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Participation patterns of the rainfall index insurance for pasture, rangeland and forage programme

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Abstract

Using a novel policyholder-level data set, we analyse participants' choices of 2-month index intervals in the Rainfall Index for Pasture, Rangeland and Forage (RI-PRF) insurance programme. We first provide a conceptual model that illustrates participation patterns of the rainfall index insurance. We then connect these predicted patterns to some empirical evidence from the policyholder-level data set, which is a subset of data provided by the USDA Risk Management Agency for all RI-PRF participants in Nebraska and Kansas during the years 2013–2017. Because the correlations between forage yield and precipitation and the expected premium subsidy vary by month, different degrees of risk aversion may predict distinctively different choices of the 2-month intervals. Using cluster analysis, we group the participants with similar allocation patterns across the 2-month intervals. We observe that the number of participants displaying relatively low levels of risk aversion increase over time. We connect this to the fact that premium subsidies and producer returns associated with non-growing season (risk-increasing) months are often greater than those for growing season (risk-reducing) months, and this has important implications for policy design. Our findings suggest that more research in this area could assist policymakers in keeping the RI-PRF programme in line with its objective of reducing risk for livestock producers.

Keywords Index insurance · RI-PRF programme · Expected utility theory · Cluster analysis

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Introduction

Rainfall Index for Pasture, Rangeland and Forage (RI-PRF) is an insurance product developed to provide livestock producers with a tool to mitigate drought risk. RI-PRF is in the U.S. Federal Crop Insurance Program, though it differs from crop insurance products for traditional commodities, partly because of its nature as an index insurance product and also regarding the participants' additional decision of the time of year to insure. The RI-PRF programme is based on rainfall indices that are calculated using precipitation measured over 2-month intervals within a specified grid area. Participants must choose 2-month intervals and allocate their insurance coverage across the various intervals selected. When the realised precipitations for the given grid in the selected 2-month intervals are lower than the participant-chosen guarantees, an indemnity is paid based on the difference between the two.

Since its appearance as a pilot programme in 2007, RI-PRF has expanded significantly. Insured acres nearly doubled from 2007 to 2016, and the insured liability in 2016 was about four times greater than in 2007 (RMA 2018c). In 2016 the RI-PRF programme 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 that about 415 million acres were devoted to "permanent pasture and rangeland." This suggests a relatively low participation rate in RI-PRF, particularly compared to the major field crops where insured acres usually represent 80% or more of total planted acres (NASS 2014; RMA 2018c).

While the scale of the programme and its importance have increased over the last 5 years, only a few studies have investigated the RI-PRF programme (e.g. Yu et al. 2019; Westerhold et al. 2018; Diersen et al. 2015; Ifft et al. 2014; Nadolnyak and Vedenov 2013). To our knowledge, there is no study that investigates observed patterns in participants' choices of which 2-month intervals to insure. This is due in part to the complexity of examining choices across 11 index intervals, in addition to the absence of a data set that links an individual's interval choices. We utilise a novel policyholder-level data set and employ a rigorous statistical method to incorporate the complexity of the RI-PRF choices so that we may investigate the participation patterns of the RI-PRF programme.

Given the substantial amount of premium subsidies in the U.S. Federal Crop Insurance Program, understanding the demand for crop insurance is important for investigating the efficacy of the RI-PRF programme. The demand for crop insurance has been studied extensively in the context of the U.S. Federal Crop Insurance Program (e.g. Goodwin 1993; Just et al. 1999; Babcock 2015 and Du et al. 2016). Previous studies such as Goodwin (1993) and Just et al. (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.

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 is exposed to basis risk, which is the risk of imperfect correlations between insurance indices and individual outcomes.

Several studies examine the demand for index insurance focusing on basis risk and risk preferences (e.g. Elabed et al. 2013; Elabed and Carter 2015; Petraud et al. 2015; Clarke 2016). Clarke (2016) uses standard expected utility theory and explains how basis risk reduces index insurance demand, whereas Petraud et al. (2015) find that cumulative prospect theory is more consistent in explaining the willingness-to-pay for an index insurance product. While there are ongoing debates on the capability of each theory in the context of explaining the demand for index insurance, we use a simple mean–variance expected utility framework to relate the RI-PRF participation patterns to different degrees of risk aversion.

Given that the subsidy rate, i.e., premium subsidy as a proportion of the total premium, is equal across different 2-month intervals and the intervals in the non-growing season have higher premiums, allocating more liability to the non-growing season increases the expected profit (assuming actuarial fairness of the premium). We exploit this nature of the RI-PRF programme to infer the risk preferences of Midwest forage producers. In order to analyse participation patterns in the RI-PRF programme, we use administrative rules to construct a novel policyholder-level data set from data provided by the Risk Management Agency (RMA) that contain information on interval choices. We contribute to the literature by empirically documenting the participation patterns of the RI-PRF and linking the empirical patterns to the different degrees of risk aversion.[1] By examining the observed choices of the rainfall index insurance in the U.S., we provide a useful discussion on the demand for index insurance and risk preferences.

Recent studies have documented that the different RI-PRF choices can lead to different degrees of risk reduction or even increases in income risk (e.g., Yu et al. 2019; Westerhold et al. 2018; Diersen et al. 2015). Westerhold et al. (2018) show that insuring rainfall in winter months increases income risk, and similarly, Yu et al. (2019) provide empirical evidence that basis risk is larger for winter months. While these studies analyse how the different RI-PRF choices affect portfolios of participants, we contribute to the literature by empirically analysing the observed participation patterns of producers in Kansas and Nebraska over the years 2013–2017. We find that participation in RI-PRF has trended towards risk-increasing behaviour as defined by Westerhold et al. (2018) and Yu et al. (2019). We show that this has important implications for policy design, given that premium subsidies and producer returns associated with non-growing season (risk-increasing) months are often greater than those for growing season (risk-reducing) months.

The remainder of the paper is as follows. First, we provide some additional background regarding the RI-PRF programme. Next, we describe the stylised model of RI-PRF interval choices, followed by a discussion of how the data set was

[1] We recognise that risk preferences may not be the only influence on index interval choices and that influences such as credit and insurance market accessibility, crop insurance agent influence, learning, or social networks should be explored in future research on RI-PRF.

constructed. We then outline the cluster analysis and describe the results, including the trends in interval choices. Finally, we provide a discussion of RI-PRF outcomes from the RMA summary of business data, and then discuss our conclusions.

Rainfall Index insurance programme in the United States

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

The RI-PRF programme 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 2-month interval using weighted averages from nearby National Oceanic and Atmospheric Administration (NOAA) weather stations. Precipitation in each 2-month interval is normalised by the historical average based on precipitation history from 1948 (RMA 2018a).

The participants of the RI-PRF programme choose coverage levels, a productivity factor that adjusts the dollar coverage, and allocation percentages for each 2-month interval. The coverage level refers to the threshold of the rainfall indices that 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, i.e., rainfall is less than 90% 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).[3] The allocation percentages chosen by participants represent the share of insured liability assigned to each 2-month interval.

Figure 1 illustrates the average premium rates, which is premium per dollar of insured liability, and the average subsidy per dollar of insured liability for grazing at the 90% coverage level across participants in Kansas and Nebraska in 2017 (RMA 2018c). 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

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

[3] If the index falls below the trigger, the payment is defined by the payment calculation factor, which is the share of the difference between the trigger and the actual index over the trigger, times the liability (Westerhold et al. 2018). Note that premium rates are set at per liability basis and the only stochastic factor that goes into the premium rate setting is the precipitation index. Thus more volatile precipitation leads to higher premium rates.

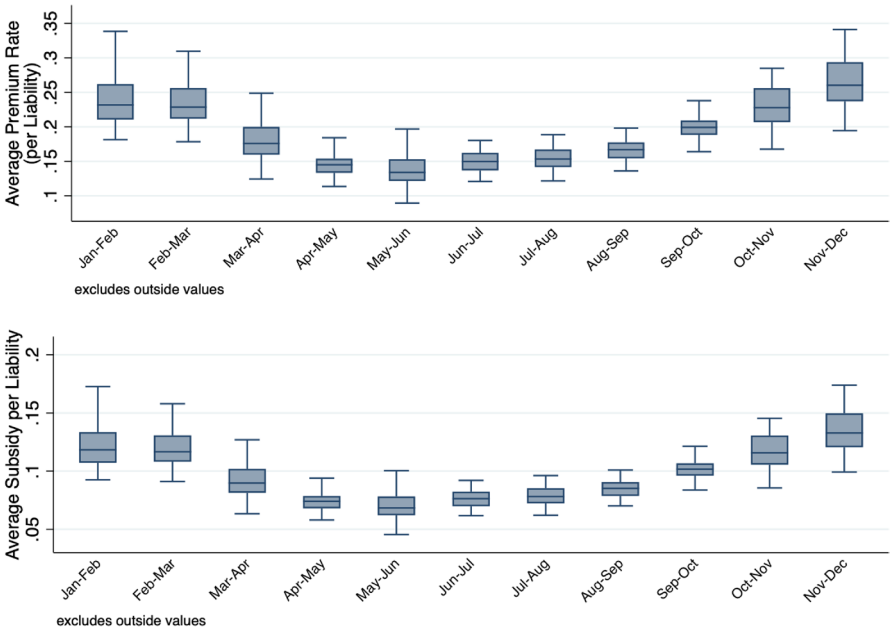

Fig. 1 Average premium rates for grazing, 90% coverage level, 2017

September are less than 20 cents. The subsidy rate, which is set legislatively, is equal across the 2-month intervals and thus the pattern of the subsidies per dollar of liability should be similar to that of the premium rates. As expected, we observe that the non-growing season intervals with higher premiums also have higher subsidy per dollar of liability (lower panel of Fig. 1).

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 penalised regressions, Yu et al. (2019) find that the most important months for precipitation for forage growth in Nebraska and Kansas are May and June. One cannot completely dismiss the value of precipitation prior to the growing season, because soils can store moisture from this period that plants may utilise when the growing season begins. This storage effect could vary significantly by soil type and other factors (slope, runoff, intensity and timing of rainfall, etc.). However, at least in the range of studies cited above, the effect of non-growing season rainfall on final forage production is minimal in Nebraska and Kansas.

Interestingly, the months with important precipitation for explaining forage yield variation have lower premium rates than other months due to relatively less variable precipitation. This provides useful variation to connect observed participation patterns to risk preferences. The predictions of the PRF-RI participation patterns

vary based on risk preferences due to the different premium rates and the different degrees of correlation between precipitation and forage yield by month.

A stylised model of PRF interval choices

Assuming that participants within a restricted geographic area had similar months that are important for rainfall, the optimal choices of the 2-month intervals would differ across participants with different risk preferences.[4] In this section, we describe the optimal choices of the 2-month intervals for the agents with different degrees of risk aversion. The illustrations and predictions from the following stylised model provide motivation for our empirical approach.

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

$$Max_{\{\delta_1,\ldots\delta_{11}\}} V = Eu(x_i(\delta_1, \ldots \delta_{11})), \tag{1}$$

where δ_k is the share of the insured liability allocated to 2-month interval k; x_i is the return at state i; and u is a von-Neumann Morgenstern utility function.[5]

The share of the insured liability decision faces three constraints:

$$\sum_{K=1}^{11} \delta_K = 1, \tag{2}$$

$$\overline{\delta_l} < \delta_k \leq \overline{\delta_u} \forall k, \tag{3}$$

and

$$\delta_k \delta_{k+1} = 0 \quad \forall k = 1, \ldots, 10, \tag{4}$$

where $\overline{\delta_l} = 0.1$ and $\overline{\delta_u} = 0.9$ are the minimum and the maximum values one can allocate for a single interval. The return, x_i, is represented by the following:

$$x_i = y_i + \sum_{k=1}^{11} \delta_k \left(Ind_{ki} - (1 - s) Prem_k \right), \tag{5}$$

[4] We assume the homogeneity across fields within a restricted geographic area (i.e. a grid cell) for the tractability of the conceptual discussion. While there may be differences in precipitation distributions, soil qualities, and management practices across fields, anecdotal evidence suggests that pasture, rangeland and forage in the study area (Nebraska and Kansas) are fairly homogenous. Also, note that Yu et al. (2019) empirically document small additional basis risk of the PRF programme from the differences between site-specific precipitation and grid-level PRF indices. This suggests little heterogeneity in precipitation distributions across fields in a grid. Thus we proceed with this homogeneity assumption.

[5] Another choice variable for the participants is the coverage level, i.e. the level of historical average precipitation that determines the indemnity trigger, but we do not explicitly model the choice of the coverage level. Under mean-variance preferences, we expect farms to buy the highest coverage level when premiums are actuarially fair and subsidised. In fact, from the county-level data, we observe that more than 85% of insured liabilities and more than 82% of insured acres are insured by the two highest coverage levels available, 85% and 90% (RMA 2018c). Thus we implicitly assume that the coverage is at the highest level and omit this variable in the model process.

where y_i is the profit of the rancher at state i; s is the subsidy rate; $Prem_k$ is the premium rate of 2-month interval k; and Ind_{ki} is the indemnity payment of 2-month interval k at state i.

Following Meyer (1987), we can rewrite the value function of Eq. (1) as the following mean-variance utility function:

$$Max_{\{\delta_1,\ldots,\delta_{11}\}} V = V\left(\mu, \sigma^2\right), \tag{6}$$

where μ is the expected return, i.e. $\mu = E\left(x_i\right)$; σ^2 is the variance of the return, i.e., $\sigma^2 = Var\left(x_i\right)$; and V satisfies $V_\mu > 0$ and $V_{\sigma^2} \leq 0$.

If we assume actuarially fair premiums (i.e. $E(Ind_{ki}) = Prem_k$), the expected return is

$$\mu = E\left(y_i\right) + \sum_{k=1}^{11} \delta_k s Prem_k, \tag{7}$$

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

$$\sigma^2 = Var\left(y_i\right) + Var\left(\sum_{k=1}^{11} \delta_k Ind_{ki}\right) + 2Cov\left(y_i, \sum_{k=1}^{11} \delta_k Ind_{ki}\right). \tag{8}$$

For simplicity and due to the limited geographic scope of the analysis, we classify the eleven 2-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 $Cov(y_i, Ind_{ki}) < 0$ and if the interval k is in the non-growing season, $Cov(y_i, Ind_{ki}) = 0$. 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 Eq. (7) we know that the premium subsidy that farms receive, and thus the expected return from δ_k, increases as the premium rate increases. Thus for risk-neutral agents, the solution to the problem Eq. (1) is to choose δ_k s that have highest premium rates and satisfy constraints Eqs. (2)–(4). As we observe in Fig. 1, the 2-month intervals in the non-growing season have higher premium rates and subsidies per dollar of liability. Therefore, risk-neutral agents are expected to allocate their liabilities in the non-growing season intervals. In other words, they choose the 2-month intervals that maximise expected profits.

A risk-averse agent will have V that satisfies $V_{\sigma^2} < 0$. As the agent becomes more risk-averse, the partial derivative, V_{σ^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.[6]

[6] Assuming the interior solution, the first-order condition of (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 δ_k increases as the degree of risk aversion increases. This can be checked by the implicit function theorem.

Our stylised model predicts that the risk-neutral farms and the risk-averse farms would reveal distinct RI-PRF participation patterns. This is because the degree of correlation between indices and forage yields and the amount of the subsidies vary by the 2-month interval. Of course, we do acknowledge that there are many other factors, such as credit and insurance market accessibility, soil and farm characteristics, learning, or social networks that may explain the choice of 2-month intervals. In the empirical analysis, however, we will classify farms based on the observed choices of δ_ks and order the groups by the share of values allocated to the "growing season." We refer to the groups with low growing season shares as displaying relatively low levels of risk aversion and the groups with high growing season shares as displaying relatively high levels of risk aversion.

Data

We analyse data provided by USDA RMA for all RI-PRF participants in Nebraska and Kansas during years 2013–2017. Each observation of the data set contains an index interval, e.g., May–June, and share of insured liability placed in that interval, e.g. 60%, selected by an RI-PRF participant in a given year. Recall that a participant must choose at least two of the eleven 2-month intervals. Each of these choice pairs (index interval and share of liability) would be separate observations in the data set. While these choices are not identified by the individual, they do include the grid and county in which the policy was purchased.[7] No other information regarding the policy is included in this data set.

We aim to analyse individual producers' choices of 2-month index intervals; however, as previously discussed, individuals are not identified in the data set. In order to group the observed choices of 2-month intervals by individual, we utilise rules of the RI-PRF programme to distinguish individuals within each grid. RMA (2018a, b) state that (1) the same acres cannot be insured in more than one grid 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, intended use, irrigated practice, organic practice, and share. Thus an individual producer's 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 only one producer by selecting grids in which the share of liability percentages sum to 100% across all chosen intervals. 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 grids containing more than one producer. Grids that have multiple possible combinations

[7] For example, if within a grid, two individuals chose January–February, March–April, May–June, September–October, and November–December intervals, we would not know if one chose March–April and May–June (growing season months) while the other chose all non-growing season months, or if they each chose some combination of growing and non-growing season months.

of interval selections and shares of liability are dropped from the data set, since we cannot exactly identify the producers' choices.

In the end, we are able to derive 1819 individual choices for the RI-PRF programme. This covers 547 grids out of the total 693 grids in the full data set. The resulting observations look like the examples provided in Table 1 where individuals' identifications are distinguished by grid ID and year. Table 2 displays the number of individuals identified by state and year. The number of individuals is divided relatively evenly between Kansas and Nebraska. Table 3 shows the proportion of total observations utilised, with the identified individuals. The resulting data set consists of roughly 29% of the original number of data points that USDA RMA provided. This is a large enough sample to gain an idea of the distribution of participants' choices.

Table 4 displays average shares of liabilities for the population and the sample of identified individuals by index interval. We do not see significant differences between the population and the sample we identified. Moreover, from Fig. 2, which shows a representation of the differences in shares of liability percentages by index interval and by year, we do not see any systematic differences between the population and the sample. Thus we conclude that the identified individuals are representative and we use them as our sample to investigate the participation patterns of the RI-PRF.

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 11 index intervals. A useful approach for identifying patterns in data is cluster analysis, which groups observations in a data set into clusters based on similar characteristics across multiple dimensions. In the following, we discuss the use of clustering methods to distinguish purchasing patterns of RI-PRF.

Cluster analysis

We utilise clustering methods to group individuals based on similar choices of the 2-month intervals and the corresponding share of insured liability. Clustering methods are exploratory, 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 utilise the K-medoids clustering algorithm, which minimises dissimilarity between observations and a centre 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 other clustering algorithms which would compare observations to an average value. Averaging values may lead to overlapping month intervals, which are not allowed in RI-PRF. The observations

Table 1 Example data points

Individual ID	JAN.FEB	FEB.MAR	MAR.APR	APR.MAY	MAY.JUN	JUN.JUL	JUL.AUG	AUG.SEP	SEP.OCT	OCT.NOV	NOV.DEC
20824_2015_1	0	0	0	0.50	0	0.5	0	0.0	0	0	0
20824_2015_2	0.22	0	0.19	0	0.15	0	0.21	0	0	0	0.23
20824_2016_1	0	0	0.5	0	0.5	0	0	0	0	0	0
20823_2015_1	0	0	0	0.6	0	0	0.4	0	0	0	0
20823_2013_1	0	0.33	0	0.33	0	0.34	0	0	0	0	0

These are hypothetical data points for illustrative purposes

Table 2 Number of individuals identified by year and state

Year	Kansas	Nebraska	Total
2013	182	204	386
2014	175	187	362
2015	181	175	356
2016	182	185	367
2017	176	172	348

Table 3 Proportion identified of total PRF policies purchased

Year	Kansas	Nebraska	Total
2013	0.31	0.25	0.27
2014	0.29	0.30	0.29
2015	0.29	0.24	0.27
2016	0.33	0.28	0.30
2017	0.32	0.29	0.30
Total	0.31	0.27	0.29

Table 4 Average share of liability (δ_k) for sample and population by index interval

Index interval	Population average	Sample average
JAN.FEB	0.24	0.23
FEB.MAR	0.31	0.30
MAR.APR	0.27	0.26
APR.MAY	0.37	0.39
MAY.JUN	0.32	0.33
JUN.JUL	0.39	0.40
JUL.AUG	0.32	0.32
AUG.SEP	0.34	0.35
SEP.OCT	0.21	0.20
OCT.NOV	0.25	0.25
NOV.DEC	0.21	0.21

are compared in the K-medoids algorithm using a dissimilarity 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 numbers of clusters. An observation's silhouette value measures how well the observation matches within its cluster in comparison to matching with other clusters. Silhouette values range from − 1 to 1, with − 1 representing an observation matched very poorly within a cluster, and 1 representing an observation matched very well. A large ASW value represents a good fit for all of the observations as a whole (Kaufman and Rousseeuw 2009).

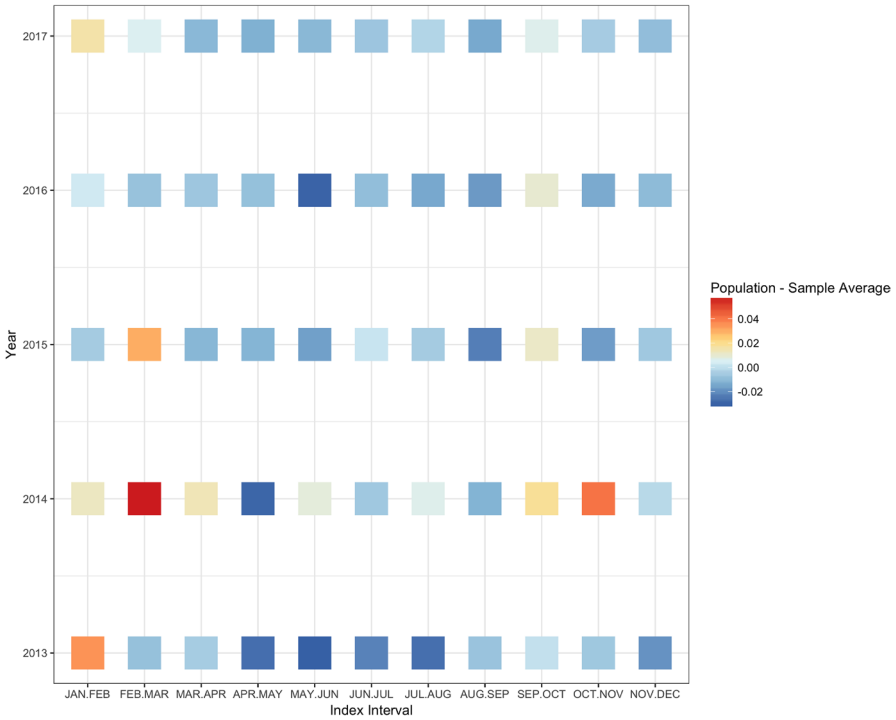

Fig. 2 Difference between population and sample average share of liability (δ_k) by index interval and year

Results

Figure 3 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 on 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 5 shows the centre observations for each cluster. As documented by Yu et al. (2019), precipitation during May through July is most important for forage growth in Nebraska and Kansas. We define the growing season as the intervals

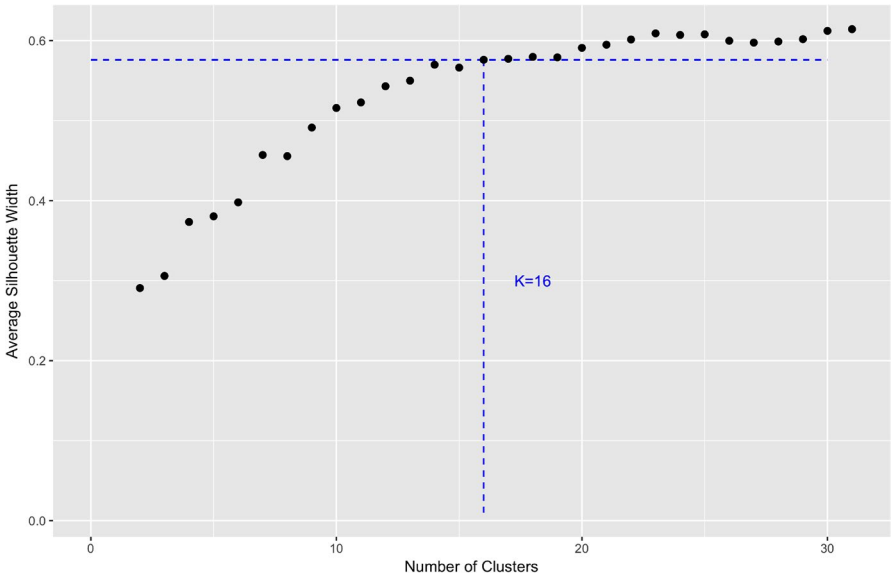

Fig. 3 K-medoids average silhouette values for cluster numbers K = {2, 3, ... ,31}

Apr–May, *May–Jun*, *Jun–Jul*, and *Jul–Aug* to encompass the months important for forage growth.[8] Table 6 shows each cluster's average share of insured liability within and outside the growing season.

The clusters in Table 6 are arranged in ascending order of the average share of liability placed within the growing season interval. Based on the stylised model, the higher the share of liability placed within the growing season, the higher the degree of risk aversion. For example, individuals in Cluster 6 would be classified as producers with relatively low risk aversion, and individuals in Clusters 11, 12 and 14 would be defined as displaying relatively high levels of risk aversion, given that nearly all of the share of liability is placed within the growing season. The stylised model defined risk-neutral producers as individuals who treat the RI-PRF programme more as an investment rather than a risk management strategy. Risk-neutral individuals would not place any share of liability in the growing season months. We do not find any clusters that fall into the risk-neutral category.

In Clusters 1–7 (i.e., producers with relatively low levels of risk aversion) the producers place some of their shares of liability in the intervals which include the forage-producing months, but the producers also place values in one or more of the following intervals that have little or no relationship with forage production: *January–February, February–March, October–November, and November–December.*

[8] 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. A simulation study of Diersen et al. (2015) finds that a producer who minimises the variance of the portfolio, which is a combination of the returns from crop production and the RI-PRF, should allocate most of the RI-PRF values to May–June and July–August intervals.

Table 5 Medoids (centre individual) by cluster K = 16

Cluster	N_c	JAN.FEB	FEB.MAR	MAR.APR	APR.MAY	MAY.JUN	JUN.JUL	JUL.AUG	AUG.SEP	SEP.OCT	OCT.NOV	NOV.DEC
1	97	0.30	0	0.10	0	0.10	0	0.10	0	0.10	0	0.30
2	74	0.25	0	0.25	0	0.25	0	0.25	0	0	0	0
3	308	0.17	0	0.17	0	0.17	0	0.17	0	0.16	0	0.16
4	44	0	0.34	0	0	0.33	0	0	0	0	0	0.33
5	78	0	0.20	0	0.20	0	0.20	0	0.20	0	0.20	0
6	28	0	0.10	0	0.10	0	0.20	0	0.25	0	0.35	0
7	50	0	0.20	0	0.15	0	0	0.25	0	0.20	0	0.20
8	92	0	0.40	0	0.30	0	0.30	0	0	0	0	0
9	167	0	0	0.33	0	0.34	0	0.33	0	0	0	0
10	88	0	0	0.60	0	0.40	0	0	0	0	0	0
11	219	0	0	0	0.50	0	0.50	0	0	0	0	0
12	41	0	0	0	0.50	0	0	0.50	0	0	0	0
13	125	0	0	0	0.33	0	0.33	0	0.34	0	0	0
14	210	0	0	0	0	0.50	0	0.50	0	0	0	0
15	156	0	0	0	0	0	0.50	0	0.50	0	0	0
16	42	0	0	0	0	0	0	0.52	0	0.48	0	0

Table 6 Average shares of liability within and outside forage growing season by cluster K = 16

Cluster	Growing season	Outside growing season
6	0.19	0.79
1	0.24	0.76
4	0.27	0.73
3	0.35	0.65
5	0.38	0.62
7	0.4	0.60
2	0.4	0.59
10	0.43	0.57
8	0.48	0.52
15	0.5	0.50
16	0.58	0.44
9	0.67	0.34
13	0.68	0.33
11	0.99	0.02
12	0.99	0.01
14	0.99	0.01

Referring back to Fig. 1, these four intervals have higher premium rates, on average, than all of the other intervals.

Highly risk-averse producers would, in theory, utilise RI-PRF purely as a risk management tool, so they would purchase insurance covering the months in which precipitation is most closely related to forage production. Compared with Clusters 1–7, producers in Clusters 8–16 display higher levels of risk aversion. The intervals chosen in the Clusters 8–16 range primarily across the months of May–July, and most producers are only allocating their share of liability across two or three intervals. This is consistent with the behaviour of highly risk-averse individuals.

Trends in the participation patterns

Table 7 breaks down the number of individuals in each cluster by year. The clusters are in ascending order of the shares of liabilities placed within the growing season, which according to the stylised model corresponds to increasing levels of risk aversion. In general, we observe that the number of participants has been increasing in the clusters to be considered less risk-averse (Clusters 1–7), whereas the number of participants in clusters with relatively high risk aversion (Clusters 11–14) has been decreasing.

Figures 4, 5, and 6 also indicate that the share of relatively low risk aversion participants has increased over time. For the sake of illustration, we first group the clusters

Table 7 Number of individuals in each cluster by year

Cluster	2013	2014	2015	2016	2017
6	3	4	6	7	8
1	15	14	25	23	20
4	4	5	9	12	14
3	38	63	62	65	80
5	8	13	12	18	27
7	3	3	10	14	20
2	23	14	15	14	8
10	32	13	18	13	12
8	18	11	9	27	27
15	27	38	36	29	26
16	9	14	8	4	7
9	23	41	37	33	33
13	28	19	18	36	24
11	70	53	42	36	18
12	11	12	12	5	1
14	74	45	37	31	23

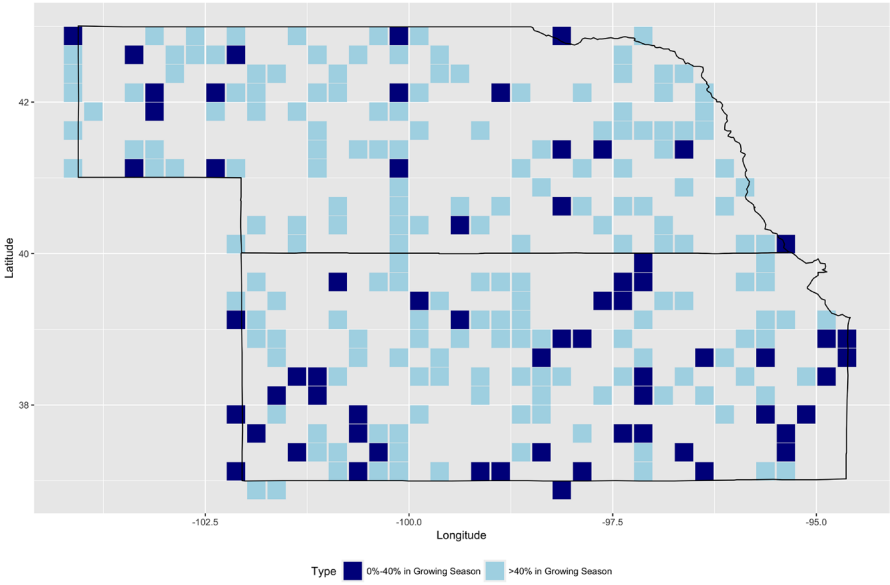

Fig. 4 2013 most frequent type by GridID

into two categories: (1) producers with growing season share less than 40% (relatively low risk aversion) and (2) growing season share greater than 40% (relatively high risk aversion). Clusters 1–7 fall into the first type and the others fall into the second. Figures 4 and 5 show the most frequent "type" of producer in each grid for years 2013 and

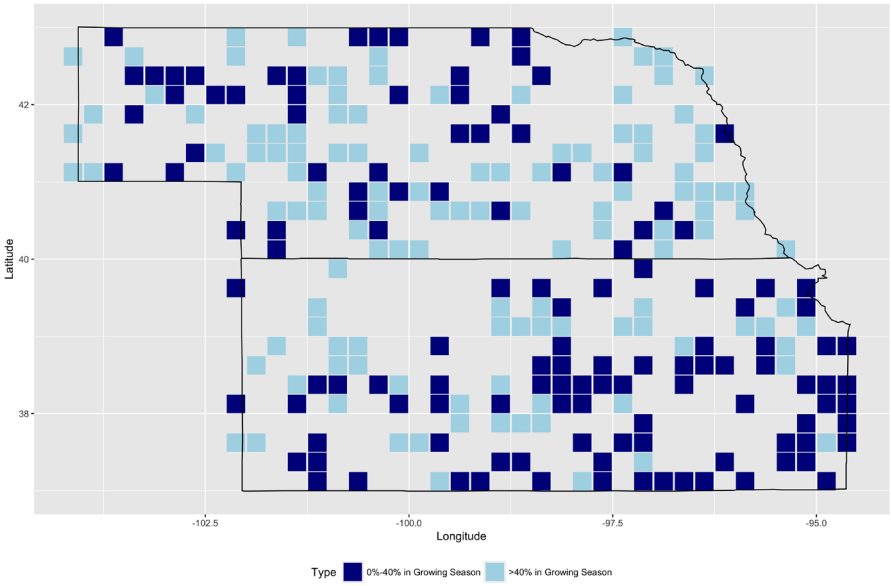

Fig. 5 2017 most frequent type by GridID

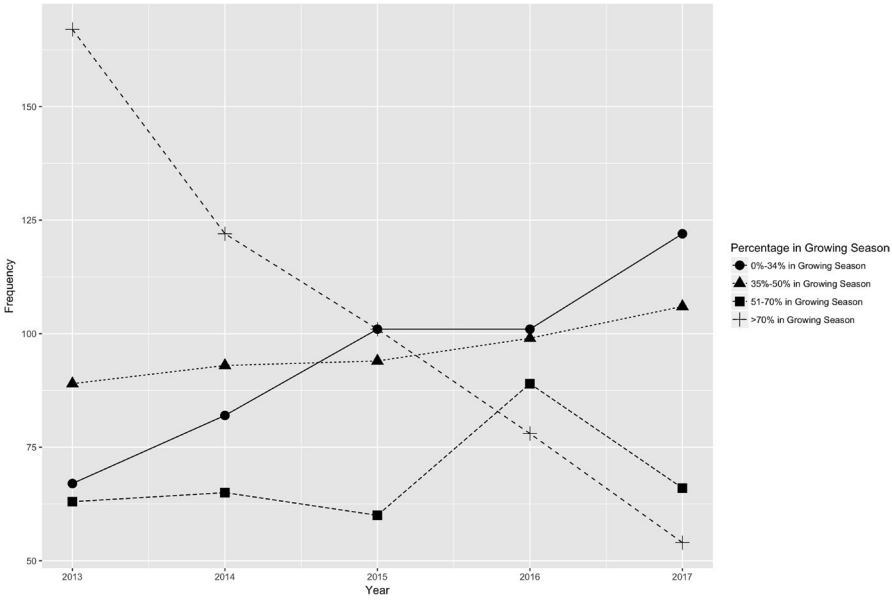

Fig. 6 Total number of participants by category by year

2017, respectively. The y-axis and the x-axis of the two figures represent the latitude and the longitude of the grids that we are analysing. In 2013, there appear to be large

Fig. 7 Liabilities insured and subsidies in Kansas and Nebraska (2013–2017)

blocks of grids which mostly exhibit more risk-averse behaviour, with less risk-averse grids randomly interspersed. In 2017, large blocks of primarily low risk aversion grids are much more prevalent. Additionally, Figs. 4 and 5 suggest there may be spatial relationships with participants in this programme.

Alternatively, we group the participants into four categories (Fig. 6). The categories are broken up as follows according to the share of liability within the growing season: ≤ 34%, 35–50%, 51–70%, and > 70%. This figure depicts the dramatic decrease in the number of individuals who use PRF for risk management purposes only, i.e., those who put more than 70% of their share of liability into months during the growing season. Also, the figure shows a fairly steady increase in the number of individuals putting less than 34% of their share of liability into growing season intervals. The middle categories show less pronounced trends over time, though the number of individuals that put 35%–50% into growing seasons months shows a slightly increasing trend.

Producer returns from the RI-PRF programme

In this subsection, we utilise another set of data from USDA RMA. The Summary of Business data set from USDA RMA provides annual county-level crop insurance information such as farm-paid premiums, premium subsidies, indemnity

Fig. 8 Returns from the RI-PRF in Kansas and Nebraska (2013–2017)

payments, and liability insured by crop insurance product. We describe the trends in the liabilities insured, the premium subsidies and the returns from the RI-PRF.

Figure 7 shows the trends in the liabilities insured and the premium subsidies that are allocated to the growing and non-growing season intervals. Consistent with Table 7 and Figs. 4 and 5, which show an increase in participants who exhibit relatively low levels of risk aversion, we see increases in the liabilities insured and the premium subsidies that are allocated to the non-growing season.

Figure 8 shows the trend of the indemnities minus total premiums including subsidies (upper panel) and the indemnities minus farm-paid premiums (lower panel) for the intervals in the non-growing season and in the growing season for Kansas and Nebraska from 2013 to 2017. From the upper panel of Fig. 8, we observe that the participants almost always incur net losses if premium subsidies are excluded from the calculation, regardless of which intervals they allocate their liabilities to. The lower panel shows the actual net returns to the participants from the RI-PRF. With premium subsidies, participants who allocate their liabilities to the intervals in the non-growing season gain more compared to participants who allocate their liabilities to the growing season intervals.

The main implication from Figs. 7 and 8 is that the liabilities insured, the premium subsidies allocated to, and the returns from the non-growing season intervals are greater than those paid into the growing season intervals. Partly, this is due to the higher premium rates for the non-growing season intervals, which lead to

larger subsidy payments. However, the trends are likely associated with the changes in the participation patterns.

Discussion and conclusions

It is important to highlight the limitations of this data that could influence some of the identified trends in RI-PRF participation. Our data set does not have a variable that uniquely identifies each participant over the years. Thus there are two possible explanations for the trend towards participation by individuals displaying relatively low levels of risk aversion: (a) over time, proportionately more individuals with low levels of risk aversion have entered the programme compared to those with high levels of risk aversion,[9] or (b) participants have learned more about the distribution of index values and changed their choices over the years.

Given that the programme is relatively new, it is possible that participants have learned more about the programme and the payment distribution over time.[10] The large blocks of adjacent less risk-averse grids in 2017 may reflect information dispersion from crop insurance agents or other farmers within an area. Therefore, it is important to analyse the long-run trends of PRF participation pattern as the programme matures, considering possible peer effects or learning.

Anecdotally, we have also learned from conversations with crop insurance agents that they often recommend certain strategies for participants to maximise the chance of receiving an indemnity, e.g., placing some of their share of liability into non-growing season months or spreading liabilities evenly across intervals. This anecdotal evidence is supported by the spatial nature of the transition, as displayed in Figs. 4 and 5. Further research utilising the notion of loss aversion and reference points would provide more insights into explaining the participation patterns on the RI-PRF programme.

We observe increasing trends in the share of participants who are classified as less risk-averse, in addition to increases in insured liability allocated to the non-growing season 2-month intervals. The large portions of premium subsidies and indemnities are paid to the non-growing season 2-month intervals, and the producer returns from these intervals are larger than those from the growing season 2-month intervals. It is possible that the definition of the growing season may differ across geographic regions, but the large portion of premium subsidies and indemnities to

[9] For example, as illustrated by Clarke (2016), basis risk can reduce the demand for index insurance. If the basis risk is large enough with RI-PRF, we might also see relatively high risk-averse individuals exiting the programme, while low risk-averse individuals enter.

[10] The premium rate setting formula may have changed over the life of the RI-PRF programme and may have affected the participation patterns we observe. However, anecdotal evidence suggests that the rate setting mechanism has rarely changed since the pilot of RI-PRF. Another possible explanation behind the observed participation patterns can be offered by the cumulative prospect theory, which models the behaviour with subjective probabilities and loss aversion. See Babcock (2015) for the use of the cumulative prospect theory to describe crop insurance choices for field crops.

winter months suggests that the programme has not been utilised strictly as a risk management tool by many producers in Nebraska and Kansas.

Our results have important implications for policy makers in relation to the design of this programme by highlighting the importance of identifying the participation patterns. In this study, we document a trend of an increasing share of Midwest participants who choose intervals outside the growing season that likely increase their income risk. We also find that the producer returns from and the government expenditure on the non-growing season intervals are greater than those of the growing season intervals. While restricting the RI-PRF choices to the growing season can be a policy solution, as suggested by Westerhold et al. (2018), this takes away some of the programme's flexibility and would likely be met with pushback from those participating, in addition to complicating RMA's administrative process.

Although we do not offer specific policy solutions, which would be beyond the scope of this article, we have provided useful insights by documenting outcomes and trends in the RI-PRF programme. The data set we constructed and analysed in this article allowed us to differentiate producers by their combined choices across all 11 intervals, rather than summarising by grid or interval. This provided a clear depiction of actual programme outcomes to link with previous studies on this programme. Better policy designs result from a fundamental understanding of risk preferences of producers and associated behaviour. Further research exploring geographic heterogeneity, learning over the years, and the long-run programme performances would provide more insight for programme design.

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