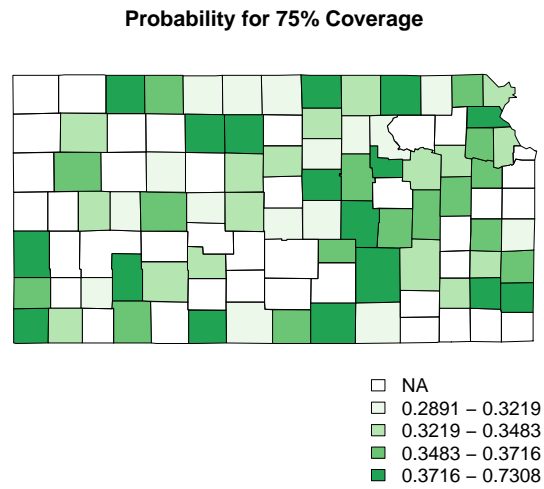
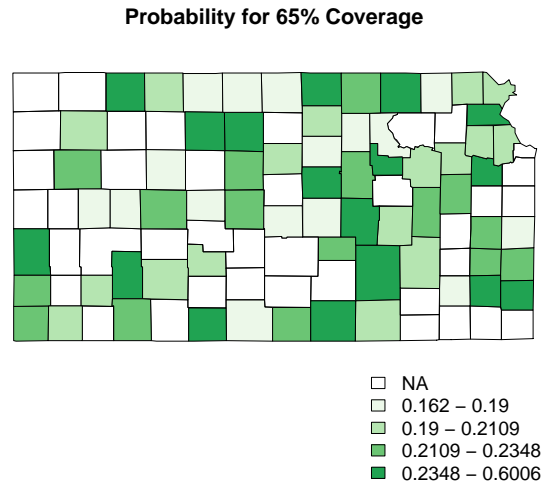


Figure 16: Probability for the three coverage levels of irrigated wheat of the model with independent counties.

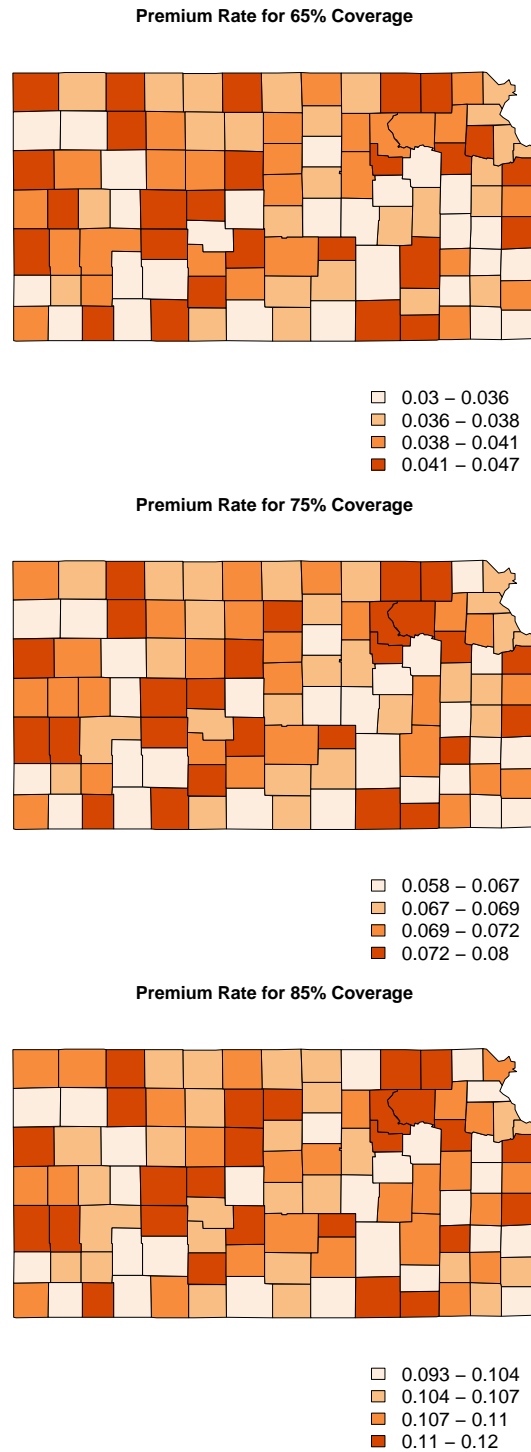


Figure 17: Premium rates for the three coverage levels of dryland wheat of the best fitting model.

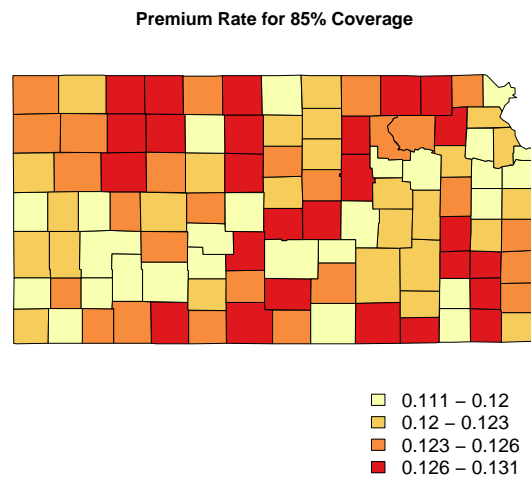
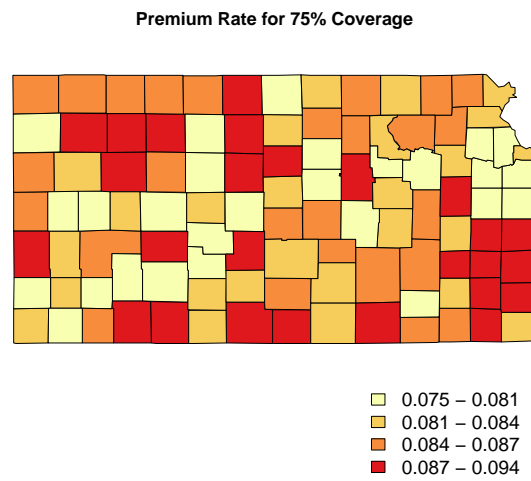
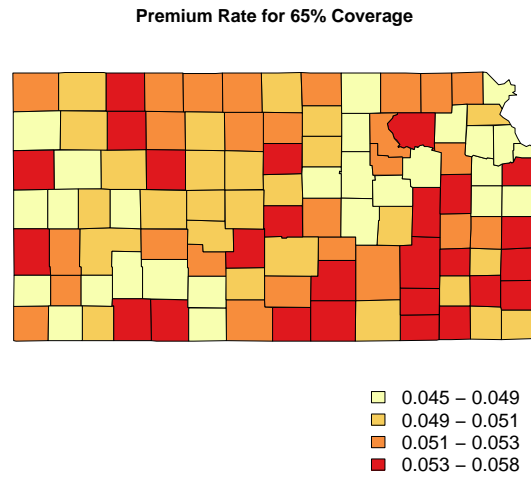
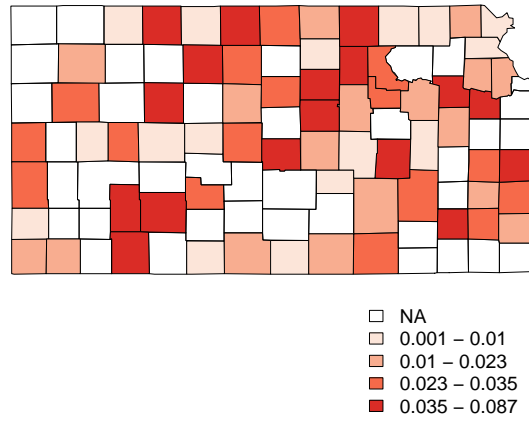
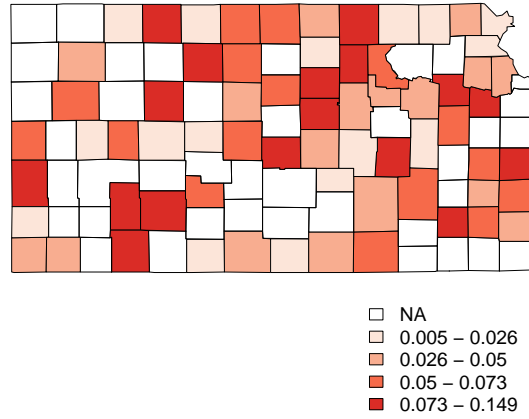


Figure 18: Premium Rates for the three coverage levels of dryland wheat of the model with independent counties.

Premium Rate for 65% Coverage



Premium Rate for 75% Coverage



Premium Rate for 85% Coverage

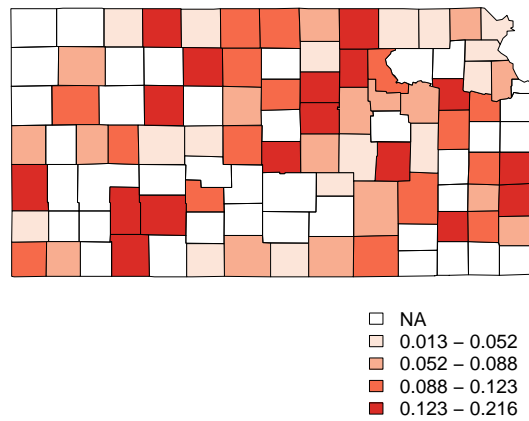
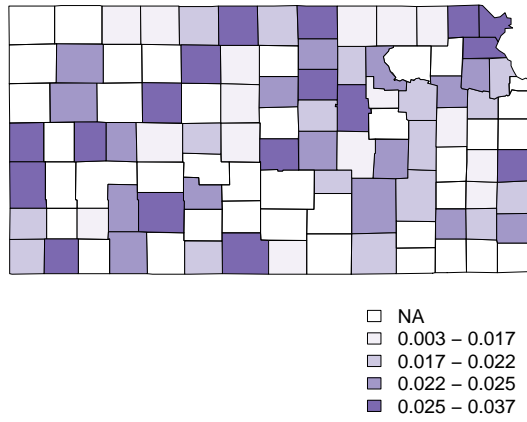
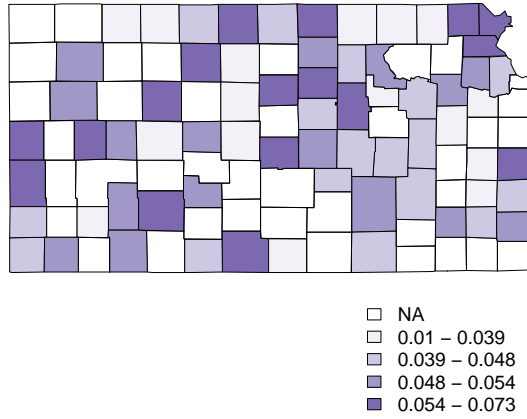


Figure 19: Premium rates for the three coverage levels of irrigated wheat of the best fitting model.

Premium Rate for 65% Coverage



Premium Rate for 75% Coverage



Premium Rate for 85% Coverage

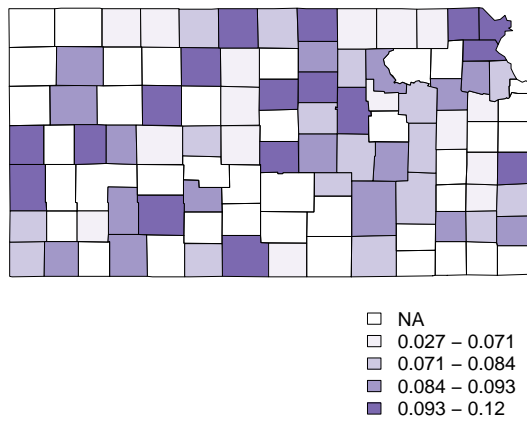


Figure 20: Premium rates for the three coverage levels of irrigated wheat of the model with independent counties.

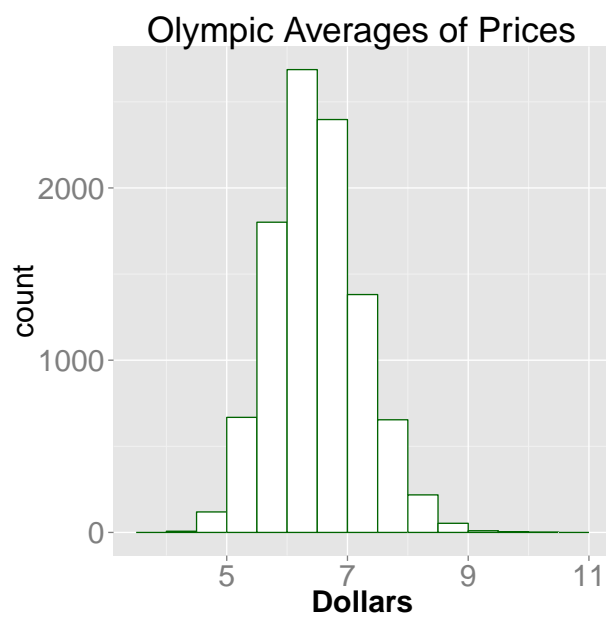
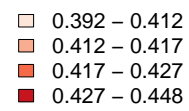
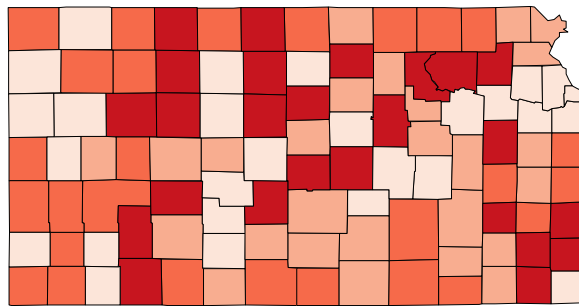


Figure 21: Distribution of Olympic average of prices

Dryland Wheat



Irrigated Wheat

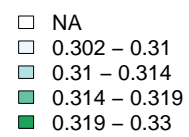
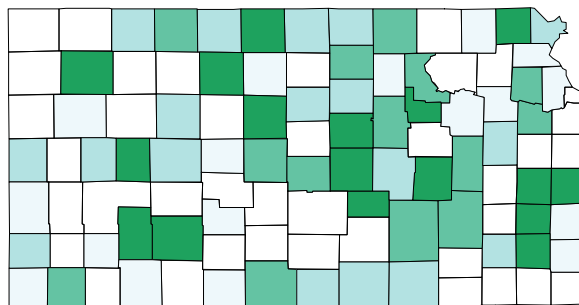


Figure 22: County probability from the ARC program

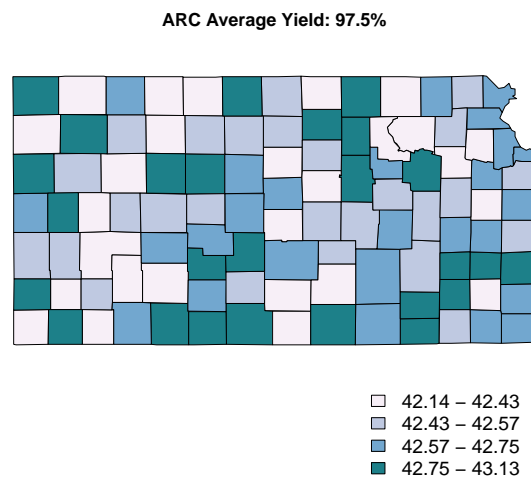
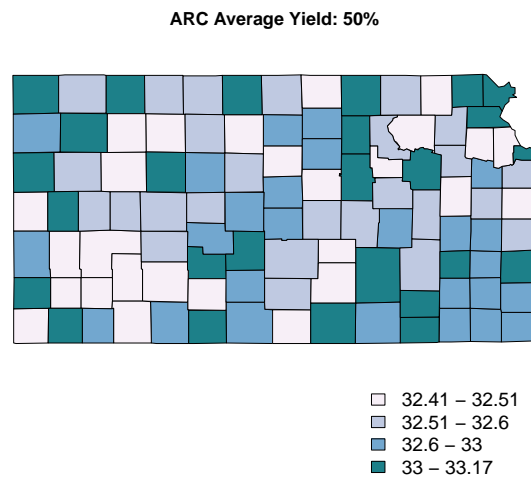
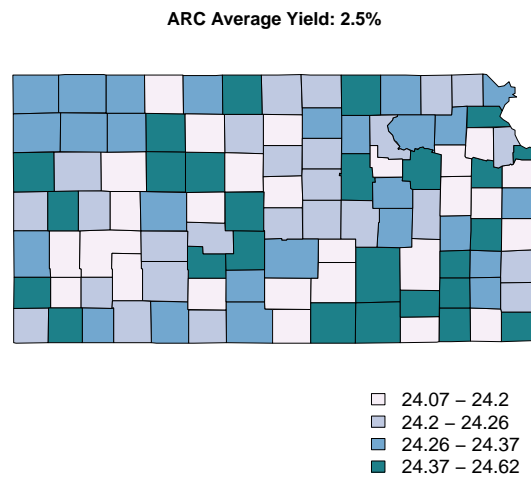
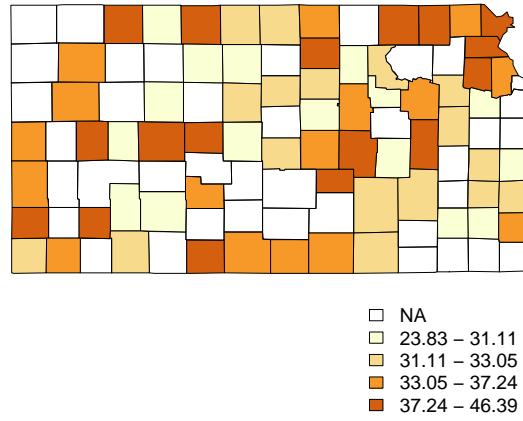
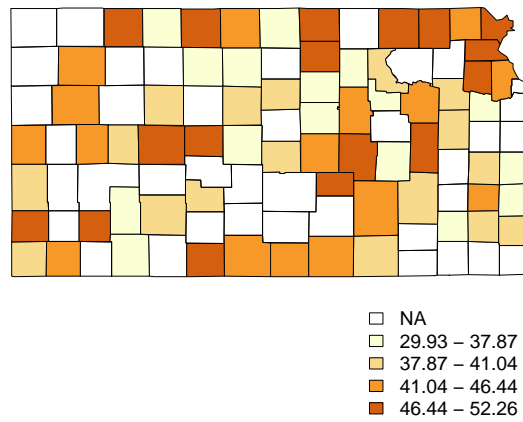


Figure 23: Percentiles of the Olympic averages for dryland wheat.

ARC Average Yield: 2.5%



ARC Average Yield: 50%



ARC Average Yield: 97.5%

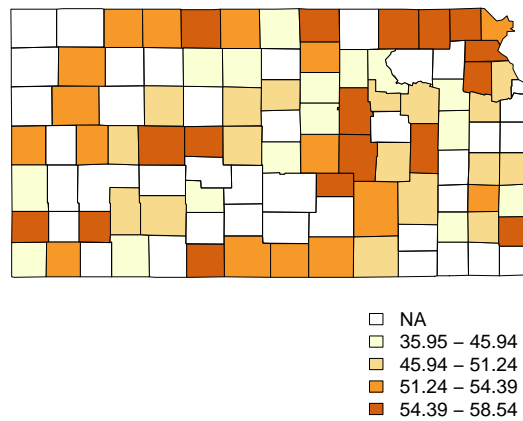


Figure 24: Percentiles of the Olympic averages for irrigated wheat.

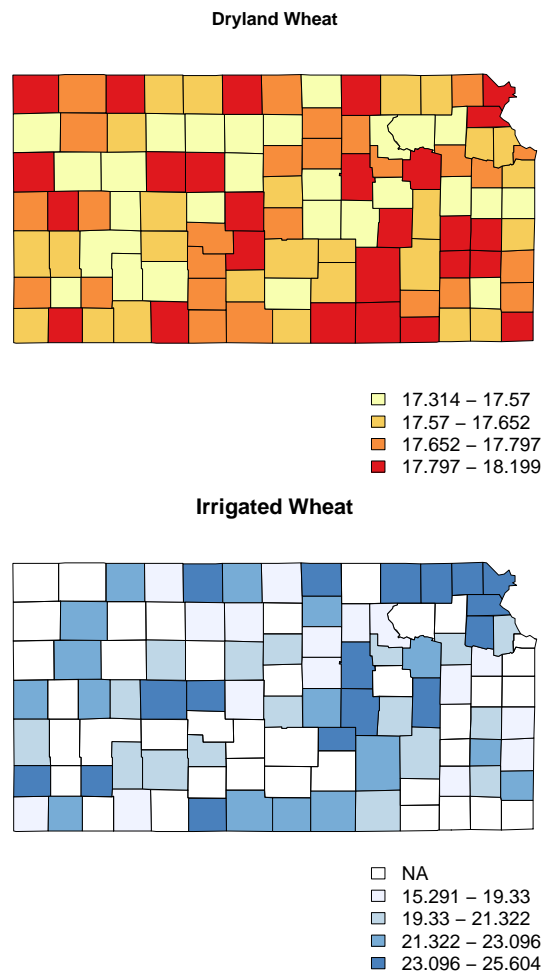


Figure 25: Median of the expected payout for the ARC program.

References

- [113th Congress(2014)] 113th Congress. 2014. “Agricultural Act of 2014.” <https://agriculture.house.gov/farmbill/>.
- [Babcock, Hart, and Hayes(2004)] Babcock, B., C. Hart, and D. Hayes. 2004. “Actuarial Fairness of Crop Insurance rates with Constant Rate Relativities.” *American Journal of Agricultural Economics* 86:563–575.
- [Banerjee, Gelfand, and Carlin(2003)] Banerjee, S., A. Gelfand, and B. Carlin. 2003. *Hierarchical Modeling and Analysis for Spatial Data*, 1st ed. Chapman and Hall/CRC;.
- [Coble et al.(2010)] Coble, Knight, Goodwin, Miller, and Rejesus] Coble, K., T. Knight, B. Goodwin, M. Miller, and R. Rejesus. 2010. “A Comprehensive Review of the RMA APH and COMBO Rating Methodology.”, March 15, pp. .
- [Gelfand and Smith(1990)] Gelfand, A., and A. Smith. 1990. “Sampling-Based Approaches to Calculating Marginal Densities.” *Journal of the American statistical association* 85:398–409.
- [Gelman et al.(2004)] Gelman, Carlin, Stern, and Rubin] Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin. 2004. “Bayesian data analysis. Texts in statistical science series.”
- [Gilks, Richardson, and Spiegelhalter(1996)] Gilks, W., S. Richardson, and D. Spiegelhalter, eds. 1996. *Markov Chain Monte Carlo in Practice: Interdisciplinary Statistics*. Chapman and Hall/CRC.
- [Glauber(2004)] Glauber, J. 2004. “Crop insurance reconsidered.” *American Journal of Agricultural Economics* 86:1179–1195.
- [Goodwin(2001)] Goodwin, B. 2001. “Problems with Market Insurance in Agriculture.” *American Journal of Agricultural Economics*, pp. .

- [Goodwin and Ker(1998)] Goodwin, B., and A. Ker. 1998. “Nonparametric estimation of crop yield distributions: implications for rating group-risk crop insurance contracts.” *American Journal of Agricultural Economics* 80:139–153.
- [Goodwin and Smith(2013)] Goodwin, B., and V. Smith. 2013. “What Harm is Done By Subsidizing Crop Insurance?” *American Journal of Agricultural Economics* 95:489–497.
- [Ifft et al.(2012)Ifft, Nickerson, Kuethe, and You] Ifft, J., C. Nickerson, T. Kuethe, and C. You. 2012. “Potential Farm-Level Effects of Eliminating Direct Payments.”
- [Jaffee and Russell(1976)] Jaffee, D., and T. Russell. 1976. “Imperfect information, uncertainty, and credit rationing.” *The Quarterly Journal of Economics* 90:651–666.
- [Johansen(1988)] Johansen, S. 1988. “Statistical analysis of cointegration vectors.” *Journal of economic dynamics and control* 12:231–254.
- [Lunn et al.(2009)Lunn, Spiegelhalter, Thomas, and Best] Lunn, D., D. Spiegelhalter, A. Thomas, and N. Best. 2009. “The BUGS project: Evolution, Critique, and Future Directions.” *Statistics in Medicine* 28:3049–3067.
- [Miranda and Glauber(1997)] Miranda, M., and J. Glauber. 1997. “Systemic Risk, Reinsurance, and the Failure of Crop Insurance Markets.” *American Journal of Agricultural Economics* 79:206–215.
- [National Agricultural Statistics Service(2014)] National Agricultural Statistics Service. 2014. “Quick Stats.” <http://quickstats.nass.usda.gov/>.
- [Neuwirth(2011)] Neuwirth, E. 2011. *RColorBrewer: ColorBrewer palettes*. R package version 1.0-5.

- [O'Hagan, Forster, and Kendall(2004)] O'Hagan, A., J. Forster, and M. Kendall. 2004. *Bayesian Inference*. Arnold London.
- [Risk Management Agency(2014a)] Risk Management Agency. 2014a. "History of the Crop Insurance Program." <http://www.rma.usda.gov/aboutrma/what/history.html>.
- [Risk Management Agency(2014b)] —. 2014b. "Summary of Business." <http://www.rma.usda.gov/data/sob.html>.
- [Skees and Barnett(1999)] Skees, J., and B. Barnett. 1999. "Conceptual and Practical Considerations for Sharing Catastrophic/Systemic Risks." *Review of Agricultural Economics* 21:424–441.
- [Sturtz, Ligges, and Gelman(2005)] Sturtz, S., U. Ligges, and A. Gelman. 2005. "R2WinBUGS: A Package for Running WinBUGS from R." *Journal of Statistical Software* 12.
- [Tobin(1958)] Tobin, J. 1958. "Estimation of relationships for limited dependent variables." *Econometrica: journal of the Econometric Society*, pp. 24–36.
- [Woodard et al.(2012)] Woodard, Schnitkey, Sherrick, Lozano-Gracia, and Anselin] Woodard, J., G. Schnitkey, B. Sherrick, N. Lozano-Gracia, and L. Anselin. 2012. "A Spatial Econometric Analysis of Loss Experience in the U.S. Crop Insurance Program." *The Journal of Risk and Insurance* 79:261–285.