RI-PRF CROP INSURANCE PROGRAM DESIGN

By

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“아빠, 엄마 사랑해요!”

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Abstract:

The Rainfall Index Pasture Rangeland, and Forage (RI-PRF) crop insurance program insures revenues for producers based on rainfall, a single peril. This thesis looks for ways to improve the design of the program as well as makes recommendations for producers who want to participate in the program. Three possible issues are considered i) how well the rainfall index matches actual rainfall, ii) whether the county base values can be made more accurate using spatial smoothing, and iii) optimal choices of RI-PRF crop insurance alternatives for producers. Of particular interest is reducing the number of choices that producers have to make. The rainfall index accuracy is evaluated using actual rainfall from the Oklahoma Mesonet stations. The rainfall index has a strong positive correlation with actual rainfall, but the correlation is lower in the low rainfall areas with fewer rainfall events and fewer Federal weather stations. Each county base value in Oklahoma is imputed using Bayesian Kriging, while the RI-PRF uses only nine regional values. The 77 county base values are more accurate relative to the nine regional base values. Lastly, the expected profit maximizing and risk minimizing strategies were found. The expected profit maximization strategy increases risk by using the maximum coverage level, the maximum productivity factor, and putting all the weight on the low-rainfall winter months. With the risk minimization strategy, the optimal productivity factor is 45%, which is below the lowest productivity factor of 60% that RMA currently offers. The risk minimizing strategy puts all of the weight on growth months of spring and early summer. Reducing the number of choices is suggested. For that, offer only a coverage level of 90%, restrict the bi-monthly index intervals to growth periods, and lower the range of productivity factors. The productivity factor should be renamed “hedge ratio” to better communicate how it is be used if the RI-PRF is to become an insurance program rather than an income transfer program.

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CHAPTER I

INTRODUCTION

The Rainfall-Index Pasture, Rangeland and Forage (RI-PRF) crop insurance program is an area-based insurance plan that covers perennial pasture, rangeland, or forage used to feed livestock. The RI-PRF crop insurance program protects producers from a single peril - losses brought about by the lack of precipitation. Payments are based on deviations from a rainfall index based on historical nearby rainfall (USDA-RMA, 2017a). The RI-PRF crop insurance program was established in 2007 as a pilot program by the Risk Management Agency (RMA). The RMA expanded the program to the 48 contiguous states in 2016.

The 2012 Census of Agriculture indicates that total pasture and rangeland in the United States is 649.5 million acres (USDA, 2014). The percentage of insured acreage was 8% in 2016 and increased to 22% in 2019 (USDA-RMA, 2019a; Figure 1). However, adoption is still low considering that subsidies account for more than 50 percent of total insurance premiums (Table1**)**. The question addressed here is can the RI-PRF crop insurance program be redesigned to appeal more to producers? This paper considers three possible issues: i) how well the rainfall index corresponds with actual rainfall, ii) the accuracy of county base values, and iii) optimal RI-PRF crop insurance program choices for producers. Reducing the number of choices that producers have to make could increase program participation.

The RI-PRF rainfall index was created by the National Oceanic Atmospheric Administration Climate Prediction Center (NOAA CPC). The RI-PRF rainfall index values are interpolated to the weighted average of rainfall from the closest four reporting NOAA stations (Maples et al., 2016). Index values are based on a grid system which is unlike other federal area insurance plans that are based on county boundaries (USDA-RMA, 2017). Weather index insurance can effectively include spatially covariate risks and resolve the problems of missing data that actual stations have (Barnett and Mahul, 2007; Nadolnyak and Vedenov, 2013; Dalhaus and Finger, 2016). However, accuracy of the index is required to reduce basis risk (Breustedt et al., 2008; Smith and Watts, 2009). The correlation between the RI-PRF rainfall index and actual rainfall is assessed to see if there is high basis risk. Oklahoma is a suitable place to evaluate the accuracy of the index because of the state's Mesonet stations. Mesonet stations provide actual rainfall data from multiple weather stations and can indicate how well actual rainfall data correlates with the rainfall index.

The RI-PRF crop insurance program uses county base values of hay production as standard hay production values to calculate indemnities. Even though the rainfall index values differ by grid, the base values of hay are based on the county level. Oklahoma's 77 counties are further aggregated to nine sectors. Using only nine values could increase basis risk. Park et al. (2018) suggested a Bayesian Kriging approach that imputes county base values that are considered using the spatial effect which states that closer areas tend to have similar rainfall. The Bayesian Kriging approach can provide an estimate for the spatial structure across 77 counties in Oklahoma through the spatial weights based on a function of the Euclidean distance between the counties. This approach can be compared with the nine county base values currently used by the RMA to see how much accuracy is gained by predicting a base value for each county.

The RI-PRF crop insurance program offers producers a wide variety of options to reduce basis risk. Literature about the RI-PRF crop insurance program is currently thin. Diersen et al. (2015) showed producers earned higher returns per acre with lower risk when they participated in the RI-PRF crop insurance program and May-June and July-August intervals were the important months for managing the risk in South Dakota. Westerhold et al. (2018) showed that basis risks differ by the selection of rainfall index insurance intervals due to the variability of precipitation. Yu et al. (2019) estimated the overall basis risk of the RI-PRF crop insurance program and the rainfall index-related basis risk is relatively small. The RI-PRF crop insurance program offers many options to producers that include combinations of coverage levels, productivity factors, and index intervals. Producers can also select various weights for index intervals. Different choices are evaluated to determine how well they reduce risk. In addition to evaluation of the risk, producers could benefit from recommendations about how to choose from the many available choices.

Iyengar and Lepper (2000) argued that offering many choices to those tasked with decision-making does not always result in better decisions. Such an excessive-choice effect means that large choice sets can lead to confusion or avoidance of making a decision. The various choice options of the RI-PRF crop insurance program are likely to have this effect. Schwartz et al. (2002) classified choice taskers as maximizers who pursue the best and satisficers who focus on making a satisfactory choice. They concluded that maximizers tend to have an excessive-choice effect that reduces their utility when presented with a large number of choices. Arunachalam et al. (2009) showed that the utility maximizers were more likely to experience utility losses when faced with relatively large choice sets where it was hard to pick the best option. Moreover, Iyengar and Kamenica (2010) found choice taskers preferred reduced choice sets. A different set of literature describes decision fatigue (Pignatielle et al., 2018) where the quality of choices is reduced as the number of choices goes up. As a means of reducing decision fatigue, President Obama reduced the choices he had to make by doing such things as wearing the same type of suit every day.

With the RI-PRF program, producers may be asked to make choices when they do not have sufficient knowledge to make optimal choices. Disutility from an excessive choice effect and poor choices due to decision fatigue are legitimate concerns. This research seeks to guide policy makers in how best to reduce the number of choices or provide information to producers for making the best choices that can protect them from potential losses due to lack of precipitation.

This study evaluates the RI-PRF crop insurance program to determine ways to improve the program's design. First, the correlations between the rainfall index and the actual rainfall in Oklahoma's counties is estimated. Second, a Bayesian Kriging method is used to impute more accurate county base values. Third, two strategies are used for choosing coverage options for producers; an expected profit maximizing strategy and a risk minimizing strategy. The expected profit maximizing strategy selects the maximum coverage level and productivity factor while selecting the most variable rainfall indices. The Jan.-Feb. interval is the one most often selected by producers (USDA-RMA, 2019a), which suggests that producers are currently using the program as an income transfer rather than as an insurance program. The risk minimizing strategy uses a high coverage level, a low productivity factor, and selects months that are correlated with yield. The risk minimizing productivity factor is not currently available to producers. This thesis recommends reducing the choice set by using only one coverage level, restricting, and renaming the productivity factor, and only allowing rainfall index intervals that are critical for forage growth.

CHAPTER II

CONCEPTUAL FRAMEWORK

Hay producers must decide whether they will sign the RI-PRF contract or not. After they decide to sign the contract, producers must choose various coverage options including coverage levels, productivity factors, and index intervals. Coverage can be selected from 5 levels at 70%, 75%, 80%, 85%, and 90%. Policyholders can choose a productivity factor ranging from 60% to 150% of county base value in 1% increments. The program is also available for 11 index intervals: Jan.-Feb., Feb.-Mar., Mar.-Apr., Apr.-May, May-June, June-July, July-Aug., Aug.-Sep., Sep.-Oct., Oct.-Nov., and Nov.-Dec. Producers must select at least two intervals. Producers cannot select overlapping periods, for example Jan.-Feb. and Feb.-Mar. The maximum number of intervals is six. Interval weights must equal 100%, each interval weight can be no less than 10%, and the maximum interval weight is dependent on the county as published by RMA in the actuarial documents. For Oklahoma, the maximum is 60%.

Based on Iyengar and Lepper (2000), having so many different coverage options can be confusing to decision makers. Learning enough to make optimal choices can take considerable time. In some cases, producers might choose to not purchase insurance to avoid making choices (Anderson, 2003; Grant and Schwartz, 2011). Maximizer's utility can decrease as the number of choices increases (Schwartz et al., 2002; Parker et al., 2007).

The theoretical producer's expected utility function includes an excessive-choice effect (ECE) that can reduce utility:

$$(1) \qquad \max_{\substack{C^* \in \{0,1\} \\ CL \in \{70,75,80,85,90\} \\ 60 \le PF \le 150 \\ w_i \in \{1,2,\cdots,11\}}} EU(\pi, N) = \iint U(\pi, N) f(\lambda, Y) d\lambda dY$$

where the arguments are defined by the following equality constraints:

$$(2) \qquad \pi = P \cdot Y + C^* \left(PF \cdot NetReturn\left(CL, \underline{W}\right)\right) - \mathbf{r}'\mathbf{z}$$

$$NetReturn(CL, \underline{W}) = \left(\sum_{i=1}^{11} w_i \cdot \max\{CL - F_i, 0\} - Premium_i(CL)\right)$$

$$Premium_i(CL) = premiumrate_{iCL} \cdot (1 - subsidy_{CL})$$

$$\sum_{i=1}^{11} w_i = 1; \quad U'(\pi) > 0, U''(\pi) \le 0, and\ U'(N) < 0$$

where $U(\pi, N)$ is expected utility of profit and number of choices (N), RI-PRF crop insurance program policy represents by coverage level (CL), productivity factor (PF), weighted time interval selection ($\underline{W}$), w_i, is the weight of bi-monthly time selection ($i = 1,2, \ldots, 11$; Jan.-Feb., Feb.-Mar., Mar.-Apr., Apr.-May, May-June, June-July, July-Aug., Aug.-Sep., Sep.-Oct., Oct.-Nov., and Nov.-Dec.), λ is the rainfall index value, Y is hay production function, $C^*$is a discrete variable equaling 1 when a producer contracts and 0 if not, P is price of hay price, F_i is final rainfall index grid in i time interval, $\mathbf{r}$ is a vector of other input costs, $\mathbf{z}$ is a vector of other inputs, $premiumrate_{iCL}$is the premium rate that differs by time selection and coverage level, $subsidy_{CL}$ is the subsidy rate that differs by coverage level, $U'(\pi)$ and $U''(\pi)$ are the first and second derivatives of the expected utility of profit function, and $U'(N)$ is the first derivative of expected utility with respect to the number of choices function and it is negative. That means the expected utility is decreased as increase the number of choices. Since the number of choices N is the same in all cases, it is not considered in the optimization, but it is included here to illustrate how a large number of choices can reduce participation.

CHAPTER III

DATA

Rainfall Index and Actual Rainfall

The actual monthly rainfall data is available from the Oklahoma Mesonet weather stations (Brock et al., 1995; McPherson et al., 2007) The monthly rainfall includes snowfall as well as rainfall. The Oklahoma Mesonet provides historical rainfall data from 1994 to 2017 from 131 weather stations. These include stations that have been retired or relocated. There are currently 120 weather stations in operation. Rainfall index data for each grid ID with a Mesonet station were collected from the USDA RMA's decision tool program (USDA-RMA, 2019c). There were 11 bi-monthly rainfall indices for each grid ID. The actual rainfall was aggregated over two month intervals to match the bi-monthly rainfall indices.

Hay Yield County Base Value

The USDA RMA's actuarial information browser (AIB) provided hay yield base values for each county (USDA-RMA, 2019b). Non-irrigated hay yield county base values were collected. All of the historical hay yield data were collected except for the alfalfa hay from the USDA National Agricultural Statistics Service (NASS) annual reports that stated the historical all other hay yield data by county in Oklahoma from 1994 to 2017. NASS annual reports had problems with missing data, especially in 2008 where only 11 county hay yields were recorded. For the Bayesian Kriging method, historical actual hay yields in Oklahoma from 1994 to 2016 were used as well as the physical locations for each county. In the case of several stations located in the same county, the latitude and longitude for each station location were averaged.

The USDA RMA also provided information to estimate the indemnities and premium rates of the RI-PRF crop insurance program (USDA-RMA, 2019b). The premium rates by each grid ID were collected. However, the RI-PRF crop insurance program launched starting from 2011 in Oklahoma, and premium rates were collected only after 2011.

CHAPTER IV

PROCEDURE

Pearson Product-Moment Correlation Analysis

Correlation analysis is used to evaluate how well the rainfall index matched actual rainfall. Correlation analysis has been used to evaluate the level of basis risk of index insurance (Norton et al., 2012; Maples et al., 2016). The PROC CORR procedure of SAS (SAS Institute, 2008) was used to calculate the correlation for the 131 Mesonet station's locations. The Pearson product-moment correlations were calculated following

(3)

$$r_i = \frac{n \sum RI_{it} R_{it} - (\sum RI_{it})(\sum R_{it})}{\sqrt{[n \sum RI_{it}^2 - (\sum RI_{it})^2]\,[n \sum R_{it}^2 - (\sum R_{it})^2]}}$$

where r_i is the Pearson product-moment correlation of each Mesonet station ($i = 1,2,\ldots,131$) and n is the number of observations used to show the relationship by each locations i and year ($t = 1994,\ldots,2017$), between rainfall indices ; RI_{it} ,and actual rainfall; R_{it}.

Bayesian Kriging

The county base values that the RI-PRF crop insurance program currently offers and the average hay yield by each county from a Bayesian Kriging method (Park et al., 2019) were compared to the actual hay yield in Oklahoma. The Bayesian Kriging method imputes the mean and variance of hay yield densities by each county. This method used the estimation of counties historical yield densities when data has missing values based on an assumption that closer regions have spatial similarity than farther regions. Oklahoma has 77 counties for which hay yield densities have to be estimated in year *t*; 1994-2016. Hay yield Y_{it} in year t for county i is:

(4) $$Y_{it} \sim N(\alpha_i, \gamma_i)$$

where α_i are the mean of each county hay yield, and each county yield is assumed to have a normal density, where $\gamma_i$is the variance.

Following the Bayesian Kriging approach (Park et al., 2019), this model has three hierarchical layers. First, the likelihood layer is the crop yield distribution of each county i. The parameter vector the ϕ_i= (α_i, γ_i) includes two parameters that define the mean and variance for the hay yield densities. The likelihood layer is:

(6) $$\boldsymbol{Y} \sim p_1(\boldsymbol{Y}|\boldsymbol{\phi})$$

where $\boldsymbol{Y}$ is the 77×23 matrix of yields from all counties and all years and $\boldsymbol{\phi}$ is the 77×2 matrix of hay yield density parameters for all counties.

Second, the process layer models the spatial process of the parameters. This layer is composed with the parameter $\boldsymbol{\phi}$; $\boldsymbol{\alpha}$ is the mean of each county's hay yield and $\boldsymbol{\gamma}$ is the variance and the Kriging parameters; range (θ) and sill (ρ), based on the distance from latitude and longitude between the counties that implied spatial similarities. Moreover, this process uses a Gaussian spatial process with an explicit functional form of spatial covariance matrix. This layer is specified as:

(7) $$\boldsymbol{\phi} \sim p_2(\boldsymbol{\phi}|\boldsymbol{\lambda})$$

where $\boldsymbol{\phi}$ is the 77×2 matrix of hay yield density parameters for all counties and $\boldsymbol{\lambda}$ is a vector of hyper parameters that comprise the parameters that determine the parameter $\boldsymbol{\phi}$, including the Kriging parameters (sill and range). The third layers are hyper priors that consists of the prior parameters for the covariates of the process layer and Kriging parameters (range and sill) in the spatial covariance matrix. The hyper priors form is:

(8) $$\boldsymbol{\lambda} \sim p_3(\boldsymbol{\lambda})$$

The hay yield densities are determined by the posterior distribution of the parameters. The likelihood $p_1(\boldsymbol{Y}|\boldsymbol{\phi})$, the process layer $p_2(\boldsymbol{\phi}|\boldsymbol{\lambda})$, and the hyper priors $p_3(\boldsymbol{\lambda})$ are proportional to the joint posterior distribution of parameters. The joint posterior distribution of parameters is:

(9) $$p(\boldsymbol{\phi}, \boldsymbol{\lambda}|\boldsymbol{Y}) \propto p_1(\boldsymbol{Y}|\boldsymbol{\phi}, \boldsymbol{\lambda}) p_2(\boldsymbol{\phi}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda})$$

and is mathematically shown as:

(10)

$$p(\boldsymbol{\phi}, \boldsymbol{\lambda}|\boldsymbol{Y}) = \frac{p_1(\boldsymbol{Y}|\boldsymbol{\phi}, \boldsymbol{\lambda}) p_2(\boldsymbol{\phi}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda})}{\int_{\boldsymbol{\phi}} \int_{\boldsymbol{\lambda}} p_1(\boldsymbol{Y}|\boldsymbol{\phi}, \boldsymbol{\lambda}) p_2(\boldsymbol{\phi}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda}) d\boldsymbol{\lambda} d\boldsymbol{\phi}}$$

The likelihood function for historical data is

(11)

$$p_1(\boldsymbol{Y}|\boldsymbol{\phi},\boldsymbol{\lambda}) = \prod_{i=1}^{N}\prod_{t=1}^{T}\frac{1}{\gamma_i}exp\{-\frac{(Y_{it}-\alpha_i)^2}{2\gamma_i}\}$$

For the Gaussian spatial process, each parameter is presumed to be independent. The spatial process of the mean of each county hay yield equation is:

(12)
$$\boldsymbol{\alpha} = MVGP(\boldsymbol{\mu}, \Sigma_{\boldsymbol{\alpha}})$$
$$\mu_i = \beta_{0i} + \epsilon_i$$
$$\Sigma_{\boldsymbol{\alpha}} = \psi(D_{ij}; \theta_{\boldsymbol{\alpha}}, \rho_{\boldsymbol{\alpha}})$$
$$\epsilon_i \sim MVN(0, \Lambda)$$

where $\boldsymbol{\alpha} = \alpha_1, \cdots, \alpha_{77}$ is the vector of average hay yield for all counties in Oklahoma, and is assumed to follow a multivariate Gaussian process (MVGP), $\boldsymbol{\mu}$ is the vector of deterministic intercept of the Gaussian process, $\Sigma_{\boldsymbol{\alpha}}$ is the covariance matrix in the Gaussian process of $D_{ij}, \theta_{\boldsymbol{\alpha}}$, and $\rho_{\boldsymbol{\alpha}}$; D_{ij} is the distance between counties i and j measured from longitude and latitude coordinates, $\theta_{\boldsymbol{\alpha}}$ is the range parameter and $\rho_{\boldsymbol{\alpha}}$ is the sill parameter, and ϵ_i is a non-spatial error component that follows $\epsilon_i \sim MVN(0, \Lambda)$, where Λ is a diagonal matrix with diagonal elements of υ^2 and all other elements are zero.

The covariance between two counties is an exponential function of the distance measured from longitude and latitude, and the range and sill parameters:

(13)
$$\psi\left(D_{ij}; \theta_{\boldsymbol{\alpha}}, \rho_{\boldsymbol{\alpha}}\right) = \rho_{\boldsymbol{\alpha}} e^{-\frac{D_{ij}}{\theta_{\alpha}}}$$

The mean and variance for hay yield for each of the 77 counties in Oklahoma are imputed and compared with county base values that are offered by the RMA. The actual hay yields by each county as dependent variables are regressed linearly as dependent variables with the nine values that RMA used as well as the 77 mean values from the Bayesian Kriging. Both linear regressions are estimated without intercept. Their results of the R-squared and mean squared errors are compared.

Expected Utility Optimization

Through the expected utility optimization, the optimal choices of RI-PRF crop insurance program for producers are found. The expected utility optimization problem used data from 2011 to 2017, when RI-PRF crop insurance program was first offered in Oklahoma. Therefore, only 43 counties in Oklahoma have no missing hay yield data issues over 2011 to 2017. The producer's weighted allocation choice problem is

$$\max_{CL,PF,w_i} EU(\pi) = \sum_{k=1}^{43} \sum_{j=1}^{7} \sum_{CL}^{5} \sum_{i=1}^{11} E\left(U\left(P_j \cdot Y_{kj} + PF \cdot V_{kjCLi} * w_i\right)\right) \quad (14)$$

$$s.t. \quad U'(\pi) > 0, U''(\pi) \leq 0;$$

$$\sum_{i=1}^{11} w_i = 1; \quad w_i \cdot w_{i+1} = 0 \quad \forall\, i = 1,2, \dots ,11$$

$$w_i = \begin{pmatrix} 0.1 \leq w_i \leq 0.6 & w_i > 0 \\ 0 & w_i = 0 \end{pmatrix}$$

$$0 \leq PF \leq 150; \quad CL = 70, 75, 80, 85 \text{ and } 90$$

where $EU(\pi)$ is expected power utility function for profit, k is a county (j=1,2,…,43), j is a year of county (j=1,2,…,7; 2011 to 2017), i is invest ($i = 1,2, \dots ,11$), CL is coverage level ($CL = 1,2, \dots ,5; 70\%, 75\%, \dots ,90\%$) P_j is a hay price in year j, Y_{kj} is the hay yields of county k in year j , and PF is the productivity factor, V_{kjCLi} is the mean return from RI-PRF crop insurance program by a year of county, w_i is an invest allocation for each bi-monthly period i and that can be given weight 0.1 to 0.6 that is the maximum weight in Oklahoma or 0, $U'(\pi)$ is first derivative of utility function, $U''(\pi)$ is second derivative of utility function.

To compare the risk by choice selections, two strategies are considered: expected profit maximization and risk minimization. The expected profit maximization assumes that producers are risk neutral. This strategy uses the maximum coverage level and productivity factor and bi-monthly periods that are selected through the optimization problem for maximizing the profit. The other is a risk minimization strategy that uses high coverage level and bi-monthly periods that are selected through the optimization problem for minimizing risk. In order to find the optimal productivity factor that has minimum risk, the productivity factor range was expanded from 0 to 150 even though the RMA range of productivity factor is set from 60 to 150. The GAMS software is used to solve both optimization problems for maximizing the profit and minimizing risk. Moreover, the optimal productivity factor was determined that has a minimum risk as well as finding the optimal choices of RI-PRF crop insurance program for producers.

CHAPTER V

RESULTS

Correlations between Rainfall Index and Actual Rainfall

The estimated Pearson product-moment correlations between rainfall index and the actual rainfall have an average 0.95 correlation with actual rainfall across the 131 Mesonet locations from 1994-2017 and this average number is little higher than an average 0.94 that is estimated for each interval (Table 2). However, the correlations of each Mesonet station exhibits a tendency that gradually decreases from east to west in Oklahoma. The correlation is higher when annual precipitation is higher. Especially, the correlations in Panhandle districts are lower than other regions (Figure 2). The density of NOAA stations fluctuates based on population, and this tendency shows especially in low-rainfall western areas (Figure 3).

Bayesian Kriging Hay Yield County Base Value

The Bayesian Kriging approach was used to impute average hay yield of all 77 counties in Oklahoma (Figure 4-5). The RI-PRF base values are constant across different sets of counties. The regression using the actual hay yields in 2017 as dependent variables without an intercept was used to determine out of sample relative accuracy of the Bayesian Kriging method and the RMA base values. The base values from Bayesian

Kriging increased R-squared from 0.9780 to 0.9881 (Table 3). Moreover, mean squared error decreased from 0.2864 to 0.2133. These 77 county base values from Bayesian Kriging can be used for each county to more precisely insure the losses of producers.

Optimal Productivity Factor

The expected profit maximizing strategy uses the maximum coverage level of 90%, and the maximum productivity factor of 150%. Jan-Feb and Nov-Dec are selected and have weights 0.4 and 0.6 (Figure 6). These two bi-monthly rainfall indices accord with the most variable rainfall indices, so they had a larger variance range than the other index intervals. This is because during low precipitation periods the average is low, so the index changes more sensitively.

The risk minimization strategy also uses the highest coverage level, 90%, and a productivity factor that can reduce risk. In finding the optimal productivity factor to minimize the risk, the productivity factor was varied from 0 to 150. As the productivity factor increases, risk decreases, but after the 45% mark, risk increases again (Figure 6). Jacobs et al. (2018) showed higher expected profit but also increased risk variability when producers relied on changes in precipitation to hedge. When the productivity factor is higher than 89%, risk increases more than having no contract at all. The risk-minimizing strategy also selected only two critical growth periods even though producers can choose any of the periods up to six. Mar-Apr and Jul-Aug are selected and have weights 0.4 and 0.6. However, every county in the state was restricted to pick the same monthly intervals and some do not fit well. Therefore, the 43 counties are optimized separately with risk minimization and finding the optimal productivity factor as well as the selections of bi-monthly intervals. Most counties had an optimal productivity factor below 120%, and only four counties (Adair, Delaware, Mayes and Pottawatomie) had over 120% (Figure 7). These optimal productivity factors do not match with the optimal number of 0.45 as the optimization using all observations because only seven observations were used by each county and considered the selections of bi-monthly intervals by each county. The selections of bi-monthly intervals also sometimes selected October through February that is not in the critical period interval.

The expected payoff ratios are calculated as the returns from insurance divided by the premium (without subsidies) (Table 4). Thus, the average of the payoff ratio in Table 4 is 86%. Others have calculated actual and expected payouts of the program at only 90% of total premiums (Maples et al., 2016; Pan et al., 2019). The government pays 51% of the total premium with 90% coverage, so an Oklahoma producer would have averaged getting back 1.76 times the amount paid (0.86/0.49). The lowest return in Table 4 is 9% for Kingfisher county.

CHAPTER VI

CONCLUSION

This thesis finds that the rainfall index is well designed because it has a strong positive correlation with actual rainfall. This correlation is a little higher than found in previous research such as Maples et al. (2016) whose correlations averaged 0.94, so the overall correlation in Oklahoma is adequate for the RI-PRF crop insurance program to reduce risk. However, The correlation drops when moving from east to west in Oklahoma. The correlation is lower in the low rainfall areas with fewer rainfall events, especially in Panhandle regions. More NOAA stations are generally located in populated areas and so station density may also explain the correlation pattern.

The nine county base values that RMA currently uses are working well and, these values have similar trends with actual hay yield in Oklahoma. The Bayesian Kriging approach can impute each hay yield county base values. Bayesian Kriging removes about half of the variability. The nine county base values are highly correlated and the base value is not a critical number so the benefits of going to the more accurate Bayesian Kriging approach might not be large enough to be adopted.

However, expected utility optimization results show needs for improvement. The objective of the RI-PRF crop insurance program is to protect loss caused by the lack of precipitation. The program increases risk when using the expected profit maximization strategy, which is what most producers are doing. Even when using the risk minimization strategy, the risk is greater than having no contract when higher productivity factors selected were greater than 89%. The minimum risk point is also below the minimum productivity factor of 60% that RMA currently offers. The correlation with the county average will be higher than the correlation with individual producer's hay yield, so the minimum risk point, 45%, is likely overestimated. When the 43 counties are optimized separately with risk minimization, the average of optimal productivity factor of each county is 85%. With only seven observations and so many choices, the 85% is an overestimate of what a producer could expect out of sample. Therefore, this thesis highly recommends revising the range of the productivity factor to be less such as 40% to 80%. If the range is lowered, the "productivity factor" needs to be renamed as a "hedge ratio." The name productivity factor gives a psychological effect to suggest to producers that they must choose a high number (Pavia and Costa, 1993; Gunasti and Ross Jr. 2010).

Moreover, it is desirable to reduce the number of choices. Choice sets with a large number of possibilities can lead to nonparticipation in order to avoid making choices (Iyengar and Lepper, 2000; Grant and Schwartz, 2011). Research has shown that too many choices can reduce utility. Suggestions are made about how best to reduce the number of choices. First, using only the 90% coverage level is recommended since it is preferred both by the minimum risk strategy and by the expected profit maximization strategy. Furthermore, the reduction in other coverage level options will not have a significant impact on the producer because the 90% coverage level is the most common selection by producers (USDA-RMA, 2019a).

As for another recommendation, the number of monthly intervals available should be reduced. The time period most often selected by producers is the Jan.-Feb. period, which shows that producers are treating the program as an income transfer program rather than an insurance program. That is the program is not reaching its goal of reducing risk. Therefore, restricting bi-monthly index intervals to growth periods is recommended. When critical growth periods were selected, risk decreased, in contrast to selecting the low precipitation winter months. Hay is often harvested in June or July. Pasture is often utilized later in the summer, so producers insuring pasture might also benefit from including rainfall in early fall. Winter forage production has shown little correlation with precipitation (Biedenbach, 2018) and so there is little possibility of designing the winter forage program to reduce risk.

The results provide guidelines for producers who want to use the program to reduce risk. The suggested guideline is to select the 90% coverage level, a 45% hedge ratio, and restrict the bi-monthly selections to March through August. If producers simply want to maximize their expected income then they should choose the highest coverage level, the highest productivity factor, and choose the winter rainfall intervals where precipitation is typically low. Guidelines can encourage producers by reducing search costs and helping them make more optimal choices (Malone and Lusk, 2017). Guidelines can also reduce the influence of crop insurance agents who have an incentive to encourage producers to choose intervals with the highest premium rates because most agents receive a commission based on the amount of premium. The provided guidelines can thus guide producers toward choices that reduce risk and thus may encourage participation from the producers that are the target of the RI-PRF crop insurance program.

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Table 1. Summary of RI-PRF Usage in the United States, 2016-2019

Year	Number of Contracts (1)	Insured Acreage (2)	Total Subsidy (3)	Total Premium (4)
2016	25,285	51,786,314	$151,257,835	$280,761,453
2017	28,472	74,933,760	$202,993,060	$380,370,455
2018	32,709	98,330,613	$278,139,133	$520,001,827
2019	37,318	141,087,719	$294,122,947	$582,119,798

Source: USDA-RMA, 2019a

Table 2. The Estimated Pearson Product-Moment Correlations by Bi-monthly Intervals between Rainfall Index and the Actual Rainfall in Oklahoma, 1994-2017

Bi-monthly intervals	Correlations
January-February	0.9416
February-March	0.9417
March-April	0.9537
April-May	0.9607
May-June	0.9534
June-July	0.9263
July-August	0.9125
August-September	0.9040
September-October	0.9303
October-November	0.9502
November-December	0.9541

Table 3. The Results from the Regression between the County Base Values from RMA and Bayesian Kriging with Actual Hay Yields as Dependent Variables without Intercept

County Base Values	RMA (9 values)	Bayesian Kriging (77 values)
R^2	0.9780	0.9881
Mean squared error	0.2864	0.2133

Table 4. The Results of the Expected Payoff Ratio and the Bi-monthly Index Selections from the Risk Minimization Strategy

District	County	Expected Payoff Ratio	Bi-monthly Index Selections
North Central	Garfield	49%	Mar-Apr, June-July
	Major	49%	Apr-May, July-August
	Noble	113%	June-July, Sep-Oct
Northeast	Craig	66%	June-July, Oct-Nov
	Delaware	97%	Apr-May, June-July
	Mayes	125%	Apr-May, June-July
	Nowata	17%	June-July, Oct-Nov
	Osage	91%	June-July, Sep-Oct
	Ottawa	113%	June-July, Sep-Oct
	Rogers	139%	Apr-May, June-July
	Tulsa	112%	June-July, Sep-Oct
	Wagoner	106%	June-July, Oct-Nov
Central	Grady	72%	Mar-Apr, June-July
	Kingfisher	9%	Mar-Apr, Aug-Sep
	Lincoln	54%	Feb-Mar, June-July
	Logan	100%	Mar-Apr, June-July
	McClain	69%	Mar-Apr, June-July
	Payne	158%	Mar-Apr, June-July
	Pottawatomie	57%	June-July, Sep-Oct
	Seminole	33%	June-July, Sep-Oct
East Central	Adair	161%	Apr-May, June-July
	Cherokee	100%	Apr-May, June-July
	Haskell	94%	Feb-Mar, June-July
	Hughes	84%	Feb-Mar, June-July
	McIntosh	109%	June-July, Aug-Sep
	Muskogee	94%	Feb-Mar, June-July
	Okmulgee	103%	June-July, Oct-Nov
	Sequoyah	24%	Mar-Apr, June-July
South Central	Bryan	89%	Mar-Apr, July-Aug
	Coal	64%	Apr-May, June-July
	Johnston	147%	June-July, Aug-Sep
	Love	37%	Feb-Mar, June-July
	Pittsburg	46%	Feb-Mar, June-July
	Pontotoc	150%	June-July, Aug-Sep
Southeast	Choctaw	50%	Mar-Apr, July-Aug
	Latimer	82%	June-July, Sep-Oct
	Le Flore	89%	Feb-Mar, June-July
	McCurtain	138%	June-July, Aug-Sep

	Pushmataha	125%	June-July, Aug-Sep
Southwest	Caddo	82%	Mar-Apr, June-July
West Central	Beckham	59%	Mar-Apr, Sep-Oct
	Blaine	63%	Feb-Mar, July-Aug
	Washita	67%	Feb-Mar, Aug-Sep

Notes: Only 43 counties data used and Panhandle districts are not considered due to missing data and the average of expected payoff ratio is 86%.

Table 5. The Results of the Bi-monthly Index Selections from the Risk Minimization Strategy with Historical Data Set

District	Bi-monthly Index Selections
North Central	June-July, Sep-Oct
Northeast	Feb-Mar, June-July
Central	Feb-Mar, June-July
East Central	Feb-Mar, June-July
South Central	Apr-May, June-July
West Central	Mar-Apr, May-June
Southeast	June-July, Sep-Oct
Southwest	Jan-Feb, June-July
Panhandle	Apr-May, Aug-Sep

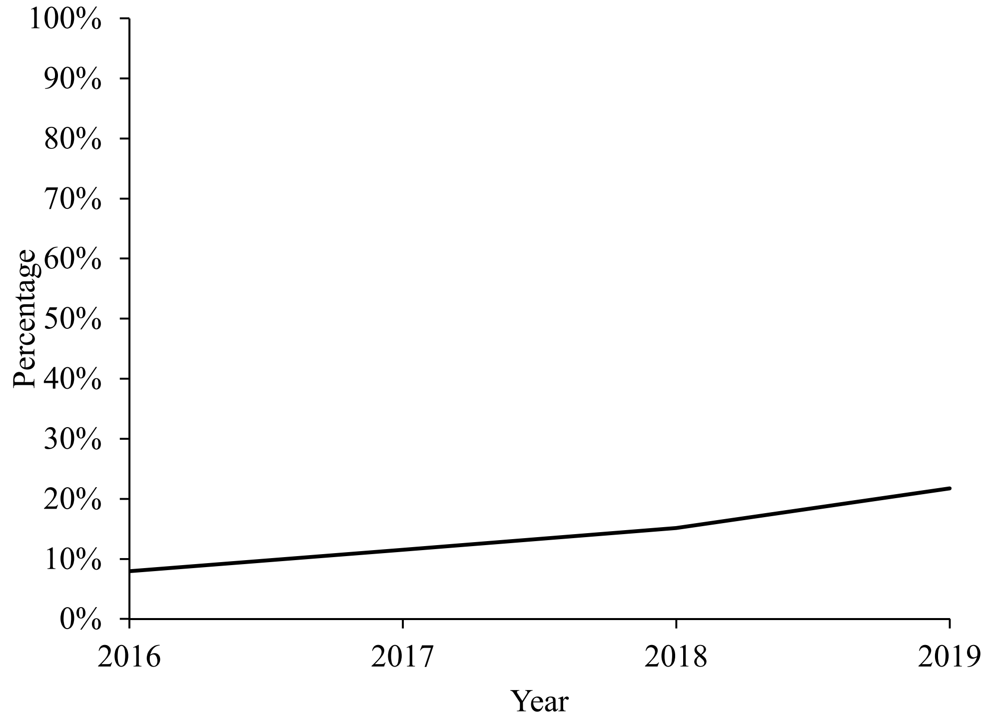

Figure 1. Insured acreage percentage of the total pasture and hay land in the United States, 2016-2019 (USDA-RMA, 2019a)

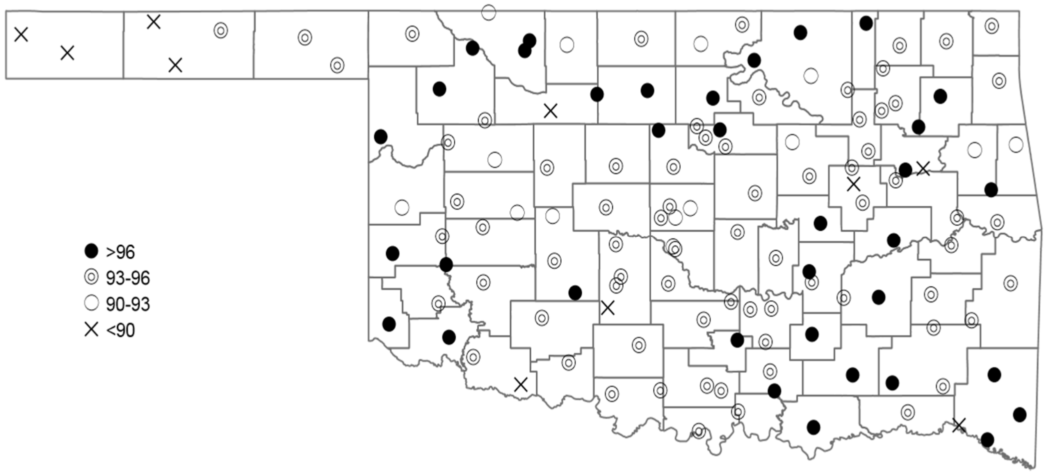

Figure 2. The estimated Pearson product-moment correlations between rainfall index and the actual rainfall in Oklahoma, 1994-2017

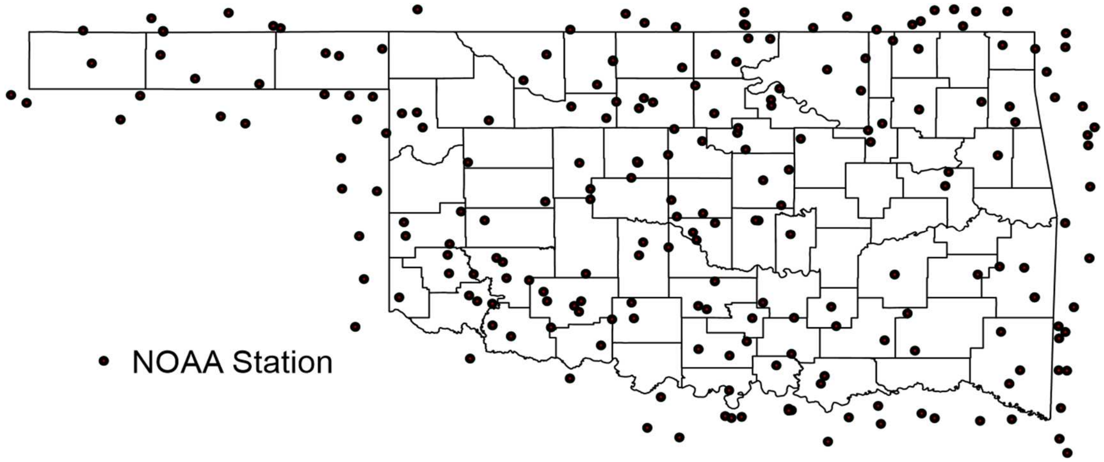

Figure 3. Active NOAA Master Stations around Oklahoma in 2019
Source: National Oceanic and Atmospheric Administration National Climatic Data Center (NOAA-NCDC): https://www.ncdc.noaa.gov/homr/reports/mshr

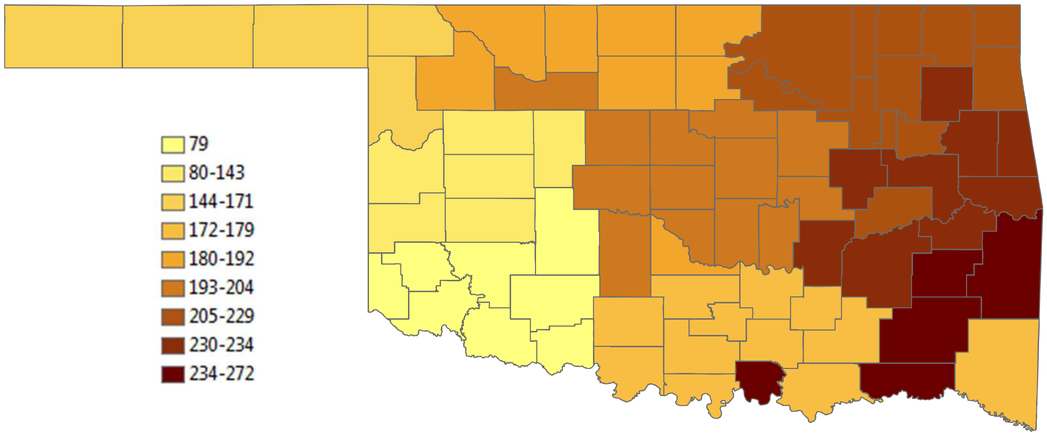

Figure 4. The Risk Management Agency 9 county base values in Oklahoma, 2018

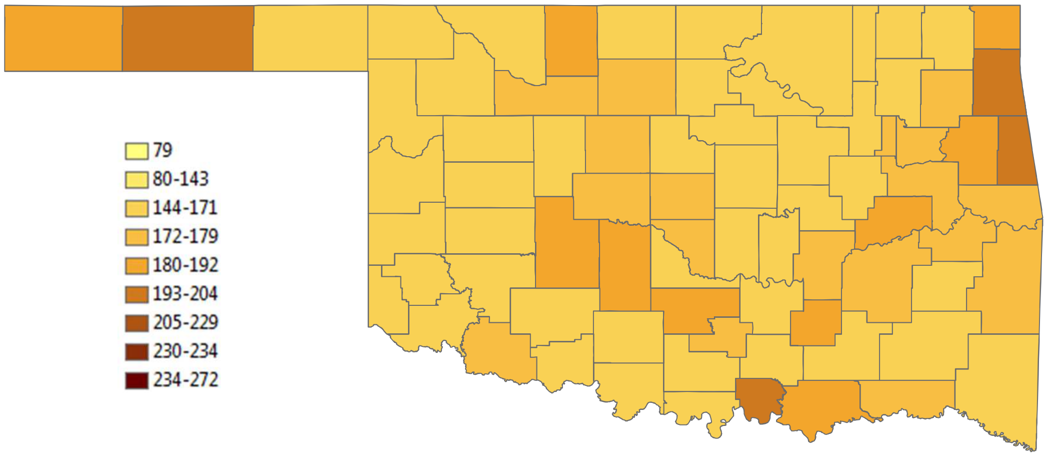

Figure 5. The Bayesian Kriging 77 county base values in Oklahoma

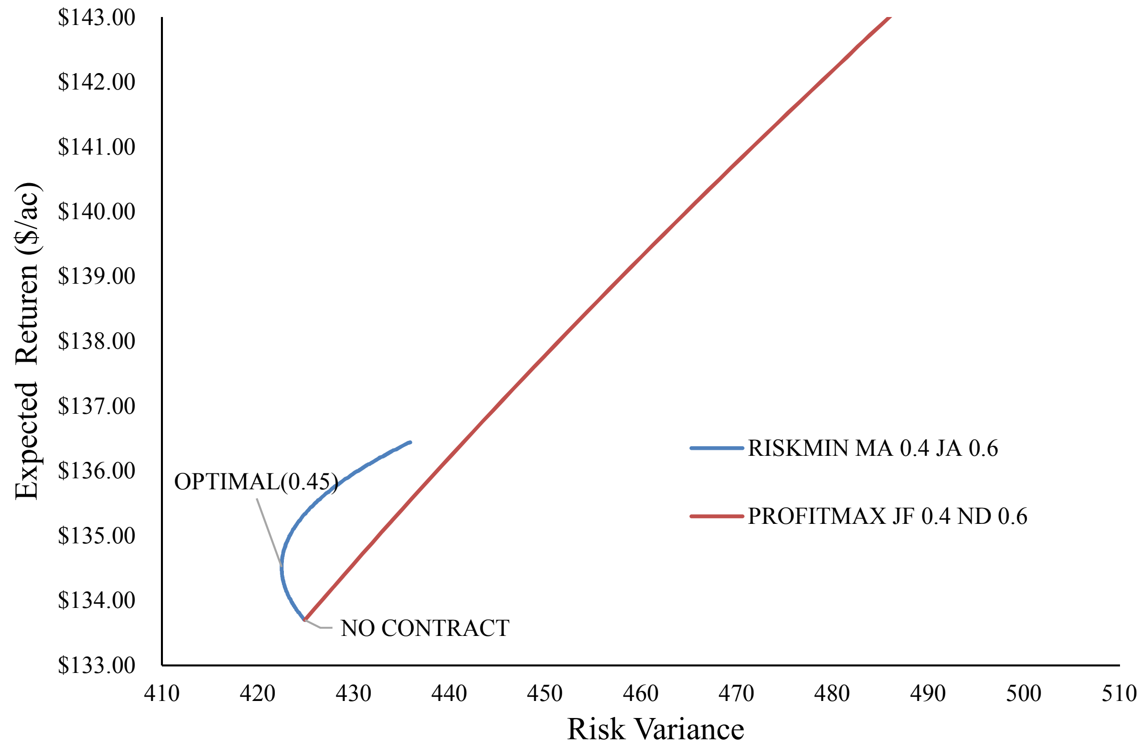

Figure 6. The results of expected utility optimization problem by two strategies

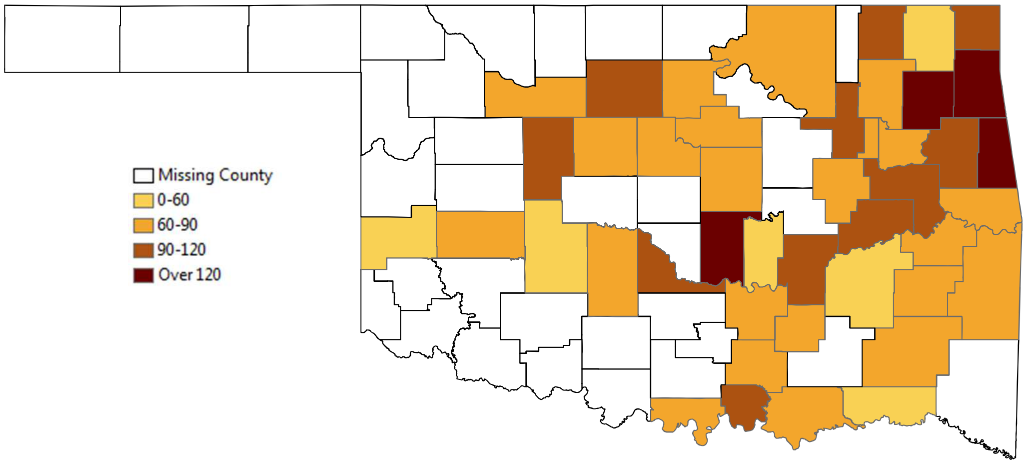

Figure 7. The results of optimal productivity factor from the risk minimization strategy by each county in Oklahoma, the average of optimal productivity factor is 85%.

VITA

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