Risk Preferences and the Participation Pattern of Rainfall

Index Insurance

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Risk Preferences and the Participation Pattern of Rainfall Index Insurance

Abstract

This study analyzes participation patterns of the Rainfall Index Insurance for Pasture, Rangeland and Forage (PRF-RI) program using a novel policyholder-level dataset. We first illustrate a conceptual model for various degrees of risk aversion that lead to different predictions regarding participation patterns of the rainfall index insurance. We then connect these predicted patterns to some empirical evidence from the policyholder-level dataset, which is a subset of data provided by USDA RMA for all PRF-RI participants in Nebraska and Kansas during years 2013-2017. We also investigate the changes in the participation patterns over time. Because the correlations between forage yield and precipitation vary by month, the choice of the two-month intervals and the coverage allocation of the participants indicate their risk preferences. We exploit this nature of the PRF-RI program to infer the distribution of risk preferences of Midwest forage producers. We find that the number of individuals who are classified as “risk-neutral” has increased over time, whereas the number of individuals who are classified as “risk-averse” has decreased. Rather than attribute this trend to a change in risk preferences, we believe that some participants have learned more about the distribution of the indemnity payments and have adjusted the participation pattern over time. Our findings suggest that more research in this area could assist policymakers in keeping the PRF-RI program in line with its objectives.

Key words: Index insurance, PRF-RI program, Expected utility theory, Cluster analysis

JEL classification: Q18, Q12
Rainfall Index Insurance for Pasture, Rangeland and Forage (PRF-RI) is an index insurance product in the U.S. federal crop insurance program developed to provide livestock producers with a way to manage some of their input cost risk. Since its pilot program in 2007, PRF-RI has expanded significantly. Insured acres have nearly doubled from 2007 to 2016 and the insured liability in 2016 is about four times greater than that in 2007 (RMA 2018c). In 2016, the PRF-RI program was the ninth largest commodity in terms of insured liability in the U.S. federal crop insurance program (RMA 2018c). However, only about 50 million acres were insured in 2016 whereas the 2012 Census of Agriculture indicates about 415 million acres were devoted to “permanent pasture and rangeland” which suggests low participation rate (NASS 2014; RMA 2018c).

Past literature regarding index insurance has focused on explaining the low participation rates of various index insurance products. A number of studies have examined the demand for index insurance using standard expected utility theory or behavioral economic frameworks such as cumulative prospect theory (e.g. Clarke 2016; Babcock 2015; Elabed and Carter 2015). We contribute to this literature by exploiting a novel dataset and the structure of the PRF-RI program that allows us to connect observed participation patterns to those predicted by the different risk preferences.

This study analyzes participation patterns of the PRF-RI program using a novel policyholder-level dataset. We first develop conceptual models for various risk preferences that lead to different predictions regarding participation patterns of the rainfall index insurance. We then connect these predicted patterns to some empirical evidence from the policyholder-level dataset. We also investigate the changes in the participation patterns over time.

The PRF-RI program is based on rainfall indices that are calculated using precipitation measured over two-month intervals within a specified grid area. During the sign-up period, participants must choose two-month intervals and allocate their insurance coverage across the various intervals selected. If actual precipitation levels in the selected two-month in-
tervals are lower than the participant-chosen guarantees, an indemnity is paid based on the
difference between the actual precipitation and the guarantees. The likelihood of precip-
itation, the correlation between forage yield and rainfall index, and the implied premium
subsidy all differ by two-month interval, indicating that the choice of intervals and cov-
erage allocation could produce significantly different levels of risk reduction. We exploit
this nature of the PRF-RI program to infer the distribution of risk preferences of Midwest
forage producers.

**Risk Preferences and Demand for Insurance**

Given the substantial amount of premium subsidies in the U.S. Federal Crop Insurance
Program, understanding demand for crop insurance is important to investigate the welfare
impact of the program. The demand for crop insurance has been extensively studied in
the context of the U.S. Federal Crop Insurance (e.g. Goodwin 1993; Just, Calvin, and
Quiggin 1999; Babcock 2015 and Du, Feng, and Hennessy 2016). Previous studies such
as Goodwin (1993) and Just, Calvin, and Quiggin (1999) suggest that the demand for crop
insurance is mostly driven by incentives from adverse selection or premium subsidies and
that risk-aversion has little impact.

Recently, by analyzing policy unit-level insurance data for corn and soybeans in Midwest
and Great Plains, Du, Feng, and Hennessy (2016) find no empirical evidence that supports
the expected utility theory. The simulation results of Babcock (2015) suggest that the
cumulative prospect theory explains crop insurance choices better than expected utility.
We contribute to the literature by deducing coexisting risk preferences from observed crop
insurance choices.

Index insurance has gained significant attention as a cost-effective risk management tool.
Unlike conventional individual-based crop insurance, index insurance has lower costs since
it is relatively free from information asymmetry problems (Miranda and Farrin 2012).
However, despite its advantages, index insurance creates basis risk, which is the risk of
imperfect correlations between insurance indices and individual outcomes. The interaction between basis risk and different risk preferences is crucial to understanding the demand for index insurance and thus, the effectiveness of index insurance as a risk management tool.

Several studies examine the demand for index insurance focusing on basis risk and risk preferences (e.g. Elabed et al. 2013; Petraud et al. 2015; Clarke 2016). Clarke (2016) uses standard expect utility theory and explains how basis risk reduces index insurance demand, whereas Petraud et al. (2015) find that cumulative prospect theory is more consistent explaining the willingness-to-pay for an index insurance product. By examining the observed choices on the rainfall index insurance in the U.S., we provide a useful discussion on the demand for index insurance and risk preferences.

Rainfall Index Insurance Program in the United States

In 2007, the Risk Management Agency (RMA) piloted a rainfall index insurance program for pasture, rangeland and forage producers (PRF-RI) in several counties in seven states (Colorado, Idaho, North Dakota, Pennsylvania, South Carolina, and Texas).¹ The pilot programs gradually expanded to other states and starting in 2016, producers in all 48 contiguous states were eligible for the program (RMA 2015b).

The PRF-RI program is based on indices calculated for grid areas, which are 0.25 degrees longitude by 0.25 degrees latitude.² For each grid, rainfall indices are computed for each two-month interval using weighted averages from nearby National Oceanic and Atmospheric Administration (NOAA) weather stations. Precipitation in each two-month interval is normalized by the historical average based on precipitation history from 1948 (RMA 2018a).

The participants of the PRF-RI program choose coverage levels, a productivity factor that adjusts the dollar coverage, and allocation percentages for each two-month interval. The coverage level refers to the threshold of the rainfall indices which triggers an indemnity payment. For example, if a participant chooses a coverage level of 90 and selects the
January-February and May-June intervals, then the participant will receive an indemnity payment if either of the PRF index values for January-February or May-June fall below 90 percent, i.e., rainfall is less than 90 percent of its historic average level for the interval. The indemnity payment is based on grid-specific dollar values per acre, and participants can adjust the dollar values to reflect the expected value of their forage production by choosing the productivity factor (RMA 2015a). The allocation percentages chosen by participants represent the share of insured liability assigned to each two-month interval.

Figure 1 illustrates the average premium rates for haying at the 90% coverage level across participants in Kansas and Nebraska in 2017. The premium rates are high during winter because of greater volatilities in precipitation. The premium rates for the intervals in January to March, and the intervals in October to December range from 23 cents to 26 cents per dollar of insured liability whereas the premium rates for the intervals in April to September are less than 20 cents.

Several agronomic studies such as Smoliak (1986), Lauenroth and Sala (1992), and Smart et al. (2007) examine how much of yield variation is explained by precipitation. These studies use precipitation measures from various periods (e.g. April to June, April to September, and June to July) and find that precipitation during the growing season in their respective regions is most important for explaining forage yield variation. Recently, using penalized regressions, Yu et al. (2018) find the most important months for precipitation for forage growth in Nebraska and Kansas are May and June.

Interestingly, the months with important precipitation for explaining forage yield variation have lower premium rates than other months. This provides a useful variation to connect observed participation patterns to risk preferences. The predictions of the PRF - RI participation patterns differ by different risk preferences due to the different premium rates and the different degrees of correlation between precipitation and forage yield by month.
A Stylized Model on PRF Interval Choices

Assuming that participants within a restricted geographic area would have similar months which are important for rainfall, the optimal choices of the two-month intervals would differ across participants with different preferences. In this section, we describe the optimal choices of the two-month intervals for the agents with different degrees of risk aversion. The illustrations and predictions from the following stylized model provides a motivation of our empirical approach.

We first specify the objective function of the PRF participants as:

$$\max \{\delta_1, \ldots, \delta_{11}\} \quad V = E(u(x_i(\delta_1, \ldots, \delta_{11})))$$

where $\delta_k$ is the share of the insured liability allocated to two-month interval $k$, $x_i$ is the return at state $i$, and $u$ is a von-Neumann Morgenstern utility function.

The share of the insured liability decision faces three constraints:

$$\sum_{k=1}^{11} \delta_k = 1,$$

$$\delta_k \leq \bar{\delta} \quad \forall \ k,$$

$$\delta_k \delta_{k+1} = 0 \quad \forall \ k = 1, \ldots, 10$$

where $\bar{\delta} < 1$ is a maximum value one can allocate for a single interval. The return, $x_i$, is represented by the following:

$$x_i = y_i + \sum_{k=1}^{11} \delta_k (\text{Ind}_{ki} - (1-s)\text{Prem}_k)$$

where $y_i$ is the profit of the rancher at state $i$, $s$ is the subsidy rate, $\text{Prem}_k$ is the premium rate of two-month interval $k$, and $\text{Ind}_{ki}$ is the indemnity payment of two-month interval $k$ at state $i$. 
Following Meyer (1987), we can rewrite the value function of (1) as the following mean-variance utility function:

(6) \( \max_{\{\delta_1, \ldots, \delta_{11}\}} V = V(\mu, \sigma^2) \)

where \( \mu \) is the expected return, i.e. \( \mu = E(x_i) \), \( \sigma^2 \) is the variance of the return, i.e. \( \sigma^2 = \text{Var}(x_i) \), and \( V \) satisfies \( V_\mu \geq 0 \) and \( V_{\sigma^2} \leq 0 \).

If we assume actuarially fair premiums (i.e. \( E(\text{Ind}_{ki}) = \text{Prem}_k \)), the expected return is

(7) \( \mu = E(y_i) + \sum_{k=1}^{11} \delta_k s \text{Prem}_k \)

where \( E(y_i) \) is the expected profit from the ranch. The variance of the return, \( \sigma^2 \), is

(8) \( \sigma^2 = \text{Var}(y_i) + \text{Var}(\sum_{k=1}^{11} \delta_k \text{Ind}_{ki}) + 2\text{Cov}(y_i, \sum_{k=1}^{11} \delta_k \text{Ind}_{ki}) \).

For simplicity and due to the limited geographic scope of the analysis, we classify the eleven two-month intervals into a) growing season, and b) non-growing season. We define the intervals Apr - May, May - Jun, Jun - Jul, and Jul - Aug as the growing season intervals. If the interval \( k \) is in the growing season, we assume that \( \text{Cov}(y_i, \text{Ind}_{ki}) < 0 \) and if the interval \( k \) is in the non-growing season, \( \text{Cov}(y_i, \text{Ind}_{ki}) = 0 \). Furthermore, we assume that \( \frac{\partial \sigma^2}{\partial \delta_k} < 0 \) if the interval \( k \) is in the growing season and \( \frac{\partial \sigma^2}{\partial \delta_k} \geq 0 \) otherwise.

A risk-neutral agent will have \( V \) that satisfies \( V_{\sigma^2} = 0 \). And from (7), we know that the premium subsidy that farms receive, and thus the expected return from \( \delta_k \), increases as the premium rate increases. Thus, for risk-neutral agents, the solution for problem (1) is to choose \( \delta_k \)'s that have highest premium rates and satisfy constraints (2) - (4). As we observe in figure 1, the two-month intervals in the non-growing season have higher premium rates. Therefore, risk-neutral agents are expected to allocate their liabilities in the non-growing season intervals.

A risk-averse agent will have \( V \) that satisfies \( V_{\sigma^2} < 0 \). As the agent becomes more risk-averse, the partial derivative, \( V_{\sigma^2} \), would be more negative. Since we assumed that \( \frac{\partial \sigma^2}{\partial \delta_k} < 0 \)
if the interval $k$ is in the growing season, the agents with higher degrees of risk aversion would allocate more of their liabilities to the intervals in the growing season.\textsuperscript{3}

**Data**

We analyze a subset of data provided by USDA RMA for all PRF-RI participants in Nebraska and Kansas during years 2013-2017. We aim to analyze individual producers’ choices, however individuals are not identified in the dataset. We utilize rules of the PRF-RI program to distinguish individuals within each grid. RMA (2018a) and RMA (2018b) state: 1) the same acres cannot be insured in more than one grid ID or county during the crop year, and 2) the same month cannot be included in more than one selected index interval for the same county, grid ID, intended use, irrigated practice, organic practice, and share. Thus, an individual producers’ allocation percentages, i.e., shares of insured liability, should sum to 100% across all chosen intervals within a grid and county combination.

First, we identify grids containing one producer by selecting grids in which the allocation percentage sum to 100%. Then we use the fact that within a grid, a producer cannot choose consecutive intervals, e.g. January-February and February-March, to extract individual producers from grid ID’s containing more than one producer. Grids that have multiple possible combinations of interval selections and percentages of value are dropped from the dataset since we cannot exactly identify the producers’ choices.

In the end we are able to derive 1,819 individual choices for the PRF-RI program. Table 1 displays the number of individuals identified by state and year. The numbers of individuals are divided relatively evenly between Kansas and Nebraska. Table 2 shows the proportion of total observations utilized with the identified individuals. The resulting dataset consists of roughly 29% of the total number of data points that USDA RMA provided. This is a large enough sample to gain an idea about the distribution of participants’ choices. The resulting observations look like the examples provided in table 3 where individuals’ identification are distinguished by grid ID and Year.
Empirical Strategy

The objective of the empirical analysis is to identify patterns across producers regarding the overall choices of index intervals. This becomes a complex problem, due to the fact that producers can choose to assign shares of insured liability to any of eleven index-intervals. A useful approach for identifying patterns in data is cluster analysis, which groups observations in a dataset together into clusters based on similar characteristics across multiple dimensions. In the following, we discuss the use of clustering methods to distinguish purchasing patterns of PRF-RI.

Cluster Analysis

We utilize clustering methods to group individuals based on similar choices of the two-month intervals and the corresponding share of insured liability. Clustering methods are exploratory in nature, meaning the number of groups within the data, as well as the groups’ characteristics are unknown. To explore groups in the data, the researcher must choose the clustering algorithm, the method of classifying similarity in data points, as well as the number of clusters. We utilize the K-medoids clustering algorithm, which minimizes dissimilarity between observations and a center observation (the cluster’s medoid). This algorithm was chosen for its ability to deal with outliers in the data, as well as its ability to fit the data better than comparing observations to an average because averaging values may lead to overlapping month intervals. The observations are compared in the K-medoids algorithm using a dissimilitarity matrix calculated by the Euclidean distance between observations.

Following Hennig and Liao (2013), we choose the optimal number of clusters by comparing average silhouette widths (ASW) across different specifications for the number of clusters. An observation’s silhouette value measures how well the observation matches within its cluster in comparison to matching with other clusters (Kaufman and Rousseeuw 2009). Silhouette values range from -1 to 1, with -1 representing that an observation is
matched very poorly within a cluster, and 1 representing that an observation is matched very well. A large ASW value for a specific partition of the data represents a good fit for all of the observations as a whole (Kaufman and Rousseeuw 2009).

Results

Figure 2 shows average silhouette widths for cluster numbers 2 through 31. The highest ASW is at 31 groups, however the marginal increase is fairly small between 20 and 31. Our approach follows Hennig and Liao (2013), who state that because cluster analysis is exploratory, determining the optimal number of clusters should depend not only on cluster validity statistics, but also the problem at hand. We chose 16 as the optimal number of clusters due to its’ relatively high ASW combined with the ease of interpreting fewer groups.

Table 4 shows the center observations for each cluster. As documented by Yu et al. (2018), the most important months for precipitation for forage growth in Nebraska and Kansas would likely be in May and June. We define the growing season as the intervals Apr - May, May - Jun, Jun - Jul, and Jul - Aug to encompass the months important for forage growth.

Table 5 shows each cluster’s average share of insured liability within and outside the growing season.

The clusters in table 5 are arranged in ascending order of the average share of liability placed within the growing season interval. We believe this ranking is illustrative of relative risk preferences of the clusters, where lower percentages of value placed within the growing season, e.g., Cluster 6, show relatively risk neutral participants, while the relative risk aversion increases as more percentage of value is placed within the growing season. For example, participants in Clusters 11, 12 and 14 are fairly risk averse, given that nearly 100 percent of value on average is placed within the growing season. Using this information, the clusters can be broken up and are described by our classifications of relatively risk neutral and risk averse. Relatively risk neutral individuals on average place more than 40 percent
of their shares of liability outside of the growing season, while risk averse individuals on average place at least 40 percent of their shares within the growing season.

_Risk Neutral_

Risk neutral individuals will treat the PRF-RI program more as an investment, rather than purely a risk management strategy. Risk neutral producers may utilize the PRF-RI as a risk management strategy, while also attempting to minimize their losses, or the amount of premium they would pay. We predict that these producers would select intervals during the months important forage growth, but select intervals in less important months to maximize the chance of collecting an indemnity that would cover the premium. We believe the following groups display this behavior:

- **Cluster 1:** 30% Jan-Feb, 10% March-April, 10% May-June, 10% July-Aug, 10% Sept-Oct, 30% Nov-Dec
- **Cluster 2:** 25% Jan-Feb, 25% March-April, 25% May-June, 25% July-Aug
- **Cluster 3:** 17% Jan-Feb, 17% March-April, 17% May-June, 17% July-Aug, 16% Sept-Oct, 16% Nov-Dec
- **Cluster 4:** 34% Feb-March, 33% May-June, 33% Nov-Dec
- **Cluster 5:** 20% Feb-March, 20% Apr-May, 20% June-July, 20% Aug-Sept, 20% Oct-Nov
- **Cluster 6:** 10% Feb-March, 10% Apr-May, 20% June-July, 25% Aug-Sept, 35% Oct-Nov
- **Cluster 7:** 20% Feb-March, 15% Apr-May, 25% July-Aug, 20% Sept-Oct, 20% Nov-Dec
In Clusters 1-7, the producers place some of their percentage of value in the intervals which include the forage-producing months, i.e., intervals ranging from April to August, but the producers also place value into one or more of the following intervals which should not be related to forage production: January-February, February-March, October-November, and November-December. Referring back to figure 1, these four intervals have higher premium rates on average than all of the other intervals.

**Risk Averse**

Risk averse producers in theory would utilize PRF-RI purely as a risk management tool, so they would purchase insurance covering the months that rain is most necessary for forage production. The following clusters fall into this category:

- **Cluster 8**: 40% February-March, 30% April-May and 30% June-July
- **Cluster 9**: 33% March-April, 34% May-June and 33% July-August
- **Cluster 10**: 60% March-April and 40% May-June
- **Cluster 11**: 50% April-May and 50% June-July
- **Cluster 12**: 50% April-May and 50% July-August
- **Cluster 13**: 33% April-May, 33% June-July, 34% August-September
- **Cluster 14**: 50% May-June and 50% July-August
- **Cluster 15**: 50% June-July and 50% August-September
- **Cluster 16**: 52% July-August and 48% September-October

The intervals chosen in the risk averse clusters range primarily across the months of May-July, and most producers are only allocating their percentage of value across two or three intervals. This is consistent with the behavior of risk averse individuals.
An interesting comparison between risk neutral and risk averse producers lies in the number of intervals in which producers place value. Roughly 38% of the individuals in the risk averse category chose three or more intervals, whereas 84% of the individuals in the risk neutral category chose three or more intervals. This shows the tendency for the risk neutral individuals to choose intervals in addition to those which are considered forage producing months.\(^5\)

*Trends in the Participation Patterns*

Tables 6 and 7, respectively, show the number of individuals and percentage of total individuals found to be in each category over years 2013 to 2017. It is clear from these tables that since 2013, the number of individuals exhibiting risk-neutral behavior has increased, and the number of individuals exhibiting risk aversion has decreased.

Figures 3, 4, and 5 also indicate that the share of risk-neutral participants has increased over time. Figures 3 and 4 show the most frequent type of producer for each GridID for years 2013 and 2017, respectively. In 2013, there appear to be large blocks of grids which are mostly exhibiting risk-averse behavior with risk-neutral grids randomly interspersed. In 2017, large blocks of primarily risk-neutral grids are much more prevalent. Additionally, Figures 3 and 4 suggest there may be spatial relationships with participants in this program.

Figure 5 shows the trend of participants broken into four risk categories, moderately and highly risk averse, and moderately and highly risk neutral.\(^6\) This figure depicts the dramatic decrease in the number of individuals who use PRF for risk management purposes only, paired with a fairly steady increase in the number of individuals displaying risk-neutral tendencies. The moderate categories of risk neutral and risk aversion show less pronounced trends over time.

**Discussion**

It is important to highlight the limitations of this data which could influence some of the identified trends in PRF-RI participation. Our dataset does not have a variable that uniquely
identifies each participant across years. Thus, two possible explanations of the trend towards more risk-neutral participation are: a) risk-averse participants exit the program and risk-neutral participants enter the program and b) “seemingly risk-averse” participants were in fact risk-neutral.

Given that the program is relatively new, it is possible that participants have learned more about the program and the payment distribution over time. For example, we have learned from conversations with crop insurance agents, that they often recommend a loss-minimizing strategy for participants, i.e., by placing some of their share of liability into non-growing season months, participants may not have to pay a premium. This anecdotal evidence is supported by the spatial nature of the transition, as displayed in figures 3 and 4. The large blocks of adjacent risk neutral grids in 2017 may reflect information dispersion from crop insurance agents or other farmers within an area. Therefore, it is important to analyze the long-run trends of PRF participation pattern as the program matures.

Our results have important implications for policy makers in relation to the design of this program. Our research has highlighted that it is important to determine whether individuals are transitioning their PRF-RI strategies, or if we are seeing entry by risk neutral producers and exit by risk averse producers. Both display issues that may need to be addressed with the program, but different solutions will be necessary to keep the PRF-RI program in line with its intended objective.
Notes

1 Vegetation index insurance program was also offered for producers in some states until 2015.

2 The grid system and the precipitation data are from National Oceanic and Atmospheric Administration Climate Prediction Center.

3 Assuming the interior solution, the first-order condition of the problem 6 can be simply written as:

\[
\frac{\partial V}{\partial \delta_k} = V\mu \frac{\partial \mu}{\partial \delta_k} + V\sigma^2 \frac{\partial \sigma^2}{\partial \delta_k} = 0.
\]

If the interval \(k\) is in the growing season, \(\frac{\partial \mu}{\partial \delta_k} < 0\) and \(\frac{\partial \sigma^2}{\partial \delta_k} < 0\) which indicates that \(\delta_k\) increases as the degree of risk aversion increases. This can be checked by the implicit function theorem.

4 This is a narrow definition of the growing season. Depending on how we define the growing season, a few clusters would have different classification. In future research, we will exploit the robustness with respect to the growing season definition.

5 Our definition of the growing season may affect this observation. Robustness with respect to definitions of the growing season remains as future research.

6 The categories are broken up as follows according to the percentage of value within the growing season: \(\leq 35\%\) highly risk neutral, \(36\%-42\%\) moderately risk neutral, \(43\%-68\%\) moderately risk averse, \(> 68\%\) highly risk averse.
References


Figures

Figure 1. Average Premium Rates for Haying, 90% Coverage Level, 2017

excludes outside values
Figure 2. K-Medoids Average Silhouette Values for Cluster Numbers K=2-31
Figure 3. 2013 Most Frequent Type by GridID
Figure 4. 2017 Most Frequent Type by GridID
Figure 5. Total Number in Each Risk Category by Year
Figure 6. Percentage in Each Risk Category by Year

![Graph showing percentage in each risk category by year.]
Tables

Table 1. Number of Individuals Identified by Year and State

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<th>Year</th>
<th>Kansas</th>
<th>Nebraska</th>
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<td>172</td>
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Table 3. Example data points

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These are hypothetical data points for the illustrative purpose.
Table 4. Medoids (Center Individual) by Cluster K=16

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<th>JUL.AUG</th>
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<th>SEP.OCT</th>
<th>OCT.NOV</th>
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Table 5. Average Percentages of Value Within and Outside Forage Growing Season by Cluster K=16

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Table 6. Number of Individuals in Each Category by Year

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<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
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</thead>
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<td>362</td>
<td>356</td>
<td>367</td>
<td>348</td>
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</table>
Table 7. Percentage of Individuals in Each Category by Year

<table>
<thead>
<tr>
<th>Category</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk Neutral</td>
<td>27%</td>
<td>32%</td>
<td>40%</td>
<td>41%</td>
<td>52%</td>
</tr>
<tr>
<td>Risk Averse</td>
<td>73%</td>
<td>68%</td>
<td>60%</td>
<td>59%</td>
<td>48%</td>
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</tbody>
</table>