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Sigma Agricultural Risk and Actuarial Services, LLC

Review of the Pasture, Rangeland, Forage Rainfall Index Crop Insurance Program Indexing and Rating Methodology Final Report

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Executive Summary

There are two primary objectives of this task order. First, we were asked to review the County Base Values (CBV) for the Pasture, Rangeland, Forage Rainfall Index (PRF-RI) crop insurance program. Secondly, we were asked to conduct a comprehensive review of the methodology and calculations used in the determination of the rainfall index and associated premium rates. In both cases, we were asked to provide assessments of the current program, recommendations for changes, or any other improvements that we recommend RMA consider.

A review of loss experience for the PRF rainfall index plan of insurance shows that the overall actuarial performance of the PRF plan of insurance has been strong. The loss ratio only exceeded 1.0 in three of the 13 years of experience. The summaries also make clear another point. The rate of indemnification (claims frequency) is very high for the PRF plan. The results indicate that 70-90 percent of policies had a claim. The high frequency coupled with overall very good actuarial performance probably indicates that the program suffers from a great deal of frictional cost: a high frequency of small losses that in most cases provide only a partial return of premium. It seems reasonable for RMA to explore program modifications that reduce frequency, possibly with offsetting increases in benefits for remaining claims, to better meet the needs of growers.

Overall, we find the CBV calculation methods used for each intended use covered in the PRF insurance contract (e.g., non-irrigated hay, irrigated hay, and grazing) to be appropriate. We believe that the conceptual basis for the CBV values are sound. It seems reasonable for RMA to at least explore whether it is feasible to apply a minimum CBV value that is equal to a county-level or state-level measure of pastureland cash rent.

In the current CBV methodology, NRCS Hybrid Productivity Model (HPM) derived productivity factors are utilized in the non-irrigated haying and the grazing CBV calculations. In particular, a “district-state” productivity factor is used for calculating the non-irrigated haying CBV, and a “county-state” productivity factor is used for computing the grazing CBV. These factors were derived based on the NRCS HPM model so that estimates of the district-level non-irrigated haying CBV and the county-level grazing CBV are consistent with the inherent “productivity” of the pasture at these levels of geographic aggregation. The use of these productivity factors somewhat assures that the estimated CBVs at these levels are consistent with the inherent capacity of the land to produce pasture in these areas. Aside from the NRCS HPM, the U.S. Forest Service’s “Rangeland Vegetation Simulator” (RVS) is an alternative. It seems that output from this model can serve as an alternative data source to validate the productivity values generated from the NRCS HPM.

We provide a review of scientific literature related to the pasture and rangeland insurance product. In general, this is a growing body of literature, with significant contributions in recent years. We include a discussion of recent advances in index insurance. Further, several recent papers specifically focus on the PRF program.

The current procedure used in rating the PRF product utilizes a nonparametric empirical burn rate and parametric distributions derived from the log-normal and the truncated normal. Because there are currently only 70 years of rainfall data available (in the CPC data currently used by RMA), the use of an empirical burn rate might be questionable. We believe that there is an error in the formula used to derive the BS/lognormal rates in the RMA rating program. We examined the formula and believe there is a simple correction. However, it will generally lower rates.

Our review of the PRF product leads us to make the following recommendations.

1. **Validating the HPM productivity factors against alternative models**

The U.S. Forest Service's "Rangeland Vegetation Simulator" can serve as an alternative data source to at least validate the productivity values generated from the NRCS HPM. Comparisons of the resulting CBV values from the RVS vis-à-vis the NRCS HPM can be conducted to see if there are any large discrepancies in the estimates. *In the end, exploring an alternative source for productivity values can help improve the robustness of the CBV estimates.*

2. **Modification of the County Based Value (CBV)**

Currently, there is no set minimum value for the district-level grazing CBVs used in the PRF contract. Therefore, it is possible for the district-level grazing CBV (used for a particular county) to be lower than the estimated NASS county-level pasture rental rate. Newton (2018), for example, has shown that there are cases in South Dakota where 2019 CBVs were up to 46 percent lower than NASS state-level pastureland rent in 2018. *Based on research cited in our exploration of the CBV, we recommend RMA apply a minimum CBV value that is equal to a county-level or state-level measure of pastureland cash rent (perhaps in a previous year or based on historical average). Applying this minimum (in conjunction with the other changes recommended in this report) may improve the risk mitigation benefits from the PRF product.*

We also recommend partitioning the CBV for the grazing type into improved pasture and rangeland, with the distinction being that improved pastures are managed and that "Management usually consists of cultural treatments: fertilization, weed control, reseeding". The productivity differential estimates from the papers cited in this report indicate that a rangeland-pastureland factor in the range of 60%-70% is justifiable as a “conservative” measure (especially in the Western States where there is a good mixture of unmanaged rangelands and managed pastureland). Hence, the State-level grazing CBV yield estimate can be adjusted downward by 30%-40% for insureds that self-select and say that their PRF-insured land is unmanaged rangeland. On the other hand, the State-level grazing CBV yield estimate can be adjusted upward by 30%-40% for insured that self-selects and say that their PRF-insured land is managed pastureland.

Notwithstanding this recommendation for adjusting the State-level grazing yield in the grazing CBV calculations, the recommendation in this report of using a minimum grazing CBV value based on pastureland rents should still serve as the “floor” on the calculated CBV. That is, if the resulting district-level CBV with the downward adjustment (due to using unmanaged rangeland) is lower than the minimum CBV based on pastureland rental rates, then the minimum CBV based on pastureland rental rates will be the applicable one.

3. Adjusting the CBV Productivity Range

With improvements in the CBV calculations over the last five years (that improves accuracy and precision) and implementation of the minimum grazing CBV above (Recommendation 2), we believe that it is appropriate to reduce the range of available productivity factors in the PRF insurance offering. Similar area-based insurance plans offered by RMA that triggers on a county-yield “index”, such as the Area Risk Protection Insurance (ARPI), only have a productivity range between 0.8 and 1.2 (as compared to the 0.6 to 1.5 range in PRF). Hence, *for consistency across index-based RMA product offerings and to align better with risk minimization behavior, we suggest narrowing the productivity factor to the 0.8 to 1.2 range.*

4. Continue Using the NOAA CPC Data

RMA should continue to use the NOAA CPC precipitation data. Alternative data sets (PRISM, NCEI, NEXRAD, NCDC) offer no real advantages and, in the case of the NCEI, a disadvantage in that the data are not “gridded” but rather are reported at the station level. The absence of any “ground-truthing” obviates any tangible approach to selecting one data set over another on the grounds of accuracy. Ultimately, we recommend no changes to the current data used to rate and design coverage. Although trends and structural breaks are sometimes identified in the precipitation data, such changes over time are always small and are not consistent across different grid IDs. Climatologists have provided substantial evidence of trends in temperature and intensity of storms. Our analysis suggests the amount of rainfall over a two-month period has not changed significantly. We recommend that RMA continue to use the full 1948-present CPC data in its entirety and without explicit adjustments meant to reflect climate change.

5. Actuarial Sufficiency

Overall, this program is actuarially sound. Outside of a computation error in fitting the Black Scholes parameters, we find no significant shortcomings in the general approach used by RMA to estimate premium rates. Methods currently used to bound rates and to select the final rates from among the different rate estimates are ad hoc. We recommend that RMA consider the use of goodness-of-fit tests in the selection of the final parametric distribution used to estimate rates. Of course, rates derived from parametric distributions should be compared to empirical burn rates. The truncated normal distribution is strongly supported in a majority of cases. Procedures currently used to spatially smooth rates are appropriate and we recommend no changes to these procedures.

In some cases with extremely high or low variance, convergence issues may make it difficult to adequately estimate parametric rates and thus any measure based on such rates needs a careful review. We find a connection between rating and our next recommendation. Some grids/interval combinations result in extremely high rates (greater than 50%). This typically occurs in extremely dry grid/intervals (See page 78). RMA has sometimes excluded a county if any interval rate is above 50% in that county. We recommend this rule be made permanent for all regions. It will improve rating accuracy and augment recommendation 6.

6. Focusing PRF on Viable Forage Production Areas

As mentioned in recommendation 5, we believe eliminating counties where rates exceed 50 percent will focus the program on viable regions. If RMA prefers to eliminate whole counties from the program based on the suitability of soil and climate conditions for forage production, we recommend consideration of the land capability classification. Specifically, we recommend dropping counties having more than 50% of the total area that falls into land capability class 8 and/or subclass C. Such land has been designated by NRCS to be unsuitable for cultivation. A review of the 2017 census indicates that only a very small proportion of land in such counties is used to harvest forage or hay. This recommendation comes with two caveats. First, eliminating entire counties may not be appropriate in areas where land quality is very heterogeneous. This reflects the lack of resolution in a county aggregate. Second, as is likely to be the case with any threshold criteria, the choice of 50% is admittedly arbitrary but is justified in light of the very limited acreage devoted to hay in forage in such areas.

If RMA is willing to consider a higher degree of resolution and instead eliminate individual grid points rather than entire counties, we believe that the USFS measures of forage production provide an ideal metric for selecting areas to drop from coverage. We have obtained a direct measure of average forage production for each grid point and have demonstrated the strong correspondence between precipitation and forage production. Again, one can infer that, depending on the threshold selected, this would affect few producers of forage and rangeland. This is again demonstrated by the fact that forage production is low, in terms of both output and acreage, in such areas. Once again, the threshold of rangeland production that defines dropping a grid point from the PRF plan is arbitrary but is directly justified by the very low level of forage production and concomitantly low allocation of acreage to forage in such areas.

In summary, we recommend that RMA drop any grid point and its relevant 0.25-degree surrounding area that corresponds to the lowest 1-percentile of the distribution of forage production from eligibility for PRF coverage. This would eliminate 96 of the 13,626 grid points currently in the program. We have outlined alternative thresholds that could be used to eliminate marginal forage producing areas and believe that these may form the basis for future program revisions. A less drastic step would be to allow insurance in these areas, but with a reduced CBV and to allow irrigated acres to insure. We note that we also considered eliminating intervals with extremely high rates. This is an actuarial approach, but we believe that it is also a practical approach to the problem.

7. Better Targeting of Indemnities

Our review leads us to conclude that the current program frequently pays for shallow losses that are likely not significant financial threats while at times not sufficiently compensating for deep losses that are often a part of widespread droughts driving up replacement forage costs. We believe the program can become a better risk management tool, based on the evidence we find of a relationship between the replacement cost of forage and deep losses. *We recommend dropping the maximum coverage level to 80 percent while also adding a disappearing deductible and adjustment to enhance indemnities when in an extreme loss situation. One could develop more elaborate drought triggers, but they add significant complexity. For the sake of operational simplicity, we believe the indemnity function should be in the form of a disappearing deductible and perhaps reflect an accelerated disappearing deductible.*

8. Focusing coverage on risk-reducing intervals.

Our team reviewed a variety of resources and scientific studies focusing on forage and range production practices. We also conducted statistical analysis of the relationship of measured forage production to monthly rainfall amounts. We find that there is wide variation in the relevant rainfall months due to forage species, production system, location, and rainfall patterns. However, we do find that with rare exceptions, there are no more than eight months in a year that have a significant rainfall effect. In some cases, the key months may be preseason or postseason replenishment for the following year. However, in a county-by-county analysis, we found 1,638 counties (96.35%) have 5 or fewer months of significant precipitation effect. For the Western states, 83.93% have only 3 or fewer months of significant precipitation effect.

We believe this provides strong evidence of two things. First, there is evidence in the forage literature and our analysis that producers risk management would be best served by focusing the value of the policy on the months that pose the greatest production risk. Spreading value within a year across extraneous intervals increases basis risk in the PRF product. However, because production systems sometimes vary even within a county, we believe producers may need the flexibility to choose the periods that best fit their operation and reduce the basis risk for their farm.

In the Pasture, Rangeland, Forage (PRF) Crop Provisions, section 2. (a) states:

2. Application
(a) In addition to the provisions contained in section 2(c)(1) of the Basic Provisions, a percent of value must be allocated to more than one index interval for each grid ID, intended use, irrigated practice, and share. The minimum percent of value allowed in any one index interval by grid ID, intended use, irrigated practice, and share is **10 percent.** The maximum percent of the value that can be allocated to any single index interval by grid ID, intended use, irrigated practice, and share is specified in the Special Provisions.

We note that this minimum is well below the value that would allow insuring six periods in a year (16.6%). *Ultimately, we recommend increasing the minimum percentage of value in any one index interval to 25 percent. This will allow insuring eight months of a 12 month period. (If intervals are widened to three-month intervals we suggest a 33 percent minimum value so that no more than nine months can be covered.) This will require producers to focus participation in periods that most affect production. We also believe a strong education program is needed for producers and agents to help the producer to achieve value allocations most correlated with their risk.*

9. An Alternative Approach to Reducing Frequent Shallow Losses.

Recommendation 9 is offered for consideration only if the coverage level aspect of recommendation 7 is not adopted. We demonstrate in this report that modifying the program such that three-month periods are used rather than two-month periods reduces payment frequency roughly the same as reducing coverage by 5 percent. We see no significant effect on risk reduction, and potentially this change makes the program simpler if there are fewer periods. However, if a producer has a tight window of relevant rainfall risk than a three-month period this will in a sense require covering unneeded periods.

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Chapter 1 Introduction

Objective:

There are two primary objectives of this task order. First, we were asked to review the County Base Values (CBV) for the Pasture, Rangeland, Forage Rainfall Index (PRF-RI) crop insurance program. The CBV essentially provides the liability associated with this index-based product. Secondly, we were asked to conduct a comprehensive review of the methodology and calculations used in the determination of the rainfall index and associated premium rates. In both cases, we were asked to provide assessments of the current program, recommendations for changes, or any other improvements that we recommend RMA consider.

Scope:

For each task listed below, this order will involve submitting two reports after the contractor conducts the necessary research to accomplish the specific tasks and work requirements listed. The tasks have been conducted simultaneously. The work will involve data collection, review and analysis (including a review of any relevant academic research publications or articles), and report writing.

Background of the Program

The PRF-RI crop insurance program is an area plan of insurance based on an index of historical rainfall for specific two-month periods called index intervals. The index is normalized such that 100 is approximately equal to the historical average of rainfall from 1948 to the past year.

PRF-RI utilizes a grid system rather than a county value like other area plans of insurance. The PRF-RI grid system is based on data produced by the National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA CPC). Indemnities are payable when the final grid index falls below the trigger grid index for the two-month index interval. The trigger grid index equals the expected grid index (100) times the coverage level chosen by the producer.

A producer has three primary choices for participation. First, they may select one coverage level from 70 percent through 90 percent for the county, crop, intended use, irrigated practice, and organic practice. Second, they may select only one productivity factor from 60 percent through 150 percent for the county, crop, intended use, irrigated practice, and organic practice. Third, a producer must select at least two index intervals but may select up to six index intervals. Once the intervals are chosen then they are required to allocate at least ten percent of value to each interval.

One of the complexities of this product relates to the fact that the growing season is not necessarily when precipitation is important for forage growth. In particular, preseason weather can affect forage growth. Another challenge is driven by the differences in the growing season for different species. Further, production systems may use these different growing seasons to even out the supply of forage.

Figure 1-1. shows the aggregate number of policies earning premium and the policies indemnified for 2010-2019. First, there has been a threefold increase in policies. Secondly, the number of polices indemnified is often nearly as high as the number of policies earning premium. The percentage is at least 70 percent and in some years as much as 91 percent of polices earning a premium received an indemnity for a least one index period.

Figure 1-1

Figure 1-2 shows the growth in acreage in the Rainfall Index product. Acreage has grown at a faster rate than policies earning premium in the last decade. The acres insured in the program has increased five-fold and exceeded 140 million insured acres in 2019. As a point of reference, the 2019 acreage for rainfall insurance is approximately double that of soybeans.

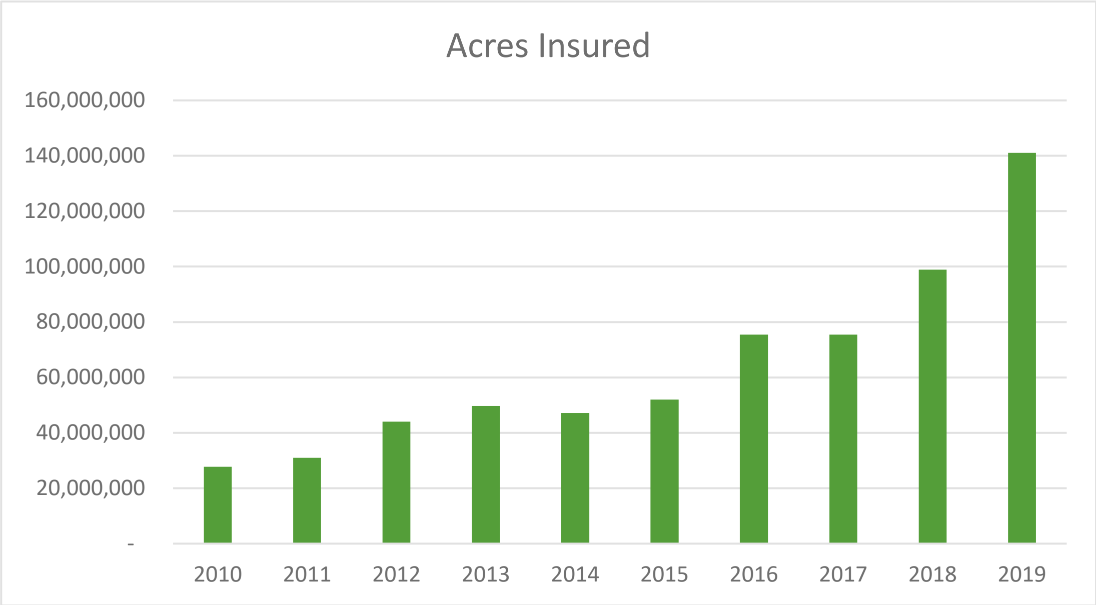

Figure 1-2

The actuarial performance of the program is shown in figure 1-3. While 2019 data may be preliminary, there is a clear indication that only one year (2011) has a loss ratio that substantially exceeds 1.0. Overall, the aggregate loss ratio for the decade is 0.85. Combined with Table 1-1, we conclude that it is an actuarially sound program with frequent indemnities. The frequency stems because a producer essentially has up to six index periods that potentially may trigger an indemnity in a year. However, it appears the program is rated correctly and collects sufficient premium. The fact that the plan pays indemnities on 70-90 percent of policies, coupled with a significant premium subsidy, means that PRF coverage is likely to frequently pay indemnities above the subsidized premium.

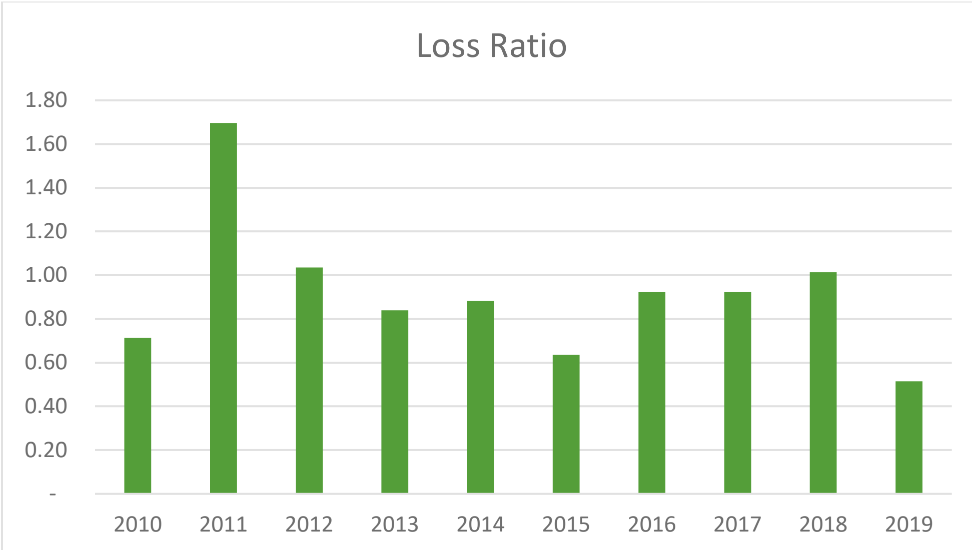

Figure 1-3

Table 1-1 summarizes the percent of total acreage insured at various coverage levels during 2010-2019. The most popular coverage level is the 90 percent coverage and the second most popular is 85 percent coverage. Combined, the top two coverage levels account for more than 70 percent of insured PRF acres. The only other coverage level of significance is the 75 percent coverage. Policies at the 65 percent coverage level are a very small portion of insured acres.

Table 1-1

COVERAGE	PERCENT OF INSURED ACRES
65%	0.004%
70%	2.35%
75%	24.36%
80%	2.05%
85%	33.44%
90%	37.80%

Discussion of Prior Experience

Table 1-2 presents a summary of business over the history of the PRF rainfall index plan of insurance. Table 1-3 presents a summary of business across states. These summaries highlight two important points. First, the overall actuarial performance of the PRF plan of insurance has been strong. The loss ratio only exceeded 1.0 in three of the 13 years of experience and the aggregate loss ratio across all years is 0.85. The program is actuarially sound

Table 1-2. Summary of Business for PRF by Year

Year	County Observations	Liability	Premium	Subsidy	Indem	Acres	Loss Cost	Loss Ratio	Pol Indem Rate	Unit Indem Rate
2007	657	325,817,906	63,523,875	37,473,952	40,471,879	24,504,699	0.1242	0.6371	0.8156	0.3429
2008	822	309,449,519	60,075,919	35,528,830	79,189,613	23,065,184	0.2559	1.3182	0.9520	0.5883
2009	1106	445,582,606	85,549,325	46,394,694	43,972,078	33,576,725	0.0987	0.5140	0.7447	0.3164
2010	1237	370,635,267	77,295,912	42,174,296	55,124,485	27,750,078	0.1487	0.7132	0.7670	0.3065
2011	1902	480,996,764	105,176,184	57,394,647	178,394,556	30,977,432	0.3709	1.6962	0.8124	0.6156
2012	2374	743,734,976	156,593,505	84,907,799	162,225,446	44,028,691	0.2181	1.0360	0.9500	0.5673
2013	3176	936,048,488	187,954,873	100,932,509	157,761,695	49,637,100	0.1685	0.8394	0.8442	0.4536
2014	3149	911,932,503	189,225,864	101,434,295	164,826,648	46,961,303	0.1807	0.8711	0.8304	0.4939
2015	3152	973,376,596	200,322,890	107,304,397	101,483,846	47,952,812	0.1043	0.5066	0.8000	0.3149
2016	3807	1,390,820,805	280,794,245	151,276,230	178,756,107	51,792,278	0.1285	0.6366	0.8529	0.3821
2017	4148	1,744,753,278	380,380,725	202,997,207	341,240,501	74,936,300	0.1956	0.8971	0.9161	0.4565
2018	4592	2,378,024,087	520,182,283	278,223,896	500,039,152	98,288,987	0.2103	0.9613	0.7900	0.4061
2019	4806	2,625,920,558	581,849,617	310,489,756	291,559,417	140,392,732	0.1110	0.5011	0.6924	0.3044

Table 1-3. Summary of Business for PRF by State

Year	County Years	Liability	Premium	Subsidy	Indem	Acres	Loss Cost	Loss Ratio	Pol Indem Rate	Unit Indem Rate
Alabama	1279	194,173,260	25,223,506	13,046,941	16,009,002	1,323,210	0.082	0.635	0.741	0.380
Arizona	232	1,211,174,726	354,954,154	187,329,797	248,453,812	97,979,353	0.205	0.700	0.660	0.363
Arkansas	711	141,448,552	21,101,887	11,159,446	11,149,390	1,000,937	0.079	0.528	0.661	0.271
California	931	529,092,833	153,387,468	83,430,636	112,252,895	27,273,848	0.212	0.732	0.724	0.471
Colorado	1335	811,446,609	170,165,702	89,019,127	133,023,522	35,550,623	0.164	0.782	0.738	0.404
Connecticut	14	514,006	48,615	26,491	12,761	1,439	0.025	0.262	0.400	0.180
Delaware	4	71,869	8,358	4,265	2,592	151	0.036	0.310	0.400	0.188
Florida	696	937,704,554	195,525,483	99,708,323	159,605,498	9,695,132	0.170	0.816	0.757	0.478
Georgia	1223	160,810,467	23,452,034	12,003,910	14,462,874	1,090,480	0.090	0.617	0.639	0.360
Idaho	326	158,459,187	33,681,048	18,060,585	15,250,904	6,727,359	0.096	0.453	0.384	0.227
Illinois	441	44,610,166	6,041,285	3,203,698	2,402,370	181,181	0.054	0.398	0.421	0.184
Indiana	324	21,504,537	2,556,956	1,336,965	708,612	91,297	0.033	0.277	0.501	0.196
Iowa	363	24,942,607	3,599,941	1,888,135	1,081,196	214,660	0.043	0.300	0.489	0.232
Kansas	2596	415,382,517	78,585,453	41,622,187	35,990,280	9,546,460	0.087	0.458	0.610	0.278
Kentucky	575	114,142,198	14,132,077	7,242,781	5,357,827	578,629	0.047	0.379	0.516	0.201
Louisiana	231	37,443,848	6,070,193	3,118,848	3,189,690	309,767	0.085	0.525	0.671	0.269
Maine	1	43,188	3,868	1,973	-	294	0.000	0.000	0.000	0.000
Maryland	131				308,437		0.050	0.456	0.496	0.296

Year	County Years	Liability	Premium	Subsidy	Indem	Acres	Loss Cost	Loss Ratio	Pol Indem Rate	Unit Indem Rate
		6,130,947	676,424	357,636		18,896				
Massachusetts	36	2,708,929	290,129	159,022	115,065	6,955	0.042	0.397	0.524	0.236
Michigan	168	20,611,542	2,254,679	1,165,370	645,042	51,520	0.031	0.286	0.433	0.206
Minnesota	775	47,981,899	7,047,258	3,705,959	3,432,017	402,331	0.072	0.487	0.597	0.304
Mississippi	264	50,047,159	6,996,169	3,612,541	2,361,800	344,286	0.047	0.338	0.466	0.212
Missouri	2002	316,835,176	51,755,764	26,570,583	22,127,310	2,856,061	0.070	0.428	0.588	0.281
Montana	1576	366,870,705	61,557,338	32,232,611	31,257,386	40,251,597	0.085	0.508	0.577	0.304
Nebraska	2143	456,245,644	72,030,851	37,903,555	30,116,299	16,954,149	0.066	0.418	0.600	0.269
Nevada	129	573,335,271	156,591,574	76,932,282	72,882,827	55,397,634	0.127	0.465	0.662	0.387
New Hampshire	4	403,218	42,711	21,783	9,259	954	0.023	0.217	0.800	0.300
New Jersey	12	714,317	89,710	45,754	53,827	1,587	0.075	0.600	0.533	0.118
New Mexico	468	575,246,566	149,583,593	81,147,732	76,437,986	49,347,821	0.133	0.511	0.684	0.341
New York	357	98,812,977	9,822,639	5,032,006	7,674,716	286,266	0.078	0.781	0.619	0.342
North Carolina	785	55,517,863	6,605,368	3,375,328	3,245,691	418,602	0.058	0.491	0.632	0.340
North Dakota	1886	595,669,875	103,655,250	54,329,685	58,293,602	26,658,263	0.098	0.562	0.703	0.347
Ohio	272	25,777,443	2,946,199	1,499,649	1,796,923	73,610	0.070	0.610	0.581	0.241
Oklahoma	1722	485,862,434	95,106,374	50,066,159	49,853,489	15,617,471	0.103	0.524	0.770	0.370
Oregon	220	301,820,585	68,699,090	36,749,133	40,730,571	15,254,536	0.135	0.593	0.559	0.328
Pennsylvania	913	191,758,209	19,967,863	10,226,951	13,608,813	511,731	0.071	0.682	0.719	0.362

Year	County Years	Liability	Premium	Subsidy	Indem	Acres	Loss Cost	Loss Ratio	Pol Indem Rate	Unit Indem Rate
Rhode Island	10	215,001	21,311	11,876	7,703	579	0.036	0.361	0.600	0.172
South Carolina	333	33,921,655	4,246,845	2,220,294	2,231,155	179,953	0.066	0.525	0.656	0.375
South Dakota	1573	687,908,605	127,360,448	65,947,643	59,381,576	20,381,212	0.086	0.466	0.552	0.270
Tennessee	490	132,060,671	17,174,022	8,751,398	6,243,484	718,369	0.047	0.364	0.555	0.225
Texas	10035	5,697,665,157	1,291,001,051	712,751,698	982,790,020	344,971,712	0.172	0.761	0.865	0.419
Utah	194	216,710,968	50,278,324	26,116,051	24,455,361	29,123,019	0.113	0.486	0.489	0.253
Vermont	7	1,339,082	123,287	62,881	72,592	4,052	0.054	0.589	1.000	0.407
Virginia	893	67,689,986	7,678,783	3,975,355	3,893,933	665,363	0.058	0.507	0.650	0.370
Washington	121	83,224,605	20,720,353	10,621,276	15,954,430	2,472,433	0.192	0.770	0.519	0.286
West Virginia	30	1,012,383	111,045	56,164	35,023	7,682	0.035	0.315	0.514	0.221
Wisconsin	747	117,745,821	14,473,120	7,782,840	4,381,314	433,469	0.037	0.303	0.441	0.299
Wyoming	264	219,953,040	40,166,981	20,108,822	21,694,547	18,349,816	0.099	0.540	0.555	0.262

The summaries also make clear another point. The rate of indemnification (claims frequency) is very high for the PRF plan. The results indicate that 70-90 percent of policies had a claim. Likewise, about 30-60 percent of individual units had a claim. The acreage insured under the PRF plan is illustrated in Figure 1-4 below. The figure demonstrates the fact that much of the participation is concentrated in the western half of the US. This partially reflects the trend toward much larger counties in this section of the country. However, even in light of this fact, participation reflects spatial heterogeneity. Figures 1-5 and 1-6 illustrate the average loss ratio and loss cost ratio. Loss ratios are the highest in Texas and southern Florida.

The relatively high cost of the program, as reflected in the loss cost ratio, is much higher in the far west and southwest. Texas appears to have high participation, high loss ratios, and high loss cost ratios. In Figures 1-7 and 1-8, we illustrate spatial patterns of claims frequency, as measured by the proportions of policies and units triggering indemnities. For the sake of comparison, we also illustrate claims frequency using the same metrics for all insured crops and all insurance plans. As we have noted, the frequency of claims for PRF appears to be far above the claims frequency for all plans and crops. Though geographic patterns of claims are similar for PRF and other plans, the rate of claims is much greater in the case of PRF.

This suggests that a tangible revision to improve the PRF plan of insurance is to undertake actions to reduce the frequency of claims while still providing growers meaningful coverage. Several different approaches to changes, including disappearing deductibles and double triggers, should be contemplated. A simple approach to modifying coverage to reduce claims while still providing protection when conditions are poor is to modify the terms of coverage by adopting differing thresholds for triggering a claim and modifying the indemnity payout in the event of a claim. A transparent approach to deriving the appropriate rating structure for such a change already exists in RMA's current rating procedures. If we decompose the determinants of the raw rate into its two components---the probability of a claim (risk) and the expected indemnity payment in the event of a claim, rates can be determined for any threshold of coverage.

Consider a hypothetical example of a unit with 70 percent and 90 percent premium rates of 0.10 and 0.27, respectively. Any rate can be decomposed as the product of the probability of a claim and the conditional expected claim (i.e. Rate= Prob(Claim) x E(Claim|Claim>0). These two components can be considered separately to determine a rate for a policy that pays 90 percent indemnities, but only if losses exceed 70 percent. Continuing the hypothetical case, consider such a policy. If the probabilities of loss for the 70 percent and 90 percent plans are 0.25 and 0.45, a rate for coverage that pays 90 percent but only if losses exceed 70 percent, would have a rate of only 0.15. Claims frequency would be reduced to a long-run average of 25 percent and producers would retain protection against catastrophic losses. We recommend that RMA consider such coverage, either as an option or as a replacement for the current plan.

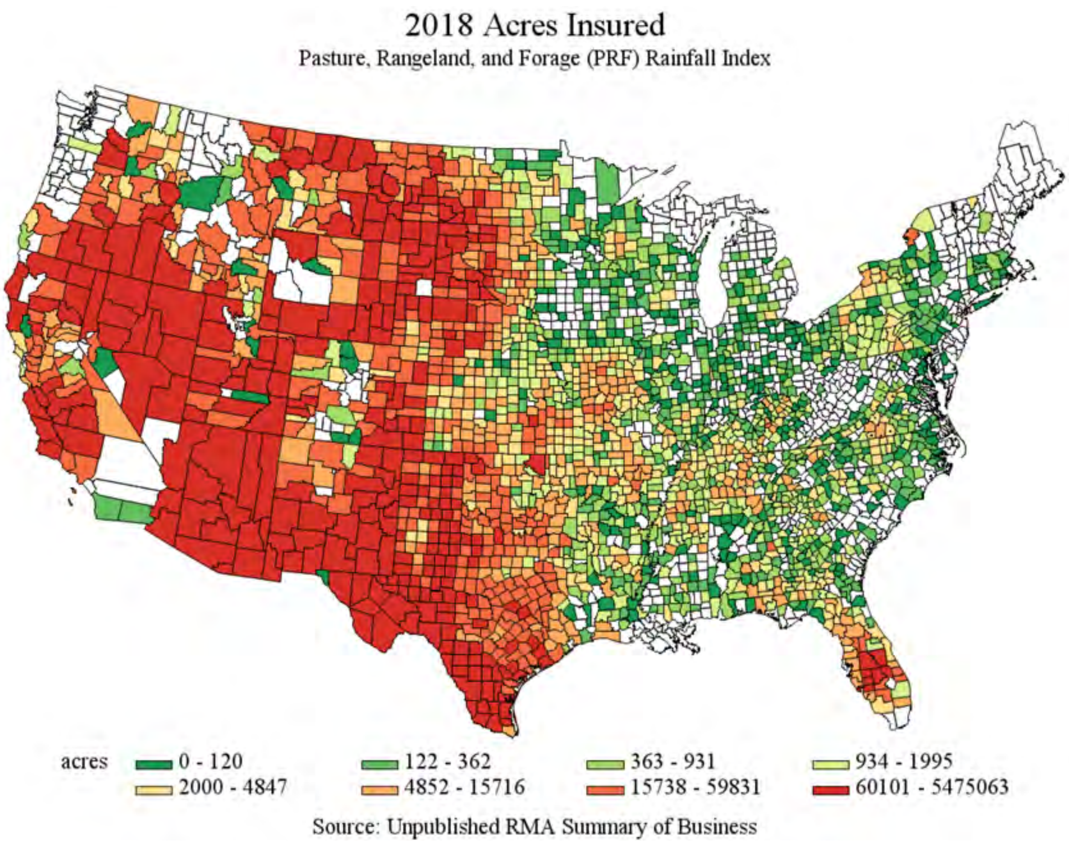

Figure 1-4

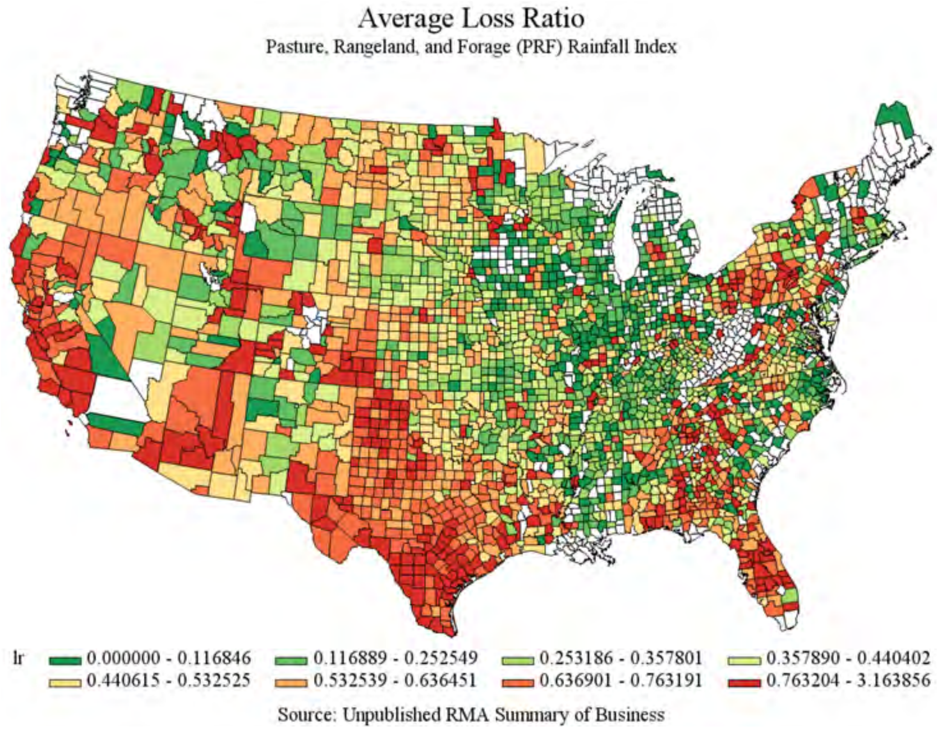
Average Loss Ratio
Pasture, Rangeland, and Forage (PRF) Rainfall Index
lr
0.000000 - 0.116846
0.116889 - 0.252549
0.253186 - 0.357801
0.357890 - 0.440402
0.440615 - 0.532525
0.532539 - 0.636451
0.636901 - 0.763191
0.763204 - 3.163856
Source: Unpublished RMA Summary of Business

Figure 1-5

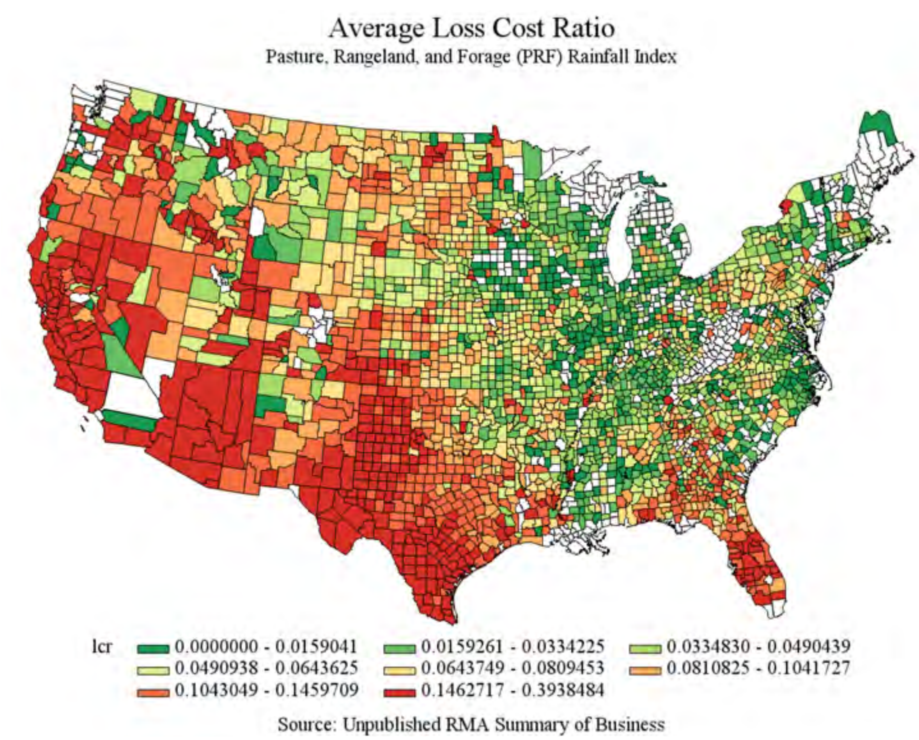
Average Loss Cost Ratio
Pasture, Rangeland, and Forage (PRF) Rainfall Index
lcr
0.0000000 - 0.0159041
0.0159261 - 0.0334225
0.0334830 - 0.0490439
0.0490938 - 0.0643625
0.0643749 - 0.0809453
0.0810825 - 0.1041727
0.1043049 - 0.1459709
0.1462717 - 0.3938484
Source: Unpublished RMA Summary of Business

Figure 1-6

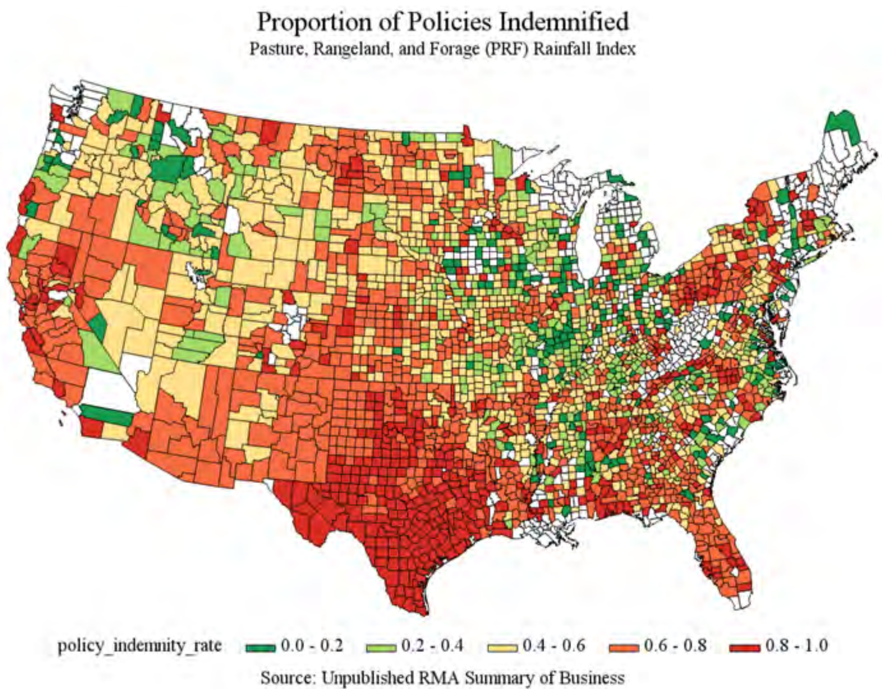

Figure 1-7

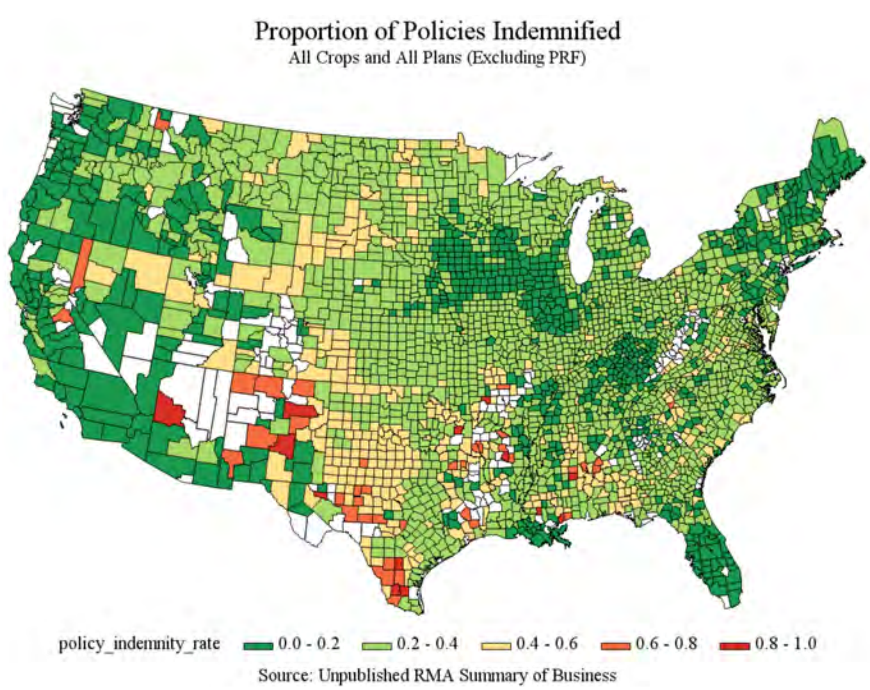

Figure 1-8

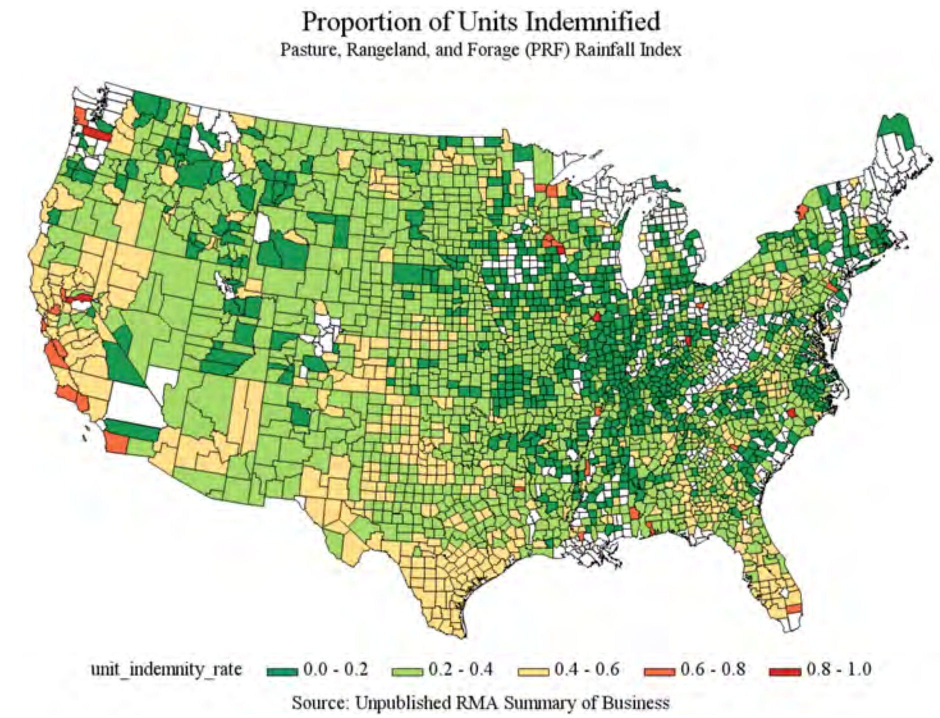

Figure 1-9

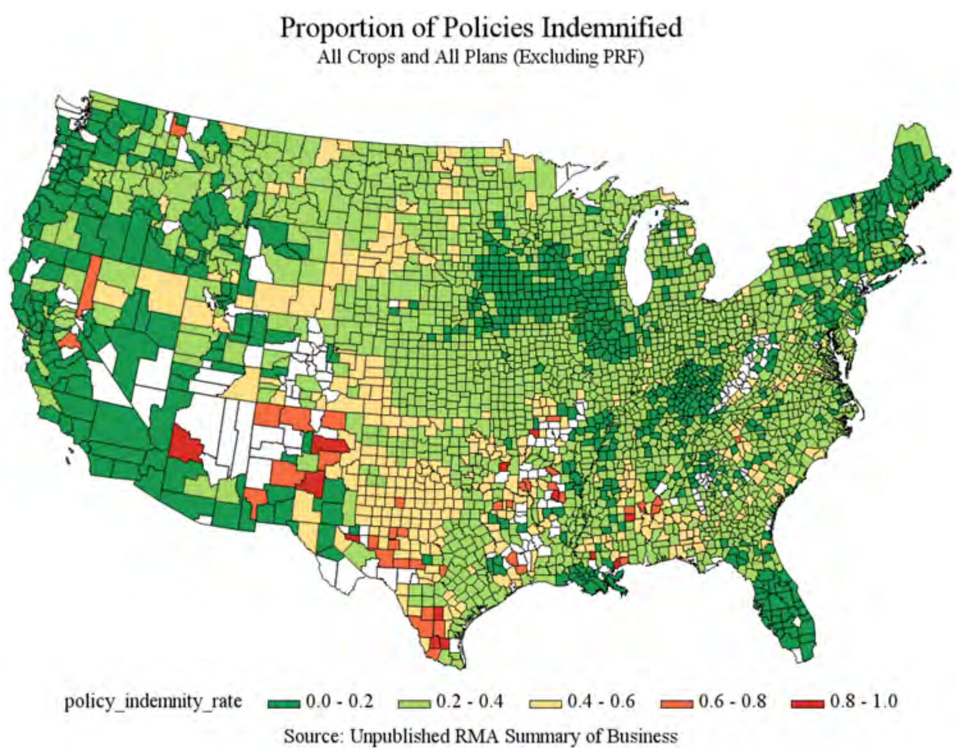

Figure 1-10

It is also relevant to note that many areas where the PRF coverage is offered are so dry as to likely preclude the long-run establishment of viable pasture and rangeland. Figures 1-11 and 1-12 below illustrate the long-run averages of temperature and rainfall in the US, calculated over the 1990-2019 period. Figure 1-13 presents 2018 premium rates for policies sold at the 90 percent coverage level. Clear patterns of heat and moisture deficiency stresses are apparent in the diagrams. Likewise, the areas that have the highest risk, highest premium rates, and highest claims frequency are largely the same. A relevant question for RMA pertains to whether coverage should even be offered in these very high-risk (excessively hot and dry) areas, which are unlikely to be viable for long-run pasture and rangeland. We recommend that RMA consider eliminating coverage in areas where the climate is not conducive to viable pasture and rangeland. Such areas may be identified through a consideration of the relevant research on the relationship between grassland and precipitation and the long-run trends illustrated in the figures.

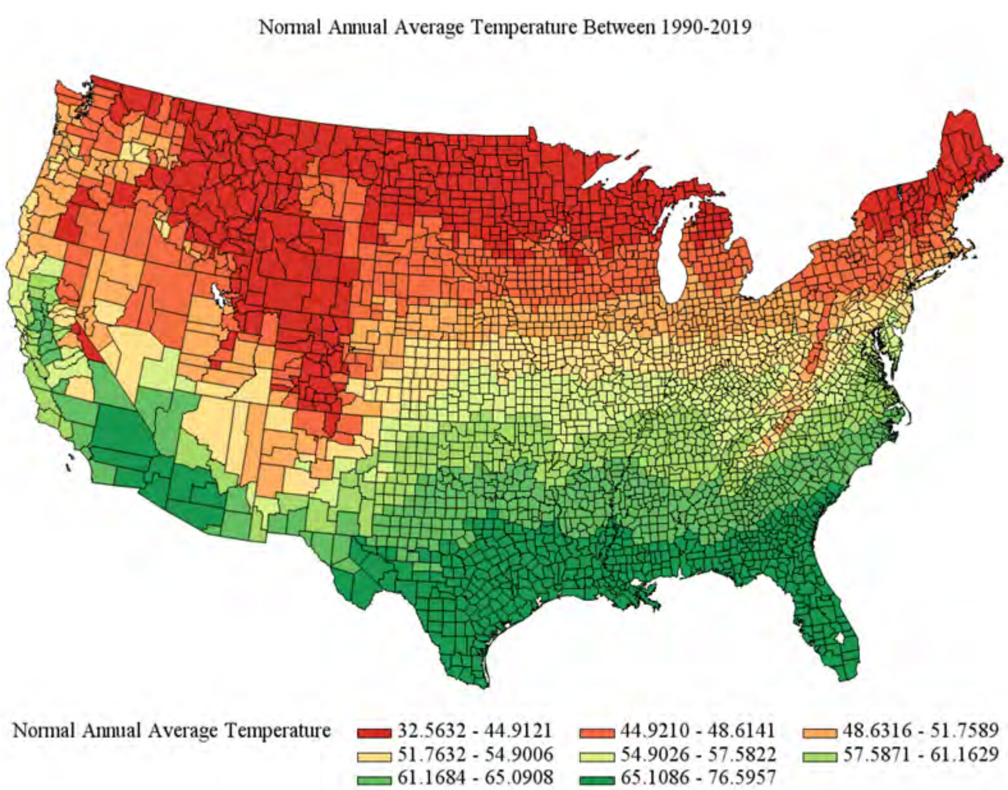

Figure 1-11

Long-Run (1990-2019 Average) Temperature

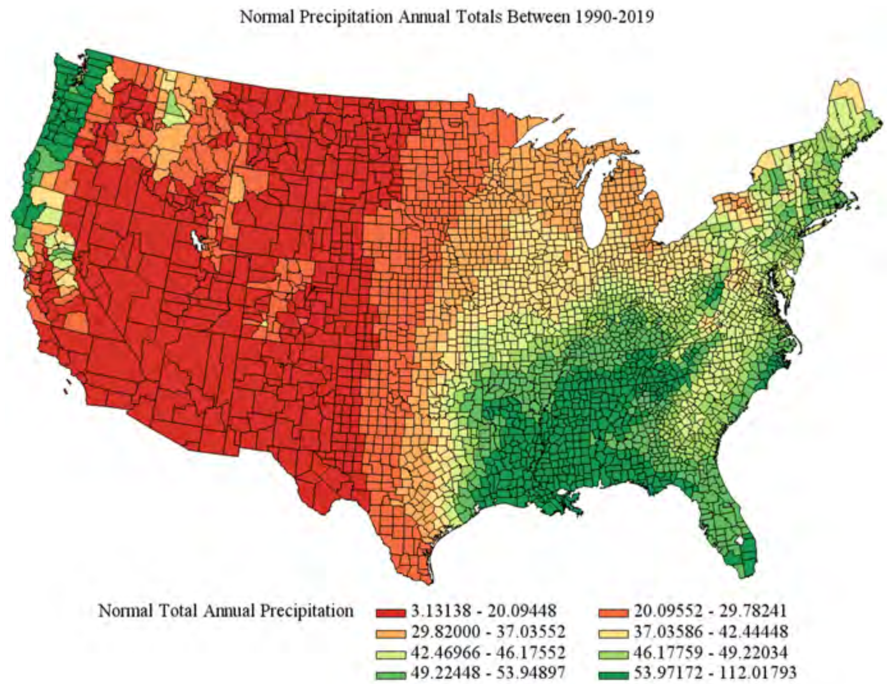

Figure 1-12

Long-Run (1990-2019 Average) Precipitation

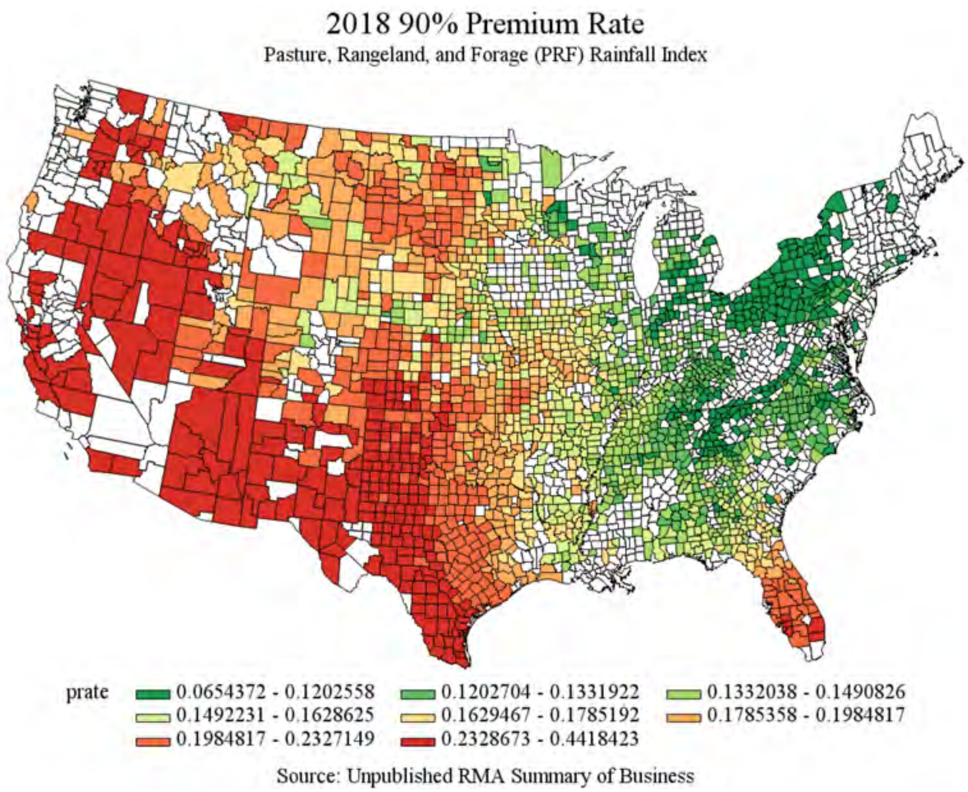

Figure 1-13

Pasture and Rangeland Production Systems

Production systems for pasture and rangeland differ widely and the PRF is asked to serve the needs of these varied production systems. Perhaps the broadest distinction falls along the line of pasture versus rangeland. Sanders, Jolley, and Dobrowolski (Figure 1-14) roughly divided the country north to south along the 99^{th} and then the 97^{th} parallel. Roughly, to the east of this line, there are improved pastures in an area of greater rainfall. To the west, there are generally more native forages produced with lower rainfall.

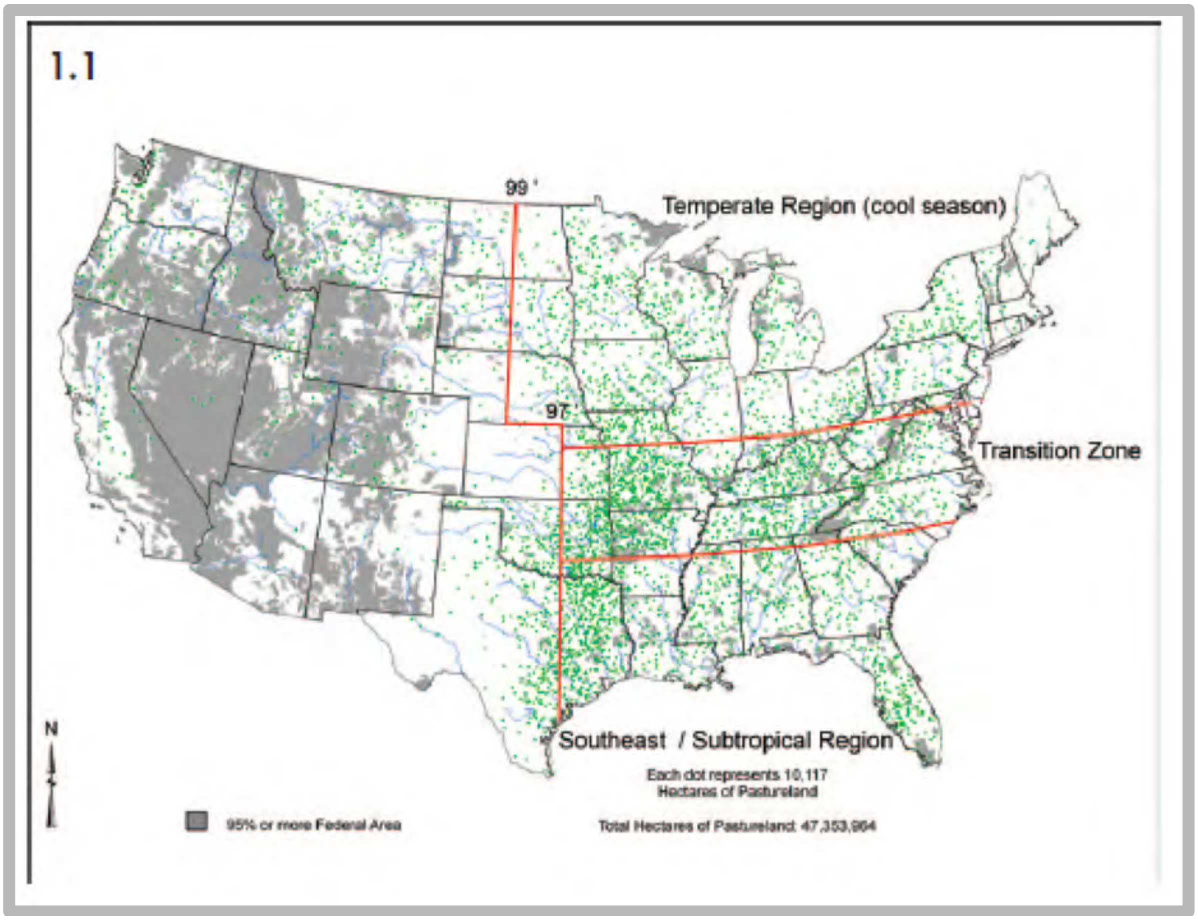

Figure 1-14

The USDA NRI Report (2018) provides a useful definition of terms relevant to pasture rangeland and cropland. That provides a distinction of the production systems where the PRF product is used.

NRI Definitions
Rangeland
A broad land cover/use category on which the climax or potential plant cover is composed principally of native grasses, grass-like plants, forbs or shrubs suitable for grazing and browsing, and introduced forage species that are managed like rangeland. This would include areas where introduced hardy and persistent grasses, such as crested wheatgrass, are planted and such practices as deferred grazing, burning, chaining, and rotational grazing are used, with little or no chemicals or fertilizer being applied. Grasslands, savannas, many wetlands, some deserts, and tundra are considered rangeland. Certain communities of low forbs and shrubs, such as mesquite, chaparral, mountain shrub, and pinyon-juniper, are also included as rangeland.

Pastureland
A land cover/use category of land managed primarily for the production of introduced forage plants for livestock grazing. Pastureland cover may consist of a single species in a pure stand, a grass mixture, or a grass-legume mixture. Management usually consists of cultural treatments: fertilization, weed control, reseeding, renovation, and control of grazing.

Cropland
A land cover/use category that includes areas used for the production of adapted crops for harvest. Two subcategories of cropland are recognized: cultivated and non-cultivated. Cultivated land comprises land in row crops or close-grown crops, as well as other cultivated cropland; for example, hayland or pastureland that is in a rotation with row or close-grown crops. Non-cultivated cropland includes permanent hayland and horticultural cropland

Source: USDA *Summary Report: 2015 National Resources Inventory (2018)*

The 2015 NRI also provides data about the relative percentages of U.S. land covers. Figure 1-15 shows the Federal Lands, Rangeland, and Forest land all three account for 21 percent of U.S. land cover (We note some federal lands are used for grazing.). Cropland is slightly behind the top three categories at 19 percent of land cover. Relevant to this study is pastureland representing 6 percent on land cover. Summed pastureland and rangeland represent more than a quarter of all land cover in the U.S. grazed Federal lands

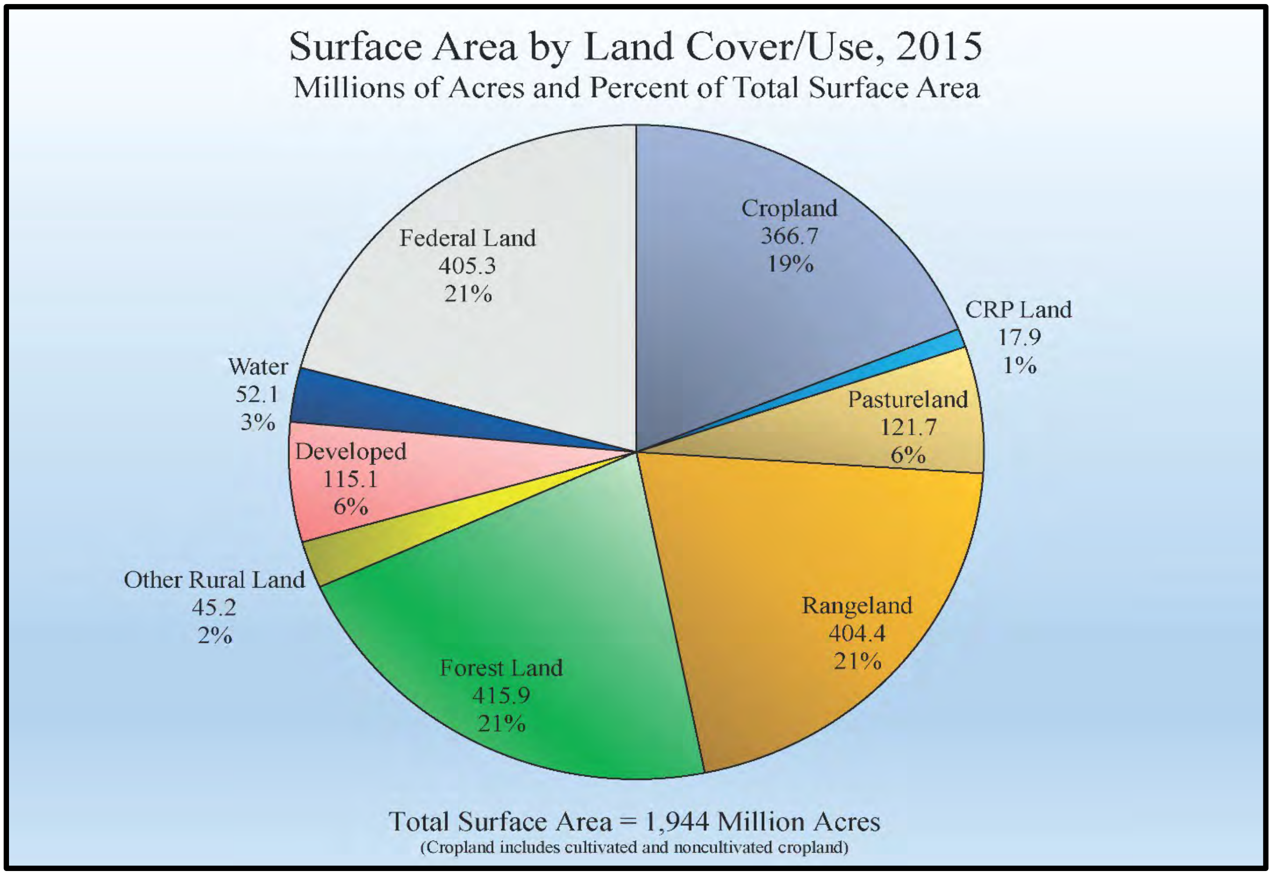

Figure 1-15

A further examination of the forage production systems shows a wide variation in management intensity of forage species and factors such as haying versus grazing. Sprinkle (2004) discuss the management side of understanding the carrying capacity of forage and also understanding the variation in forage demand resulting from differing age and species of the animals to be fed. Producers generally deal with the challenge of having sufficient forage for year-round use while there is often strong seasonality in forage production. A few strategies used to maintain forage across seasons include harvesting hay, planting forage varieties with different growing seasons, and extending production by rotations and stockpiling forage. Reeves et al. (2015) discuss new tools using weather forecast models to predict growing season forage production to better manage production.

The seasonality of production is directly related to the risk protection needed from the PRF product. Table 1-2 is from the USDA NRCS Range and Forage Handbook (2017). It reflects varieties and management systems typical of the eastern U.S. In several cases production is concentrated in a few months that leads to specific rainfall needs to produce that crop. With other species or blends, production is more spread out, but major production of these forages are primarily found in the April through November period. Herbel (2015) focuses on west Texas, Oklahoma, and New Mexico and finds that 70 percent of rainfall in the region falls in the spring to summer months making them a critical period for risk protection. Pieper survey the literature for the Central Plains and May-June rains or in another region early summer rains were highly predictive of forage production.

Various systems have been attempted to achieve a more nearly year-round production system. In colder climates, this tends to involve stockpiling un harvested forage (May et al. 2003). In Southern areas with warmer winter temperatures, annual grasses are sometimes overseeded to produce winter forage, but interestingly tend to face a problem of too much rather than too little rainfall. In drier climates, a wider forage production system is often attempted with irrigation ensuring sufficient water. However, various limitations such as the natural growth cycle of forages often come into play.

Table 1-2

Type of pasture	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
	Percentage available, by month							
Kentucky bluegrass-white clover, unimproved	25	30	10	5	10	10	5	—
Kentucky bluegrass-white clover + N, P	35	35	8	5	10	4	3	—
Renovated (continuous grazing)								
Birdsfoot trefoil-grass	10	25	25	20	10[2/]	5[2/]	5	—
Birdsfoot trefoil -grass, deferred for midsummer grazing	—	15	35	25	15[2/]	5[2/]	5	—
Tall grasses + N[3/]	30	30	10	5	10	10	5	—
Tall grasses + N, deferred for fall grazing[3/]	30	30	—	—	—	25	15	—
Renovated (rotational grazing)								
Alfalfa with smooth bromegrass or orchardgrass	20	25	25	15	5	5[2/]	5[2/]	—
Supplemental								
Sudangrass or sorghum-sudan hybrids	—	—	40	40	15	—[4/]	5	—
Sudangrass or sorghum-sudan hybrids, deferred for fall and winter grazing	—	—	—	—	—	100[5/]		
Winter rye	50	20	—	—	5	15	10	—
Miscellaneous								
Meadow aftermath-following one cutting	—	20	30	25	5[2/]	15[2/]	5	—
Meadow aftermath-following one cutting, to be plowed	—	20	30	10	20	20	—	—
Meadow aftermath-following two cuttings	—	—	10	35	25[2/]	25[2/]	5	—
Meadow aftermath-following two cuttings, to be plowed	—	—	10	25	35	30	—	—
Cornstalks	—	—	—	—	—	100	—	—

1/ Source: Schaller (1967). Compiled originally by: W.F. Wedin, Agronomy Department, Iowa State University.

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Chapter 2 Task 1: A comprehensive review of the County Base Values

The County Base Value in the PRF insurance product essentially represents the value of insurance per acre insured. The CBV is a base measure from which insureds can adjust insurance coverage amount and allocate it across the chosen intervals. Multiplying the coverage level chosen and the productivity factor to the CBV gives the dollar protection (e.g., liability amount) for the insured's PRF insurance contract. In this section, we describe the CBV calculation methodology as it is currently implemented, analyze the insurable risks present with lack of precipitation (depending on intended use), evaluate the current CBV methodology, and provide recommendations to improve the CBV calculation approach.

Current CBV Methodology (2020)

Over the last four years (2016-2019), there have been several changes made to the methodology for calculating the CBVs to improve the accuracy of this measure. The history of these changes is discussed in the RMA document titled: "Pasture, Rangeland, and Forage County Base Values Method" (RMA, 2019). The PRF insurance product insures pasture, rangeland, and forage intended for haying and grazing. Moreover, the haying practice is separated into two distinct types: non-irrigated haying and irrigated haying. Therefore, there are three different CBV calculation methodologies for each insurable intended use: non-irrigated haying, irrigated haying, and grazing. The CBV methodology for each intended use is discussed in turn below. The summary of CBV calculation steps is provided in the Appendix.

Non-irrigated Haying CBV

The CBV for non-irrigated haying practice is based on the expected annual revenue from an acre of non-irrigated hay production. That is, CBV = non-irrigated hay yield × non-irrigated hay price. The concept is such that this represents the total value of insurable non-irrigated hay production that could be lost (due to, say, lack of rainfall). In the context of the PRF insurance product, it would have been ideal if CBV values are calculated for each insurable grid (encompassing all intervals) available for the product. However, the main problem is that limited data exists for the yield and price components of the simple CBV calculation above (e.g., for non-irrigated hay revenue) at the ideal level of aggregation desired. Hence, the PRF insurance product has a CBV calculation procedure giving values at the "agricultural district" (sub-state) level based on available data and information at different levels of aggregation (e.g., state and county-level datasets are utilized to calculate the agricultural-district-level CBV for non-irrigated hay production).

The non-irrigated hay yield component (in tons/acre) of the CBV is calculated by first taking the

10-year average of state-level NASS yield data (e.g., NASS "all hay" yields in tons/acre) for each state that PRF is available. Then, a non-irrigated haying 'factor' is calculated based on the ratio of non-irrigated yield relative to the "all hay" yields based on information from the NASS Farm and Ranch Irrigation Survey (FRIS). This 'factor' is then multiplied to the 10-year state average 'all hay' yields to get an estimate of the non-irrigated hay yield for each state (in tons/acre). The non-irrigated haying 'factor' serves to adjust the average state-level "all hay" yields so that it will coincide more with non-irrigated hay production (i.e., rather than a hay yield that represents a mixture of both irrigated and non-irrigated production). To calculate an agricultural-district-level non-irrigated hay yield, the NRCS hybrid productivity model (HPM) is then utilized to estimate a percent difference between district-level and state-level net primary productivity (NPP) measures (e.g., we call this the NPP district-state factor). This NPP "district-state" factor is multiplied to the state-level non-irrigated hay yield estimate to get the agricultural-district-level non-irrigated hay yield value (in tons/acre).

On the other hand, the non-irrigated hay price component of the CBV calculation is based on three-year average state-level hay price data (in $/ton) from NASS (e.g., the NASS "all hay, excluding alfalfa" price data). This is the non-irrigated hay price procedure used for all PRF states, except for CO, ID, NV, NM, OR, and WA. For these exceptions, the reported NASS hay prices for these states mostly reflect the irrigated practice (and is valued higher). Thus, for these exception states, a regional average of the state-level non-irrigated hay price (in $/ton) in the Plains states is used instead.

The average state-level non-irrigated hay price ($/ton) is then multiplied by the agricultural-district-level non-irrigated hay yield value (ton/acre) to eventually get the district-level non-irrigated haying CBV (in $/acre) used in the PRF insurance product. Several other capping procedures are then conducted, such as limiting year-to-year CBV changes to +/-35 percent and having a maximum CBV value of $500.

Irrigated Haying CBV

In contrast to the non-irrigated haying CBV that is mainly based on an estimate of expected revenue, the irrigated haying CBV calculation method is primarily based on the cost of additional irrigation. The concept is that lack of precipitation (or rainfall) in an irrigated perennial PRF production context will generally mean that the irrigator will need to pump more water to compensate for the shortfall in precipitation. Hence, the "loss" incurred due to the lack of rainfall is the additional cost of pumping water.

Therefore, irrigated haying CBV is primarily based on information from the FRIS survey that reports irrigation costs per acre-inch by source (at the state-level). A weighted average of the irrigation costs from all sources is calculated at the state-level to estimate an overall average state-level irrigation cost per acre-inch. Adjustments to these overall state-level irrigation costs are then implemented for Kansas and Texas based on well-depth data collected from an irrigation model (e.g., we interpret this to mean that costs go up as well-depth increases in these states). No further adjustments are made for other PRF states. The estimated state-level irrigation cost per acre-inch in each state is then multiplied with rainfall levels (in inches) to get the irrigated haying CBV ($/acre) estimate. The irrigated haying CBVs are then capped at 75 percent of the non-irrigated CBV.

Grazing CBV

Much like the non-irrigated haying CBV, the grazing CBV is conceptually based on an expected hay revenue measure. The idea is that the impact of precipitation shortfalls for grazers is typically the cost of supplemental hay feeding due to the forage production lost in the field with the lack of rainfall. However, the procedure used to calculate the hay yield and the hay price components of the expected revenue measure for grazing CBV is different from the non-irrigated haying CBV. This is partly because hay yield for grazing can be more directly approximated using information about animal stocking rates and the forage consumed per animal unit. Also, hay yields intended for grazing tend to be lower (on average) relative to hay yields that are harvested for hay. The price of hay for grazing also is typically lower than the price of harvested non-irrigated hay since the harvested hay prices implicitly incorporate the higher cost of producing or maintaining pasture for haying. Pasture grass for grazing also tends to have lower-quality relative to an equivalent harvested baled hay value, which may again result in the price differential.

The grazing hay yield component of the grazing CBV is calculated based on NASS state-level pasture rental rate and grazing rate information. Yearly state-level pasture rental rates from NASS are measured on a dollar per acre basis, and the grazing rate (also called grazing fee) is measured in dollars per animal unit month (AUM). To get a ton/acre grazing hay yield value, first, a 10-year state-level average of pasture rates and grazing rates is calculated for each state where data is available. Second, the 10-year average pasture rate (in $/acre) is then divided by the 10-year average grazing fee (in $/AUM). This ratio provides an estimate of average forage consumption measured in AUMs per acre (e.g., this is an estimate of the amount of forage "harvested" by the livestock). Since an AUM is equivalent to about 0.47 tons of hay (based on NRCS data), the last step is to multiply 10-year state-level average forage consumption (in AUMs/acre) by the 0.47 tons/AUM to get an estimate of the 10-year state-level average grazing hay yield (in tons/acre). This is the estimate of the grazing hay yield component of the expected revenue.

The price component of the grazing CBV is estimated by utilizing a "blended" measure derived from state-level grazing rate information and non-irrigated hay price information. The grazing hay price estimates are based on three-year state averages of the grazing rates and non-irrigated hay prices. First, three-year averages of the state-level grazing rate data (in $/AUM) and the state-level non-irrigated hay price data (in $/ton) are calculated. Second, the three-year average state-level grazing rate is then divided by the 0.47 tons/AUM factor (as mentioned above). Recall that this latter factor represents the "ton" equivalent of the "AUM" measure of forage "harvested" by the livestock. The resulting value from this second step is an estimate of the grazing rate in the desired dollars per ton ($/ton). The last step is calculating the "blended" grazing price (in $/ton) by taking the average of the grazing rate ($/ton) calculated in the second step and the non-irrigated hay price ($/ton). The pricing procedure described above applies only to states with grazing rate information in ($/AUM). For states without grazing rate information, the state-level non-irrigated hay price is simply multiplied with a 0.762 factor, where this factor represents the ratio of grazing rates to non-irrigated hay price in the Plains states.

An initial estimate of the grazing CBV at the state-level (in $/acre) is then calculated by multiplying the grazing hay yield estimate (in tons/acre) with the "blended" grazing price estimate (in $/ton). County-level grazing CBVs are then derived from the state-level grazing CBV using the pasture productivity estimates from the NRCS HPM (as described in the non-irrigated hay CBV section above). County-level productivity measures are estimated for each county in a particular state, and then these county-level measures are divided by the state-level productivity measure to get the "county-state" productivity factor (e.g., the ratio of the county and state productivities). The "county-state" productivity factor is then multiplied by the state-level grazing CBV estimate to compute a county-level CBV (in $/acre). The county-level CBVs for all counties that comprise each agricultural district in a state are then averaged to get the district-level grazing CBV (in $/acre) that is used for the PRF insurance product.

Rangeland and Pastureland CBV differences

To follow on the previous section, we want to delve further into the differences between pastureland and rangeland CBV. In Chapter 1 of this report, NRI definitions of "rangeland" and "pastureland" were discussed to distinguish one from the other. For rangelands, one key identifying characteristic is that rangelands used for grazing typically have "little or no chemicals or fertilizer being applied." In contrast, pastureland used for grazing involves management practices that "usually consists of cultural treatments: fertilization, weed control, reseeding, renovation…" With these distinguishing characteristics, it is natural to expect that the productivity of pastureland used for grazing would be higher than rangelands for grazing since productivity-enhancing management practices are implemented in pastureland while it is not applied in rangelands. Consequently, CBV values may also then be higher for pastureland used for grazing vis-à-vis rangelands used for grazing (which would justify an adjustment factor in the grazing yield component of the grazing CBV calculation).

Using high-resolution remote sensing and satellite data sets, the study of Robinson et al. (2019) supports the existence of a productivity differential between pasturelands (that are managed) and rangelands (that are not managed). In Robinson et al. (2019), managed or improved pastureland are characterized as “private” lands where private owners actively manage their pasture through fertilization, reseeding, etc. On the other hand, what we call unmanaged rangeland in this report coincides with what Robinson et al. (2019) call “public” lands (with no or little management). In general, Robinson et al. (2019) find that the productivity of private grazing land is consistently higher than public lands. Considering the whole continental US (CONUS), productivity of public lands is about 48% of the productivity of private lands (See Figure 4 and supplemental Table S1 in Robinson et al., 2019). For the Western States (Washington, Oregon, California, Idaho, Nevada, Arizona, New Mexico, Utah, Colorado, Wyoming, and Montana), productivity of public grazing lands is 59% of the productivity of private grazing lands. These results strongly suggest that managed private lands (or pasturelands) for grazing are more productive than unmanaged public lands (or rangelands).[1]

An online resource from Michigan State University (Lindquist, 2014) also provides evidence that grazing land with no nitrogen (N) fertilization tends to be less productive than any grazing land with N application (i.e., one-time spring N application or split N applications). Based on several field trial data sets in Michigan (as reported in Lindquist 2014), the calculated ratio between the average forage yields in “no-N fertilization” lands and the “N-managed” lands ranged from 45% to 91% (with an average ratio of about 65%). Overall, these trial data results (ranging from 1966-2014) support the idea that unmanaged rangelands (without any N fertilization) are less productive than managed pasturelands (with N fertilization).

Baldwin, Hakinson, and Anderson (1974) found that a single application of 27-12-O fertilizer on native rangeland in northwestern Oregon produced a 4-year total herbage production of 2.66 times as much as on unfertilized plots produced. Higher levels of fertilizer increased the ratio. Increasing the rate of fertilization improved the strength of perennial grasses, increased utilization of herbage by cattle, and extended the forage season. Goetz (1969) found 67 pounds of nitrogen per acre increased rangeland forage production in North Dakota by 63 percent relative to no nitrogen application. Mosely, Brewer, and Skeen (2020) recommend stocking rates on healthy rangeland to be around ½ that of well-managed seeded pastures in Montana.

We also note that Hooper and Johnson (1999) conducted regression analysis examining the degree to which water and nitrogen limit dryland forage production systems. One conclusion they reach is that the relative increase in forage production due to nitrogen application is robust across different rainfall scenarios.

Observations, Analysis, and Recommendations

Overall, we find the CBV calculation methods used for each intended use covered in the PRF insurance contract (e.g., non-irrigated hay, irrigated hay, and grazing) to be appropriate. We believe that the conceptual basis for the CBV values are sound. As a risk management tool, the

[1] Note that the Robinson et al (2019) also provided a supplemental data set that includes information about the proportion of private vs. public grazing land by State (as well as the corresponding average productivity for each type of grazing land by State).

PRF insurance aims to compensate hay producers and grazers for the value of production lost in their pasture (or rangeland) when there are shortfalls in precipitation (i.e., given that rainfall, or water in general, is a major determinant of eventual pasture/rangeland/forage production). Hence, the CBV should reflect the total value at risk (i.e., 'the insurable risk' or the total value of production that can be lost) when there is effectively no rainfall (or zero pasture production).

For the case of non-irrigated hay production and/or pasture intended for grazing, having the CBVs for these intended uses conceptually linked to an expected revenue measure is reasonable. This is because expected revenue (hay yield multiplied by hay price) is generally the value of the hay lost (in $/acre) when there is a lack of sufficient rainfall. On the other hand, for irrigated hay, the 'loss' or additional cost incurred when there is a lack of rainfall is normally the additional cost of pumping more water to compensate for the shortfalls in precipitation. Hence, the irrigated hay CBV being conceptually linked to an estimate of pumping cost seems reasonable as well. These underlying conceptual linkages indicate that the CBV calculation methods are reasonably linked to the major insurable risks PRF purchasers face for each intended use when there is insufficient rainfall.

Given the general conceptual soundness of the CBV calculation methods for each intended use, the main challenge for RMA is to precisely estimate the CBVs given the inherent limitations of the data available for calculating it (e.g., limitations of data on the non-irrigated hay and grazing hay yields and prices, and the irrigation pumping costs). Hence, the remainder of this section discusses observations and recommendations concerning further improving the accuracy of CBV calculation methods and making adjustments to other PRF contract elements given the improvements in the CBV. In general, we believe that the modifications to the CBV calculation methods implemented by RMA over the last four years have already improved CBV estimates, and the suggestions here are meant to refine the CBV process further.

Setting a minimum grazing CBV: County-level NASS pasture rental rate data

Currently, there is no set minimum value for the district-level grazing CBVs used in the PRF contract. Therefore, it is possible for the district-level grazing CBV (used for a particular county) to be lower than the estimated NASS county-level pasture rental rate. Newton (2018), for example, has shown that there are cases in South Dakota where 2019 CBVs were up to 46 percent lower than NASS state-level pastureland rent in 2018. Though it should be noted that, in 2020, RMA was able to raise CBVs in South Dakota in response to this issue. There were also about 225 counties with 2019 CBVs below the 2017 NASS county-level cash pastureland rent (though there were over 1000 counties with CBVs more than 200 percent higher). Hence, Newton (2018) argues that in counties where grazing CBVs are below county-level pastureland rents, the PRF indemnity payments for a full loss will not be enough to cover the minimum cost associated with accessing forage for supplemental feeding (e.g., say if they want to rent nearby pastureland for supplemental feeding of their livestock). Pastureland rents seem to be a justifiable minimum value for the grazing intended use.

Given these arguments, it seems reasonable for RMA to at least explore whether it is feasible to apply a minimum CBV value that is equal to a county-level or state-level measure of pastureland cash rent (perhaps in a previous year or based on historical average). There is a lag in the availability of NASS county-level and state-level pastureland rental data, which may limit the feasibility of applying a minimum value. However, a one-year lagged pastureland rent value from NASS (at the county- or state-level) as a minimum bound would still be reasonable (in our opinion). Applying this minimum (in conjunction with the other changes recommended in this report) may improve the risk mitigation benefits from the PRF product.

Validating the HPM productivity factors against an alternative model

In the current CBV methodology, HPM-derived productivity factors are utilized in the non-irrigated haying and the grazing CBV calculations. In particular, a “district-state” productivity factor is used for calculating the non-irrigated haying CBV, and a “county-state” productivity factor is used for computing the grazing CBV. These factors were derived based on the NRCS HPM model so that estimates of the district-level non-irrigated haying CBV and the county-level grazing CBV are consistent with the inherent “productivity” of the pasture at these levels of geographic aggregation. The use of these productivity factors somewhat assures that the estimated CBVs at these levels are consistent with the inherent capacity of the land to produce pasture in these areas.

Aside from the NRCS HPM, Williams and Travis (2019) have used the U.S. Forest Service’s “Rangeland Vegetation Simulator” (RVS) in their study that evaluates PRF weather index products using alternative drought indices instead of a rainfall index. Reeves (2016) more fully describes how the RVS works. Williams and Travis (2019, p. 633) describe the RVS as follows: “The RVS calculates annual rangeland production for the western and central United States by combining normalized difference vegetation index (NDVI) values with precipitation data and site-specific biophysical settings (Reeves 2016). The RVS is validated with direct measurements of rangeland production values from the National Resource Conservation Service Soil Survey Geographic dataset (SSURGO; Reeves 2016). RVS data are consistent from year to year and are available from 1984 to present, thus providing the most comprehensive assessment of rangeland productivity in the United States.” Given the above description of RVS, it seems that output from this model can serve as an alternative data source to at least validate the productivity values generated from the NRCS HPM. Comparisons of the resulting CBV values from the RVS vis-à-vis the NRCS HPM can be conducted to see if there are any large discrepancies in the estimates. In the end, exploring an alternative source for productivity values can help improve the robustness of the CBV estimates.

Minor clarifications to the irrigated hay CBV and the grazing CBV procedure

One issue with the irrigated CBV is the conceptual question of whether the irrigation cost should be multiplied by the average rainfall level to get the irrigated hay CBV, or is it more appropriate to multiply the irrigation cost by an estimate of the average amount of water pumped historically (in inches) in the geographical area of interest. It seems that the 'insurable risk' associated with irrigated hay should be tied more to the actual average water used rather than the average rainfall level. Multiplying based on expected rainfall is from the notion that an irrigated producer will irrigate more than normal to make up for a shortfall from expected rainfall, which is why the CBV is set based on expected rainfall. For example, in a high rainfall area (e.g., 30 inches per year), a producer would only pump an additional 4 inches. However, in a drought year, they may pump 14 inches. For a more moderate average rainfall area (say 10 inches per year), a producer may routinely irrigate for an additional 35 inches, but the irrigated CBV only covers the 10 inches per year average. The logic above makes sense though it seems that in this example the irrigated CBV tends to overinsure irrigated areas with higher average levels of rainfall (e.g., the 30 inches of rain example), and underinsure irrigated areas with lower average levels of rainfall. As mentioned above, all we are suggesting here is to simply re-evaluate this step. Or perhaps base it on the historical "additional" pumping in severe drought events at minimum rainfall levels (i.e., the observed pumping in severe drought years relative to the "normal" pumping in "normal" rainfall years). Our point here is for RMA to simply evaluate further whether it is better to use average rainfall or some other "water quantity" to calculate the irrigated hay CBV.

In addition, we note here that there is inconsistency in the non-irrigated hay CBV procedures relative to the grazing hay CBV procedure in terms of going from the state-level estimates to the final district-level estimates. In the non-irrigated haying CBV, the state-level non-irrigated hay yield was converted directly to a district-level yield estimate using the "district-state" conversion factor (derived from the NRCS HPM). Then, the district yields are multiplied with the state-level price estimates to get a non-irrigated CBV at the district level. On the other hand, for the grazing CBV, the state-level grazing yields and state-level "blended" grazing prices are first multiplied to get an initial state-level grazing CBV. A "county-state" conversion factor (also from NRCS HPM) is used to convert this estimate to a county-level CBV and then an average across counties within a district is used to generate a district-level CBV. For consistency in procedures, we suggest that the "conversion methods" used to derive a district-level CBV for non-irrigated hay and grazing be made consistent with each other. Perhaps the decision on which conversion procedure to use for both non-irrigated haying and grazing will depend on which "conversion factor" is deemed more accurate (either the district-state or county-state). Note that the "factor" used in calculating the non-irrigated hay CBV is a "district-state" factor, while for the grazing CBV it is a "county-state" factor. In addition, for the grazing CBV, the county-level CBVs are aggregated up to the district-level (using county area as weights) to get a district-level grazing

CBV. This aggregation was not undertaken in the non-irrigated hay CBV. The difference in the "factors" used and the aggregation step for the grazing CBV would likely matter in this case. Nonetheless, our point is to simply re-evaluate these steps and perhaps make the calculations for non-irrigated haying CBV and grazing CBV more consistent with each other. One approach to make both calculations consistent is to use the same "district-state" factor in the yield calculation step of the grazing CBV calculation procedure. Alternatively, the "county-state" factor (plus aggregation to the district) can be used in the last few steps of the non-irrigated haying CBV calculation. The choice depends on which "factor" is more reliable and accurate.

Adjusting the productivity factor limits given the CBV calculation improvements?

The PRF insurance contract includes an option where producers can choose a "productivity factor" (PF) between 0.60 and 1.50, which enables them to adjust the CBV up or down to make it more commensurate with their circumstances. This provides some flexibility to adjust the insurable value (i.e., insured liability) since the CBV value is estimated at a higher geographical aggregation (e.g., at the agricultural-district-level for grazing CBV), which does not necessarily coincide with individual farmer CBVs. The productivity factor is largely considered a "correction factor" to overcome the inherent limitations of the estimated CBV and allow the insureds to adjust the policy CBV estimates to make it coincide with their individual CBV. To some degree, it also allows PRF producers to adjust their liability commensurate to their basis risk (i.e., make it such a way that basis risk is minimized). For example, insureds can increase their individual CBV value if they think productivity (or yield) of their land is higher than the productivity (or yield) implied by the more aggregate CBV value offered in the PRF policy (or vice-versa).

However, even if this is the intent behind the productivity factor theoretically, in practice most PRF producers simply pick higher PRF levels (e.g., at the state-level, PF averages are often above 1.0 and very seldom below; See Agralytica, 2014, p. 110-111).[2] This behavior of picking the highest PFs is consistent with maximizing returns to insurance rather than the risk minimization objective of the PRF offering (See Goodrich et al. 2019; Cho and Brorsen, 2019).[3] A recent USDA-OIG report (USDA-OIG, 2019, p. 10-12) provided examples where insureds were able to pick the 150% productivity factor even if the productivity of the land based on NRCS data suggests that average productivity/yields in the insured land are substantially lower than the implied productivity/yields from the CBV.

[2] Note that the Agralytica (2014) report indicate that agents and producers generally like the flexibility afforded by the current PF levels to tailor the coverage to their individual productivities and premiums they are comfortable paying. Agralytica (2014) even suggested increasing the PFs above 150% in some locations, given the belief that most of the CBV values at that time are inaccurate (and likely underestimated). But it should be noted that CBV calculation methodologies have improved since 2014, and are likely more accurate than six years ago.

[3] In their analysis, Cho and Brorsen (2019) points out that lower PF choices are more "optimal" in a risk minimization framework as compared to an insurance return maximization framework.

Nonetheless, with improvements in the CBV calculations over the last five years (that improves accuracy and precision) and implementation of the minimum grazing CBV above, we believe that it is appropriate to reduce the range of available productivity factors in the PRF insurance offering. Similar area-based insurance plans offered by RMA that triggers on a county-yield “index”, such as the Area Risk Protection Insurance (ARPI), only have a productivity range between 0.8 and 1.2 (as compared to the 0.6 to 1.5 range in PRF). Hence, for consistency across index-based RMA product offerings and to align better with risk minimization behavior, we suggest narrowing the productivity factor to the 0.8 to 1.2 range.

If the narrowing of the PRF range is implemented, it is important to monitor the effects and performance of the program from this change. First, as in the Agralytica (2014) report, it is important to continually examine the productivity choices of insured PRF growers. This analysis will give insight into whether it is still the case that most producers pick the higher coverage levels (around 1.2 or above) and not coverage levels below 0.9 (i.e., suggesting the appropriateness of increasing the lower limit to 0.8). Frequent analysis and monitoring of the impact of narrowing the productivity factor range on liability, premiums, and indemnity levels would also be valuable (especially in conjunction with the other recommendations in this report – setting a minimum grazing CBV, lowering coverage levels available, etc.). There may be a concern that reducing the maximum PF limit may result in “drastic” increases in insured PRF acres. To address this issue, one can monitor and statistically estimate the relationship of PF choice and insured acres using the policy-level administrative data. This type of recurring analysis can give an insight into whether insured PRF growers increase insured acres when picking lower productivity factor levels. Even if RMA data on “insured PRF acres” is not a perfect measure of the total acres the producer has access to, the recommended analysis here would still provide some inferences of whether farmers that choose low productivity factors to increase the PRF acres insured.

Second, for each county where PRF is offered, it would be useful to continually monitor and compare the implied yields (or productivity) from the NRCS productivity model or the US Forest Service RVS model (or other models) vis-à-vis the yields used in the CBV calculations. In particular, the estimated yields used to calculate the non-irrigated haying and grazing CBVs for each county compared to the NRCS model yields). This exercise will help determine and avoid situations illustrated in the USDA-OIG (2014) report where implied productivity of the insured land based on the PRF contract choices of the grower (e.g., 150% productivity factor, etc.) is substantially higher than what the NRCS data (or other sources) indicate. In particular, one can also determine whether the estimated yields from productivity models are consistent with the implied yields used in calculating CBVs (and maintaining program integrity). In conclusion, we believe that narrowing the productivity factor range offered in PRF is appropriate at this time, and continual monitoring of the effects of this recommendation is advisable.

Main CBV Recommendations

Validating the HPM productivity factors against alternative models

Recommendation: The U.S. Forest Service's "Rangeland Vegetation Simulator" can serve as an alternative data source to validate the productivity values generated from the NRCS HPM. Comparisons of the resulting CBV values from the RVS vis-à-vis the NRCS HPM can be conducted to see if there are any large discrepancies in the estimates. *In the end, exploring an alternative source for productivity values can help improve the robustness of the CBV estimates.*

Modification of the County Based Value (CBV)

Currently, there is no set minimum value for the district-level grazing CBVs used in the PRF contract. Therefore, it is possible for the district-level grazing CBV (used for a particular county) to be lower than the estimated NASS county-level pasture rental rate. Newton (2018), for example, has shown that there are cases in South Dakota where 2019 CBVs were up to 46 percent lower than NASS state-level pastureland rent in 2018. *Based on research cited in our exploration of the CBV, we recommend RMA apply a minimum CBV value that is equal to a county-level or state-level measure of pastureland cash rent (perhaps in a previous year or based on historical average). Applying this minimum (in conjunction with the other changes recommended in this report) may improve the risk mitigation benefits from the PRF product.*

We also recommend that the grazing CBV be partitioned to differentiate improved pasture (or pastureland) from unmanaged rangeland. To qualify as pastureland, evidence of fertilization and/or lime, seeding, weed control, or other pasture improvements would be required to receive a higher CBV for pastureland relative to rangeland. A producer would be required to self-certify that their land is pastureland or rangeland. Verification of pastureland would include input records showing "Management" of the land. A distinction between rangeland and pastureland CBV would more accurately reflect productivity. Evidence of cultural practices such as fertilization, weed control, and reseeding generally result in greater forage production and animal carrying capacity.

The productivity differential estimates from the papers reviewed above (See section above titled "Rangeland and Pastureland CBV differences") indicate that a rangeland-pastureland factor in the range of 60%-70% is justifiable as a "conservative" measure (especially in the Western States where there is a good mixture of unmanaged rangelands and managed pastureland). Hence, the State-level grazing CBV yield estimate can be adjusted downward by 30%-40% for insureds that self-select and say that their PRF-insured land is unmanaged rangeland.[4] On the other hand, the State-level grazing CBV yield estimate can be adjusted upward by 30%-40% for insured that self-selects and say that their PRF-insured land is managed pastureland.

Notwithstanding these recommendations for adjusting the State-level grazing yield in the grazing CBV calculations, the recommendation in this report of using a minimum grazing CBV value based on pastureland rents should still serve as the "floor" on the calculated CBV. That is, if the resulting district-level CBV with the downward adjustment (due to using unmanaged rangeland) is lower than the minimum CBV based on pastureland rental rates, then the minimum CBV based on pastureland rental rates will be the one that is applicable.

Adjusting the CBV Productivity Range

With improvements in the CB/V calculations over the last five years (that improves accuracy and precision) and implementation of the minimum grazing CBV above, we believe that it is appropriate to reduce the range of available productivity factors in the PRF insurance offering. Similar area-based insurance plans offered by RMA that triggers on a county-yield "index", such as the Area Risk Protection Insurance (ARPI), only have a productivity range between 0.8 and 1.2 (as compared to the 0.6 to 1.5 range in PRF). *Hence, for consistency across index-based RMA product offerings and to align better with risk minimization behavior, we suggest narrowing the productivity factor to the 0.8 to 1.2 range.*

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Chapter 3 Task 2: A review of the methodology used for the PRF rainfall index and premium rates.

Pasture and Rangeland Literature Review

This section of the report provides a review of scientific literature related to the pasture and rangeland insurance product. We begin with the origins of index insurance and then the rating of index insurance and then demand for index insurance. We conclude with a discussion of recent advances in index insurance.

Origins of index insurance

The scholarly literature on index insurance has grown tremendously over the past 20 years. A complete review of that literature would be beyond the scope of this report. Instead, we will describe some of the seminal work on index insurance and then review more recent work of particular relevance to the PRF insurance product.

Index insurance products can generally be classified into two broad categories: *products based on indexes that measure aggregate losses* over a group (e.g. Area Yield Protection, AYP or Area Revenue Protection, ARP) and *products based on indexes that are believed to be highly correlated with losses* (e.g., Pasture, Rangeland and Forage, PRF). With the former category, an index of group losses within a defined geographic region serves as a proxy for the losses of individual members of the group. The index must be based on data aggregated over a large enough scale that an individual policyholder cannot significantly influence the realized value of the index and hence, the indemnity. With the latter category, the variable on which the index is based (often, a measure of weather events) serves as an indicator or predictor of policyholders' realized losses (Murphy et al., 2011).

Why would an insurer offer index insurance instead of traditional, loss-based insurance? In many respects, traditional insurance is the most straightforward way to offer insurance protection because indemnities are based directly on the measurable losses experienced by the policyholder. But this direct connection between the loss experienced by the policyholder and the indemnity received can also create challenges. In some cases (e.g., pasture and forage), it is extremely difficult to measure the actual loss that has occurred. Other advantages of index insurance relative to loss-based insurance include less exposure to moral hazard and adverse selection and lower operational costs (since there is no need for policy-specific underwriting or on-farm loss adjustment).

The widely recognized limitation of index insurance products is that policyholders are exposed to basis risk. Technically, basis risk is the variance of the conditional distribution of the policyholder's losses given a specific value of the index. Since sufficient data are generally not available to estimate this conditional distribution, practitioners tend to measure basis risk as to the linear correlation (or covariance) between the index and a policyholder's losses. However, the simple historical correlation between the index and losses may fail to accurately assess basis risk because the dependence may not be linear (Collier, Barnett, and Skees 2011). Practically, basis risk implies that a policyholder can receive an indemnity that is either greater than or less than the actual realized loss. It is even possible that the policyholder will suffer a loss and not receive any indemnity. Likewise, the policyholder may receive an indemnity without incurring any loss.

Perhaps the earliest scholarly discussion of agricultural index insurance was Halcrow's 1949 article on area yield insurance published in the *Journal of Farm Economics*. Though Sweden introduced an area yield insurance program in 1961 and Quebec did the same in 1977, Halcrow's insight received little attention in the United States until it was revived in a 1991 article by Mario Miranda in the *American Journal of Agricultural Economics.* Using a Capital Asset Pricing Model (CAPM) conceptual framework, Miranda described how an area yield insurance program could provide risk protection for agricultural producers. Then, using yield data from west Kentucky soybean producers, Miranda provided empirical evidence of the efficacy of an area yield insurance product.

The RMA first facilitated an index insurance offer in 1993. The product was an area yield insurance product (then known as the Group Risk Plan, GRP) for soybeans in selected states. In 1994, Congress mandated that GRP be expanded "to the extent practicable." The product design and premium rating for GRP were described in Skees, Black, and Barnett (1997). An area revenue insurance product (then known as Group Risk Income Protection, GRIP) was first offered in 1999.

Various studies have examined the empirical effectiveness of area yield or revenue insurance products. Some of the seminal studies were Hourigan, 1992; Smith, Chouinard, and Baquet, 1994; Wang et al., 1998; Black, Barnett, and Hu, 1999; Barnett et al., 2005; and Deng, Barnett, and Vedenov, 2007. The findings from these studies have generally been that area yield insurance products can provide effective risk protection for many, but not all, crop producers. However, it is difficult for an area yield insurance product to compete with a highly-subsidized insurance product that makes payments based on farm-level losses.

Over time, interest in agricultural applications of index insurance spread beyond products based on indexes that measure aggregate losses over a group to include products based on weather indexes that are believed to be highly correlated with losses. In 1988, George Patrick published an article in the *Australian Journal of Agricultural Economics* proposing rainfall insurance for wheat farmers in Australia. Skees and Zeuli (1999) proposed rainfall insurance products for Australian irrigation water management districts. Others proposed rainfall insurance to protect against agricultural losses in India (Hazell, 1992; Gautam, Hazell, and Alderman, 1994), Burkina Faso (Sakurai and Reardon, 1997), and Nicaragua (Miranda and

Vedenov, 2001). Weather index insurance products were made available to crop producers in India in 2003.

In its most basic form, weather index insurance makes indemnity payments based on realizations of a specific weather variable (e.g., rainfall or temperature) over a defined period. The weather variable may be measured at a specific weather station or by other means (e.g., satellite). The policy will typically specify a threshold and a limit that establish the range of index values over which indemnity payments will be made. For an insurance policy that protects against unusually high realizations of the weather variable (e.g., excess rainfall or extremely hot temperatures), an indemnity is paid whenever the realized value of the index exceeds the threshold. The limit defines the level of the index beyond which no additional indemnity payments will be made. If the policy is protecting against unusually low realizations of the weather variable (e.g., drought or extremely cold temperatures) an indemnity is made whenever the realized value of the index is less than the threshold with the limit set lower than the threshold (Barnett and Mahul, 2007).

Two seminal articles regarding agricultural applications of weather index insurance were Martin, Barnett, and Coble's 2001 article titled "Developing and Pricing Precipitation Insurance" in the *Journal of Agricultural and Resource Economics* and Turvey's 2001 article titled "Weather Derivatives for Specific Event Risks in Agriculture" in the *Review of Agricultural Economics*. After describing the design and pricing of a rainfall index insurance product, Martin, Barnett, and Coble demonstrated how such a product could be used to protect against the risk of excessive rainfall before and during cotton harvest in the mid-South region of the United States. Turvey, likewise described the design and pricing of weather index insurance products for extreme rainfall or extreme temperature events. Turvey then demonstrated the efficacy of weather index insurance to protect against corn, soybean, and hay yield losses in Ontario.

Other early articles on weather index insurance include Mahul's 2001 article on factors that impact the optimal choice for various contract parameters, van Asseldonk's 2003 article evaluating agricultural applications of temperature-based weather index insurance in the Netherlands, and Vedenov and Barnett's 2004 article analyzing the efficiency of weather index insurance to insure corn, cotton, and soybeans in six U.S. crop reporting districts. A common in empirical studies was that the risk-reducing performance of weather index insurance varied widely across crops and regions. In one of the first studies to extend beyond crop production, Deng et al. (2007) analyzed the potential for insurance based on a temperature-humidity index to protect against dairy production shortfalls in the southern U.S.

Much of the literature on weather-based index insurance has focused on lower-income countries. Economists have long recognized that high transaction costs relative to the amount of insurance liability make traditional loss-based agricultural insurance products unworkable in most lower-income countries. Area yield index insurance is also often not possible due to limited availability or reliability of official yield data aggregated to a regional level. Since weather data are available for many lower-income countries from either ground-based weather stations or satellite platforms, weather index insurance is often viewed as a potentially viable insurance alternative.

The literature on agricultural applications of weather index insurance in lower-income countries is far too extensive to review here. The following are among the earliest studies in this area: Skees 1999; Skees, Hazell, and Miranda 1999; Skees 2000; Skees et al. 2001; Hess, Richter, and Stoppa 2002; Varangis, Skees, and Barnett 2002; Skees and Enkh-Amgalan 2002; Skees, et al. 2005; Hess et al. 2005; Lilleor et al. 2005; Skees, Hartell, and Hao 2006; Hazell and Skees 2006; Kazianga and Udry 2006; Gine´, Townsend, and Vickery 2007; J. Skees, Hartell, and Murphy 2007; Chantarat et al. 2007; and, Shynkarenko 2007. A common finding in these and subsequent studies is that for some crops in some regions, a carefully constructed weather index insurance product can provide significant risk reduction. Nevertheless, absent large subsidies, uptake of weather index insurance at the farm level has been quite limited. Collier, Barnett, and Skees (2011) is a good resource for information on the data required to develop and price weather index insurance while Murphy et al. (2011) describe the challenges associated with scaling up weather index insurance offers in lower-income countries.

Rating PRF insurance

The current RMA premium rating methodology for the PRF product is described in the following documents: (a) the original developer rating methodology document (RMA, 2005), and (b) the PRF review conducted by Agralytica (Agralytica, 2014). A PRF premium rate is calculated for each grid, interval, and coverage level available to be insured (e.g., over 400,000 unique rates for the rainfall index-based PRF annually). Rainfall index data are available from 1948 onwards and serves as the basis for the premium rate calculation.

The premium rate for each insurable unit is essentially based on a burn rate (BR) approach, which is simply the average loss over all historical values of the rainfall index (i.e., where the "loss" is just defined as the difference between the actual rainfall index amount and the "trigger" index level if index < trigger, zero otherwise). Though the BR method serves as the foundation for PRF ratemaking, several parametric distribution-based approaches are also utilized (e.g, truncated normal (TN), Black-Scholes (BS), and Gram-Charlier (GC) approaches) to supplement rates derived from the BR method. Specifically, rates from these distribution-based methods are used to generate upper and lower bounds on the BR-based raw rates (e.g., if BR is less than the minimum value from TN, BS, or GC, the smallest minimum value among the three distribution-based methods will be used; the same logic applies for the maximum). Additional smoothing and catastrophic loading procedures are then implemented to calculate the final rates.

The literature related to the rating of rainfall-index-based pasture insurance products has been limited. However, note that Agralytica (2014) carefully reviewed the rating methodology for the PRF product offered by RMA and found that the rating methods used for the rainfall-index-based coverage in PRF were generally appropriate (Agralytica, 2014 p. 102), though the report provided some minor suggestions that can potentially improve rating performance (e.g., eliminate smoothing and use Limited Expected Value Function rather the BS formulas). The Agralytica report also expressed concerns about the high frequency of indemnity payments for the PRF program.

Outside of the aforementioned Agralytica (2014) report, we only found one paper that specifically touches on rating issues for rainfall index (RI) based pasture insurance coverage – Nadolnyak and Vedenov (2013). Nadolnyak and Vedenov (2013) specifically examine the implications of utilizing information on El Nino-Southern Oscillation (ENSO) forecasts in the PRF premium rating process. They find that not using ENSO forecast information in the rating process can result in intertemporal adverse selection when this ENSO information is used by insureds in their participation decisions (i.e., purchasing more coverage when expected payouts are high (based on ENSO information), purchasing less coverage when expected payouts are low). Therefore, Nadolnyak and Vedenov (2013) recommend calculating an ENSO "forecast-conditioned" premium for the PRF insurance product, especially for areas nearer the coast (i.e., particularly the Gulf Coast, given that the study focused on the Southeastern US as the empirical application).

Most of the published studies that consider rating methodologies for a rainfall-index-based insurance product do not specifically focus on the pasture and rangeland case and cover a wide variety of crops and contexts. As already mentioned in previous sub-sections of this review, an example is the work of Martin et al. (2001), which describes the design and pricing of a rainfall insurance product to protect against the risk of excessive rainfall for US cotton. Other general rainfall-index insurance articles that describe a variety of rating approaches include (among others): Turvey (2001) for several crops in Canada, Vedenov and Barrett (2004) for a variety of US commodity crops, Deng et al. (2007) for US dairy, Chen et al. (2017) for corn in China, Zhou et al. (2018) for US corn, and Muna et al. (2019) for rice in Indonesia. Rating methodologies developed or utilized in these studies range from using copulas, parametric distribution models (e.g., Gamma), nonparametric methods (e.g., burn rate), mixture models, and combinations of various approaches (where the approach largely depends on data availability).

Demand for PRF insurance

The demand for crop insurance has a lengthy history. In the modern era, this research was often predicated on understanding why farmers were not purchasing subsidized individual coverage yield insurance. Goodwin (1993), Smith and Baquet (1996), and Coble et al. (1996) are early examples of this work. Most of this work found an inelastic demand for insurance and some evidence of producers and RMA having differing perceptions of risk. As crop revenue insurance became more popular after 1996, researchers turned to understand the demand for this new form of crop insurance. Shaik et al. is an example of this literature.

Many of the development papers confirm the basis risk problem (Barnett and Mahul (2007). Jensen, Barrett, and Mude (2016) examine the limited acceptance of livestock index insurance in a development context. In particular, they focus on direct measurements of basis risk. They used longitudinal household data to determine which factors affected the demand for index-based livestock insurance. They find that while both price and the non-price factors studied previously are important, basis risk and spatiotemporal adverse selection also play a major role in determining demand. Kost et al (2012) note that in variable topography regions, basis risk is likely more problematic. Elabed, and Carter (2015) note the basis risk problem of index insurance and investigate compound-risk aversion, and ambiguity on the willingness to pay for index insurance. They note that an index insurance contract appears to the farmer as a compound lottery, with uncertainty about individual production outcomes, as well as about the validity of the index as a reflection of individual losses. They show that this compound lottery structure reduces the demand for index insurance. Field experiments with cotton farmers in Southern Mali found that almost 60 percent of farmers are compound-risk averse and that the distribution of compound-risk aversion is such that it would nearly cut in half the potential demand for the standard index insurance contracts.

Norton et al. (2014) investigated the demand for differing coverage levels of index insurance. They used experimental games with smallholder farmers in Ethiopia. Participants in the games allocated money across risk management options including index insurance. Participants preferred insurance contracts with higher frequency payouts and insurance over other risk management options, including high-interest savings. The authors argue the preference for higher frequency payouts affects commercial sales. Wang et al. (2020) examine coverage levels and other attributes. They use a labeled choice experiment method to investigate Chinese smallholder corn growers' preferences for alternative insurance designs. In addition to traditional yield insurance, they examine farmers' willingness to pay for coverage levels in price, revenue, and weather index insurance, which are currently at the experimental stage in China. They found farmer preferences for these various types of insurance to be heterogeneous. On average, farmers are willing to pay for all types of insurance and for additional coverage but only at the current high subsidy level. They explore heterogeneity in willingness to pay and find that farmers' positive past insurance experience plays an important role in their demand for insurance.

Liu et al. (2019) estimate farmers' willingness to pay (WTP) for a hypothetical excess rainfall index insurance contract. In particular, they examine whether recent experience with catastrophic flooding influences farmers' attitudes towards the insurance product. They find that farmers from flooded areas have a higher WTP for index insurance than farmers from non-flooded areas.

Several studies have noted non-economic factors influencing index insurance demand. Porth, et al. (2015) attempt to explain the factors affecting farmers' willingness to purchase weather index insurance for crops in China, in the Province of Hainan. They conduct a survey of 134 farmers in Hainan, China, regarding their willingness to purchase weather index insurance. The results show that trust of the insurance company is among the significant factors that affect the willingness of farmers to purchase weather insurance. Patt et al. (2009) have a similar conclusion that the trust that people have in the insurance product and the organizations involved in selling and managing it strongly affects demand. They argue that data from India, Africa, and South America show that these factors may be more important than the economic factors in influencing demand. Gaurav, Cole, and Tobacman (2011) focused on farmer education and the demand for rainfall insurance in India. They specifically researched the implication of financial literacy as a determinate of insurance demand. The authors found that financial education has a positive and significant effect on rainfall insurance adoption, increasing take-up from 8 percent to 16 percent. Also, a money-back guarantee has a consistent and large effect on farmers' purchase decisions.

Ifft, Wu, and Kuethe (2014) examined the impact of publicly supported insurance on agricultural land values. Implicitly this analysis relates to the demand for subsidized insurance. The analysis employs confidential, nationally representative panel data on field-level pastureland values and exploits a natural experiment provided by gradual introduction of the Pasture, Rangeland, and Forage Insurance Pilot Program. They use a field-level fixed-effects model that controls for several time-variant factors and find that insurance availability is associated with an increase of at least 4 percent in pastureland values. This increase is comparable with increases generated by other government programs but is much smaller than the total farmland value increases experienced in recent years.

The study most directly applicable to the U.S. PRF program is likely that of Goodrich, Yo, and Vandeveer (2019). These authors specifically examine PRF participation in Kansas and Nebraska from 2013 to 2017. They pay particular attention to the intervals chosen by purchasers of the PRF product. They note many producers purchase insurance that provides coverage outside the forage growing season. Empirically this behavior appears to be growing over time. Conceptually, the authors note that because the subsidy rate is equal across all 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). The authors conceptualize purchase in non-growing periods may be attributed to a less risk-averse preference. However, they suggest that premium subsidies and producer returns associated with non-growing season months are often greater than those for growing season months. The authors also conclude crop insurance agents may be suggesting strategies for participants to maximize the chance of receiving an indemnity by placing some of their liability into non-growing season months.

Advances in index insurance since 2010

As mentioned in the first section of this literature review, there has been tremendous growth in the number of studies on agricultural index insurance over the last twenty years. Review articles by Miranda and Farrin (2012), Carter et al. (2014), Di Marcantonio and Kayitakire (2017), and Jensen and Barrett (2017) have all carefully summarized advances in the extant literature on agricultural index insurance, examined experience with agricultural index insurance in various countries, and identified lessons learned and challenges for the future. But note that these articles primarily focused on experience with agricultural index insurance in developing countries (though some of the general issues discussed apply to a developed country context as well). In general, these review articles pointed out that agricultural index insurance has great potential as a risk transfer mechanism for poor agricultural households in developing countries. However, a common observation is that the "track records" of these agricultural index insurance offerings have largely been disappointing. Each of these review papers then goes on to discuss the potential problems (or issues) that have likely caused these disappointing results in developing countries and make suggestions on how these issues can be addressed. Recommendations for future actions and research agendas to improve the performance of agricultural index insurance in developing countries are discussed.

Most of the aforementioned review articles divide the issues affecting the disappointing performance of agricultural index insurance in developing countries into the demand-side and supply-side factors. The demand-side factors frequently mentioned are: premium affordability, lack of trust in insurance providers, financial literacy of target households (linked to poverty levels), cognitive and behavioral issues (e.g., ambiguity aversion, compound risk aversion), and general low willingness to pay (or demand) for these products. For this report, the more pertinent lessons from these review papers may be the supply-side factors that have influenced the performance of index insurance programs in developing countries. The most common supply-side issues mentioned are: basis risk (and related quality of index design issues), lack of quality data, institutional and government support issues (i.e., lack of enabling environments, delivery mechanisms, regulatory mechanisms, etc.), and issues with reinsurance markets (e.g., reinsurance charging high uncertainty premiums, driving up index insurance premiums).

As would be expected, all of the review articles cited above overwhelmingly raised the supply-side issue of basis risk (as related to the quality of the product design) and discussed ideas that may help reduce it. Dalhaus and Finger (2016) categorize basis risk into three components: spatial, temporal, and design. Spatial basis risk occurs when the index is not measured at the same location as the underlying insured crop is situated. This, for example, occurs when indices are based on measurements from remote weather station(s) far from the insured crop. Temporal basis risk emerges due to a biased temporal aggregation of observations, mainly because observations are aggregated into months (or seasons or years), while the risk vulnerability of plants is more related to plant phenological phases (Conradt et al., 2015; Dalhaus et al., 2018). Design basis risk is present when the chosen underlying index is not a good approximation of the underlying sources of yield or revenue variability. Given these basis risk categories, much of the recommendations put forth by the review articles mentioned above try to address some aspect of these basis risk types.

Carter et al. (2014) suggest that solutions that can minimize basis risk can be classified as technological, contractual, and institutional. Much of the technological solutions involve the collection and use of better quality data that can further reduce spatial, temporal, and design risks. Technological suggestions in this vein include the use of indices with finer resolutions (e.g., gridding, spatial interpolation, etc.), use of more advanced satellite and remote sensing images (as the primary or a complementary index), and use of mobile weather stations (to increase coverage). Satellite and remote sensing data are viewed as potential paths to reduce spatial basis risk (e.g., better spatial coverage), temporal basis risk (e.g., better coincide index to the timing of loss), and design basis risk (e.g., may better correlate with actual losses). But note that empirical evidence as to the performance of these satellite or remote sensing-based index insurance designs is still lacking. Some contractual solutions suggested by Carter et al. (2014) include the use of secondary, backup, or audit indices (or triggers). The use of index insurance at higher levels of aggregations (e.g., meso-level index insurance for cooperatives) has also been recommended.

Contractual changes that better match the time window of actual crop losses to the time window for the index offering have also been shown to improve temporal basis risk. For example, Conradt et al. (2015), Dalhaus and Finger, 2016, and Dalhaus et al., 2018 have shown that index insurance contracts that are more closely tied to the phenological growth phases of the underlying cash crop being insured are better able to insure losses (more on this below as it relates to PRF). Lastly, institutional solutions include efforts to develop institutions (governmental or otherwise) to improve quality standards for index insurance offerings, better targeting of initial pilot sites, better design of subsidies (e.g., smart subsidies), support of informational and educational efforts, bundling index insurance offerings with credit (or other financial instruments), and further research on the impacts of index insurance (as well as behavior towards risk and insurance). Another common recommendation is to conduct research that measures basis risk for particular index products offered, which involves the collection of farm-level yield/loss data in index coverage areas to assess the performance of these products.

Even though there is a robust literature on agricultural index insurance and there are several review articles that have summarized advances and identified limitations/challenges, studies that specifically focused on index insurance for pasture, rangeland, and forage (PRF) (or so-called grassland-based agricultural systems) have been limited. Nonetheless, the review article by Vroege et al. (2019) provides an important discussion of advances and challenges with regards to index insurance for PRF in the US and Europe. First, Vroege et al. (2019) find that three different insurance types exist in the US and Europe: area-yield-based (like Area Risk Protection Insurance (ARPI) in the US), weather-index-based, and satellite-imagery-based. They find that the single weather-index-based types are the predominant type offered for PRF coverage. Second, Vroege et al. (2019) point to the potential of using advances in satellite and remote sensing technologies in developing PRF index insurance products. The article noted that indices based on satellite or remote sensing measures related to yields and the plant growth environment have the potential for innovative index insurance designs.

Recent studies by Bacchini and Miguez (2015) in Argentina, Roumiguie et al. (2017) in France, and Jensen et al. (2019) in Kenya also largely point to the potential effectiveness of offering satellite-based index insurance contracts. In particular, a recent paper on the PRF design in the US by Williams and Travis (2019) find that a PRF index insurance offering based on a drought index performs better than when a rainfall index is used (as is currently done). Williams and Travis (2019, p. 629) further suggest that "drought indices have a higher correlation with range production, a tendency to incentivize growing-season protection, more even geographic distribution of risk, reduced policyholder ability to seek higher payments through strategic coverage choices, and increased provider ability to adjust payment patterns to reduce the risk of nonpayment given loss."

However, Vroege et al. (2019) still note that past index insurance offerings based on satellite images of the normalized difference vegetation index (NDVI) have had limited success. Thus, Vroege et al (2019) recommend further study and development of a satellite-based index design that: (a) has an area-yield format using alternative satellite measures of vegetative growth (e.g., more transparent measures than NDVI such as the Forage Production Index (FPI) in France that measures the fraction of the ground covered by grass), (b) has an area-yield format that uses imagery to supplement index construction, (c) uses a satellite-imagery-based weather index (rather than a satellite-based measure of the vegetation itself like NDVI), and (d) has a double-trigger approach where the trigger is based on satellite imagery vegetation and/or weather measures. Even with these recommendations, however, the authors point out that the use of more complex indices that can reduce basis risk may result in reduced transparency and possibly increased moral hazard (e.g., this tradeoff exists especially for vegetative indexes of high resolution).

The Vroege et al. (2019) paper also highlighted better matching of phenological growth stages of the underlying crop to the structure of the index insurance window(s) as another potential avenue for reducing basis risk (specifically, temporal basis risk) and improving the performance of agricultural index insurance. As already alluded to above, Conradt et al. (2015), Dalhaus and Finger (2016), and Dalhaus et al. (2018) have shown that index insurance contracts that are more closely tied to the phenological growth phases of the underlying cash crop being insured can reduce temporal basis risk and perform better (e.g., better downside risk protection).

Since Yu et al. (2019) find that spatial basis risk for PRF in Kansas and Nebraska is likely less important relative to temporal and design basis risks, further improvements in PRF contract structure in terms of more closely tying the PRF contract design to the most vulnerable PRF growth phases may help improve performance. Note that in the current PRF design, insureds can choose to insure at least two fixed two-month intervals (as long as they are not adjacent) and can assign coverage levels and liability weights on each period insured. However, Belasco and Hungerford (2018) find that in the US Mountain West region producer selections of time intervals are spread fairly evenly throughout the year, despite rainfall during late spring and early summer being the most critical to grass growth in this region. Many producers choose to insure during the winter months despite little evidence that forage production is impacted by snowpack (Frank, 1973). In a study that explores optimal interval choice for PRF in South Dakota, Diersen et al. (2015) suggest that the most risk efficient intervals are May-June and July-August and these choices are most consistent with the desire to have payments that offset the highest expected forage risk. Westerhold et al. (2018) also find that intervals that coincide with the actual growing season in Nebraska are the ones where PRF provides the largest risk reductions. This study recommended dropping intervals in the PRF contract that do not coincide with the growing season since these intervals tend to be used as an income maximizing strategy rather than for risk reduction. Maples et al. (2016), in a study of the Rainfall Index Annual Forage pilot program (RIAFP), which is similar in structure to the PRF offering, find that the rainfall index used has a high correlation with actual rainfall, but does not correlate very well with actual forage yields in their data (e.g., design basis risk). Maples et al. (2016, p. 47) also suggest that the performance of RIAFP may improve by including intervals that closely match the time of production. In general, these studies seem to suggest that there may be merit to exploring PRF contract design modifications with regards to PRF intervals (e.g., intervals offered, interval lengths, interval availability, interval weight limits, and available interval coverage level choices) being more closely matched to the region-specific growing season (or phenological growth states). Modifications here may also help address concerns about the frequency of "shallow" PRF payments across different intervals.

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Chapter 4 Review and analyze the methods used in the development of the expected rainfall amount

Discussion of Data

The PRF product bases coverage on recorded precipitation made across an extensive network of weather stations. The specific source for the accumulated rainfall data used to construct the rainfall index is the National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (CPC). These data are available back to 1948 and consist of spatially smoothed and interpolated measures of monthly rainfall. These data are smoothed to provide a resolution of 0.25 degrees, which is approximately 28 square kilometers. The CPC data only report precipitation and do not consider other weather variables that may also be relevant to the condition of pasture, rangeland, and forage.

In a separate department of NOAA, the National Climate Data Center, a similar gridded set of data is available. These data also include temperature (monthly high, low, and average) and report data back to 1895. The NCDC data are available on a much finer grid, providing measures at the 1/24th degree level of resolution (about a 4 square kilometer grid). Thus, the resolution of the NCDC data is about 36 times greater than that of the CPC. Discussions with the NOAA scientist in charge of providing the NCDC data, Russell Vose, indicated that the two alternative sources of weather data are largely independent and are constructed by different teams using different smoothing algorithms. Concerns have been raised as to the timeliness of the NCDC data (i.e., the time lag associated with providing near real-time weather observations) and the extent to which the climate data may be subject to retrospective revisions. We do not believe that such concerns necessarily present any legitimate barriers to basing coverage on the NCDC data.[5]

Finally, other suitable weather data sets are publicly available and could be used to develop rates and terms of coverage for PRF. NOAA produces a couple of data sets that are in addition to those noted above. Primarily, the PRISM data are synthesized from NOAA's station-level data and are available from Oregon State University. These data are essentially analogous to the NCDC data. The data are also provided on a 4 square kilometer grid and include precipitation, minimum temperature, maximum temperature, and average temperature. Station-level data, such as NOAA's NCEI (National Centers for Environmental Information) data, also offer detailed data on a worldwide range of climate

[5] In an email exchange, Dr. Vose reported that the NCDC data are released on the first day into the month subsequent to the observations to coincide with the monthly Climate Report. He also indicated that the data are typically not subject to revisions once released.

variables. Station data could certainly be interpolated as is the case for the existing CPC and NCDC data and therefore used to form a grid. However, we see no utility in repeating the spatial smoothing used by NOAA to grid the NCDC and CPC data for the station-level data.

In a fashion similar to that considered for the NCDC data, we aggregated the PRISM precipitation data and undertook a comparison to the CPC data currently in use. A comparison of the CPC and aggregated PRISM data are presented below. The comparison indicates that, again, similar differences in the alternative measures of precipitation are apparent. The degree of difference appears to be slightly higher in the case of the PRISM data, though both diagrams indicate substantial differences, even in very dry or very wet conditions. Finally, we directly compared similarly aggregated CPC and PRISM data.

The differences in precipitation measurements obtained from the alternative sources have been noted in the literature. Gao et al. (2017) compared the NCDC, PRISM, and data consolidated from the NEXRAD weather monitoring system.[6] Figure 4-7 reproduces a diagram from their paper that demonstrates the differences observed in a comparison of NEXRAD and PRISM data.

We see no reason to necessarily prefer one data source over another. Absent any "ground-truthing" that would be made by comparing to actual precipitation, there is no tangible way to compare one data set to another. The advantages of PRISM and NCDC data include a finer (4km) grid and a much longer history. Further, these two data sets contain additional climate variables, including temperature extremes. If, at some point in the future, an index that considers both temperature and precipitation could be constructed, the alternative NCDC data might offer advantages. This would require the construction of an index that accurately specifies the relationship between forage output, heat, and precipitation. We considered state-level yield and price data to evaluate the relationship between heat, precipitation, and hay yields. Likely because of the very aggregate nature of the NASS yield data (at the state level), we were unable to adequately define an index that relates both temperature and precipitation to hay yields, even though the relevant literature has determined that both variables are relevant to hay yields.

One alternative to incorporating temperature into the PRF coverage would be to establish dual thresholds that provide a dual trigger that would result in indemnity payments. If a threshold of extreme temperature beyond which hay is damaged could be defined, it may be possible to include a temperature trigger that would also result in indemnities. For example,

[6] Gao, J., A. Y. Sheshukov, H. Yen, and M. J. White. "Impacts of alternative climate information on hydrologic processes with SWAT: A comparison of NCDC, PRISM and NEXRAD datasets," Catena, 156, September 2017, 353-364.

if it could be established that hay yields fall, regardless of available moisture, at temperature maximums of 95 degrees or higher, an indemnity could be paid solely based on the high temperature. Rating such coverage would be trivial in that it could be handled exactly as the rainfall index is currently applied. However, much as is the case with the County Base Values (CBV), the payoff schedule is problematic.

An additional finding that merits discussion relates to any differences that may exist between the NCDC and CPC sources of precipitation. We aggregated the finer NCDC precipitation data to a similar level of aggregation underlying the CPC data and compared the two alternative measures of monthly rainfall. Figure 4-1 illustrates relationships between the two alternatives across a wide geography that includes a large portion of the Corn Belt and Great Plains.[7] The figure demonstrates the fact that alternative rainfall measures can be very different. This naturally reflects the differences in smoothing and reporting algorithms.

We believe that this does raise an important policy consideration for RMA. The differences highlight the fact that alternative measures of rainfall at specific points in the network of Grid Codes currently used by the RMA (from the CPC data) can be very different. This challenges the fundamental framework of basing coverage on a finely defined grid. If pasture and rangeland are sensitive to precipitation shortfalls, one would need an accurate measure of precipitation for establishing the terms of coverage. The comparison of the alternative NOAA sources on monthly rainfall indicates that the relationship between *measured* rainfall and hay and pasture yields is inaccurate. This is because significant differences between two equally valid measures of rainfall are apparent and the accuracy of either measure is unknown. This is a natural result of using synthesized data where the data are generated using different methods.

One would expect that these differences would be much smaller for more aggregated data. Figures 4-2 and 4-3 present the two alternative measures of monthly rainfall aggregated to the county and state levels, respectively. The differences do indeed diminish when a higher level of aggregation is considered, though meaningful differences persist across aggregation. Of course, alternative sources of the county and state level rainfall measurements are available.[8] We recommend that RMA consider basing coverage on rainfall measured at a higher level of aggregation—possibly the county or NOAA weather district. Using district-level data has another important advantage in that an array of different weather variables, including numerous soil moisture and drought indicators, are available. Such variables may

[7] We included the area spanned by longitudes between -102 and -98 degrees and latitudes between 40 and 44 degrees. Figure 2-4 below illustrates this area, which also formed the basis for our extensive evaluation of premium rates. We aggregated all NCDC grid points that were within 15 kilometers of the centroid of the CPC grid points.

[8] The NCDC reports county level data on rainfall and precipitation.

exhibit a stronger relationship with pasture, rangeland, and hay yields.

Trend Analysis

The extent to which measurable changes in precipitation patterns may exist is also an important consideration. Such changes may appear as statistically significant trends or changes in patterns of seasonality, or both. We randomly selected 100 grid IDs and fit the trend and seasonal cycles to each of the points using the CPC data from 1948-2017. We used a first-order Fourier series expansion to capture cyclical seasonality patterns across different months of the year. Examples of the predicted trend and cyclical patterns are presented below in Figures 4-7 through 4-9. It is important to note that any deliberate adjustments to compensate for any implied trend or structural breaks reflecting climate change would necessarily lower premium rates. Such an adjustment removes variability from the precipitation data and thus decreases the amount of unexplained variability in historical precipitation patterns. In light of the considerable debate surrounding the climate change issue and the effect of lowering premium rates, we do not recommend explicit changes that would remove trends or that would account for structural change unless such changes are large and unambiguously apparent. The existing scientific evidence as well as the following statistical tests of trends and structural change do not, at present, provide such unambiguous conclusions regarding climate change and we thus do not recommend any changes to the sample sizes or incorporation of trends or structural change.

Table 4-1 presents only the trend parameter estimates for the 100 randomly selected IDs. The results indicate a statistically significant trend effect in most cases, although the trends that are implied are almost always very small. The statistical significance of the trend parameters reflects the significantly large number of monthly observations available for analysis. We do not recommend any changes in current rating procedures that would incorporate these small trend effects.

We also divided the precipitation data into two halves and considered standard Chow tests of structural changes in the seasonal and trend components. The results of these tests are presented in Table 4-2. The Chow test results suggest structural breaks in a minority of cases. In light of the impact of lowering rates and that there is greater ambiguity regarding the effect of climate change on rainfall intervals than for temperature and storm intensity, we do not recommend incorporating structural breaks into the rating process.

Data Recommendations

RMA should continue to use the NOAA CPC precipitation data. Alternative data sets

(PRISM, NCEI, NEXRAD, NCDC) offer no real advantages and, in the case of the NCEI, a disadvantage in that the data are not “gridded” but rather are reported at the station level. The absence of any “ground-truthing” obviates any tangible approach to selecting one data set over another on the grounds of accuracy. Each of the alternatives exhibits significant differences concerning the CPC data currently used (and with one another). These differences must be acknowledged but we recommend no changes to the current data used to rate and design coverage.

Although trends and structural breaks are sometimes identified in the precipitation data, such changes over time are always small and are not consistent across different grid IDs. Any attempt to explicitly account for trends or structural breaks will have the effect of lowering premium rates. In the absence of firm scientific conclusions regarding climate change effects on rainfall periods, we recommend that RMA continue to use the full 1948-present CPC data in its entirety and without explicit adjustments meant to reflect climate change.

Table 4-1 Trend Parameter Estimates in Precipitation Data

NOAA GRID ID	Trend Estimate	Standard Error	Value t Statistic	Probability t-Stat	Statistically Significant p<.05
18129	1.9968	0.8982	2.22	0.0265	*
18415	0.3771	0.5662	0.67	0.5055	
18695	0.3107	0.3513	0.88	0.3768	
18714	-0.5346	0.5388	-0.99	0.3214	
18990	1.1471	0.2896	3.96	0.0000	*
19013	0.1648	0.5456	0.3	0.7626	
19014	0.2533	0.5276	0.48	0.6312	
19021	1.4258	0.6639	2.15	0.0320	*
19033	2.2183	0.8821	2.51	0.0121	*
19284	1.0125	0.3546	2.86	0.0044	*
19317	0.5197	0.5824	0.89	0.3724	
19335	2.5977	0.9114	2.85	0.0045	*
19336	1.7356	0.908	1.91	0.0563	
19922	0.2414	0.6638	0.36	0.7162	
19926	1.7016	0.76	2.24	0.0254	*
19939	3.2134	0.9805	3.28	0.0011	*
20218	0.9314	0.5901	1.58	0.1148	
20234	2.0079	0.9093	2.21	0.0275	*
20786	0.043	0.3988	0.11	0.9142	
20803	1.0154	0.3682	2.76	0.0059	*
21109	1.4307	0.4376	3.27	0.0011	*
21119	1.7537	0.6249	2.81	0.0051	*
22029	2.2398	0.7446	3.01	0.0027	*
22035	0.7275	0.8518	0.85	0.3933	
22324	1.0332	0.637	1.62	0.1052	
22575	1.04	0.364	2.86	0.0044	*
22584	1.0392	0.3121	3.33	0.0009	*
22587	1.7566	0.2899	6.06	0.0000	*
22594	1.8038	0.3977	4.54	0.0000	*
22625	0.1396	0.6641	0.21	0.8336	
22635	2.0973	0.8609	2.44	0.0150	*
22915	1.5607	0.4915	3.18	0.0015	*
22934	1.6176	0.821	1.97	0.0491	*
22935	1.3317	0.8253	1.61	0.1070	
23201	1.1539	0.3896	2.96	0.0031	*
23474	2.0420	0.3994	5.11	0.0000	*
24103	-0.058	0.3609	-0.16	0.8723	
24113	0.4957	0.455	1.09	0.2763	
24414	1.4844	0.4936	3.01	0.0027	*

NOAA GRID ID	Trend Estimate	Standard Error	Value t Statistic	Probability t-Stat	Statistically Significant p<.05
24687	0.0353	0.3011	0.12	0.9068	
24711	0.467	0.4455	1.05	0.2949	
25037	1.1449	0.7695	1.49	0.1371	
25270	1.9066	0.3269	5.83	0.0000	*
25301	1.1044	0.3613	3.06	0.0023	*
25593	5.4909	0.3688	14.89	0.0000	*
25874	0.9399	0.5409	1.74	0.0826	
25879	1.9843	0.2524	7.86	0.0000	*
26177	1.5708	0.3447	4.56	0.0000	*
26178	1.6778	0.3382	4.96	0.0000	*
26224	2.9097	0.5784	5.03	0.0000	*
26816	0.9557	0.4876	1.96	0.0503	
26817	0.5159	0.4801	1.07	0.2829	
27125	1.2333	0.5453	2.26	0.0240	*
27394	2.1212	0.3804	5.58	0.0000	*
27436	0.8047	0.625	1.29	0.1983	
27974	2.7835	0.4128	6.74	0.0000	*
27996	0.8098	0.4008	2.02	0.0437	*
28280	4.8567	0.4718	10.29	0.0000	*
28307	1.689	0.4421	3.82	0.0001	*
28314	0.2698	0.4390	0.61	0.5391	
28566	0.5178	0.4398	1.18	0.2394	
28576	1.892	0.4473	4.23	0.0000	*
28580	5.6791	0.5733	9.91	0.0000	*
28591	3.4719	0.3426	10.13	0.0000	*
28888	0.7547	0.2415	3.12	0.0018	*
29176	-0.7248	0.8002	-0.91	0.3653	
29193	0.9221	0.4603	2	0.0455	*
29218	1.5464	0.4564	3.39	0.0007	*
29465	0.713	0.3514	2.03	0.0428	*
29467	5.1334	0.3331	15.41	0.0000	*
29472	1.1218	0.4454	2.52	0.0120	*
29813	1.0682	0.4462	2.39	0.0169	*
29816	1.3033	0.4824	2.7	0.0070	*
30066	1.5755	0.5797	2.72	0.0067	*
30667	0.1329	0.336	0.4	0.6926	
30674	2.8203	0.3967	7.11	0.0000	*
30708	0.8404	0.41	2.05	0.0407	*
30723	1.8726	0.4875	3.84	0.0001	*
30965	-0.4044	0.4456	-0.91	0.3644	

NOAA GRID ID	Trend Estimate	Standard Error	Value t Statistic	Probability t-Stat	Statistically Significant p<.05
30983	0.8276	0.3975	2.08	0.0376	*
30995	0.9872	0.4239	2.33	0.0201	*
30996	1.0447	0.4264	2.45	0.0145	*
30999	1.3399	0.4289	3.12	0.0018	*
31003	1.4633	0.4189	3.49	0.0005	*
31005	1.4032	0.411	3.41	0.0007	*
31013	0.3181	0.4161	0.76	0.4448	
31270	0.4681	0.3511	1.33	0.1828	
31309	-0.0761	0.4501	-0.17	0.8658	
31565	0.6407	0.4653	1.38	0.1689	
31566	4.5922	0.4251	10.8	0.0000	*
31572	3.72	0.372	10	0.0000	*
31588	1.4953	0.3830	3.90	0.0001	*
31595	1.0195	0.4037	2.53	0.0117	*
31624	1.5624	0.4773	3.27	0.0011	*
31625	1.634	0.5092	3.21	0.0014	*
31640	-1.0246	0.6027	-1.70	0.0895	
31886	1.4889	0.3878	3.84	0.0001	*
31917	1.2838	0.4754	2.7	0.0071	*
31933	1.98	0.5133	3.86	0.0001	*
32220	1.5336	0.4903	3.13	0.0018	*

Table 4-2. Chow Tests of Structural Breaks in Precipitation Trends and Cycles

NOAA GRID ID	Value t Statistic	Probability F-Stat	Statistically Significant p<.05	NOAA GRID ID	Value t Statistic	Probability F-Stat	Statistically Significant p<.05
18129	0.96	0.4260		26816	0.69	0.5978	
18415	0.72	0.5751		26817	0.69	0.6016	
18695	1.78	0.1306		27125	0.54	0.7064	
18714	2.39	0.0493	*	27394	5.15	0.0004	*
18990	1.77	0.1327		27436	0.32	0.8624	
19013	1.33	0.2587		27974	3.93	0.0036	*
19014	1.31	0.2639		27996	1.71	0.1465	
19021	0.92	0.4514		28280	9.30	0.0000	*
19033	1.05	0.3781		28307	0.45	0.7707	
19284	0.28	0.8938		28314	0.44	0.7769	
19317	0.71	0.5827		28566	5.77	0.0001	*
19335	1.31	0.2652		28576	3.51	0.0075	*
19336	0.87	0.4794		28580	11.51	0.0000	*
19922	1.17	0.3209		28591	1.84	0.1188	
19926	0.37	0.8314		28888	0.33	0.8545	
19939	0.69	0.5991		29176	17.55	0.0000	*
20218	0.45	0.7709		29193	0.90	0.4662	
20234	1.40	0.2310		29218	1.46	0.2136	
20786	3.69	0.0055	*	29465	9.33	0.0000	*
20803	5.15	0.0004	*	29467	18.20	0.0000	*
21109	6.04	0.0000	*	29472	0.34	0.8509	
21119	0.24	0.9170		29813	0.26	0.9021	
22029	0.58	0.6794		29816	1.16	0.3290	
22035	0.48	0.7483		30066	17.60	0.0000	*
22324	0.12	0.9761		30667	3.25	0.0118	*
22575	4.27	0.0020	*	30674	8.07	0.0000	*
22584	0.95	0.4370		30708	1.46	0.2139	
22587	1.19	0.3156		30723	2.62	0.0338	*
22594	2.09	0.0799		30965	1.03	0.3885	
22625	0.10	0.9814		30983	0.74	0.5671	
22635	0.71	0.5872		30995	1.61	0.1701	
22915	0.49	0.7440		30996	1.54	0.1878	
22934	0.22	0.9273		30999	1.35	0.2491	
22935	0.24	0.9140		31003	1.11	0.3483	
23201	2.64	0.0327	*	31005	0.53	0.7124	
23474	8.56	0.0000	*	31013	0.54	0.7040	
24103	0.81	0.5215		31270	4.02	0.0031	*
24113	0.80	0.5263		31309	1.56	0.1823	

NOAA GRID ID	Value t Statistic	Probability F-Stat	Statistically Significant p<.05	NOAA GRID ID	Value t Statistic	Probability F-Stat	Statistically Significant p<.05
24414	0.53	0.7131		31565	18.67	0.0000	*
24687	7.78	0.0000	*	31566	8.30	0.0000	*
24711	0.64	0.6353		31572	7.29	0.0000	*
25037	0.91	0.4547		31588	1.19	0.3149	
25270	2.76	0.0266	*	31595	0.62	0.6489	
25301	1.14	0.3341		31624	1.64	0.1615	
25593	13.44	0.0000	*	31625	1.61	0.1697	
25874	6.47	0.0000	*	31640	2.82	0.0242	*
25879	2.10	0.0786		31886	0.75	0.5574	
26177	4.23	0.0021	*	31917	0.85	0.4949	
26178	1.93	0.1026		31933	0.71	0.5870	
26224	1.48	0.2058		32220	2.04	0.0865	

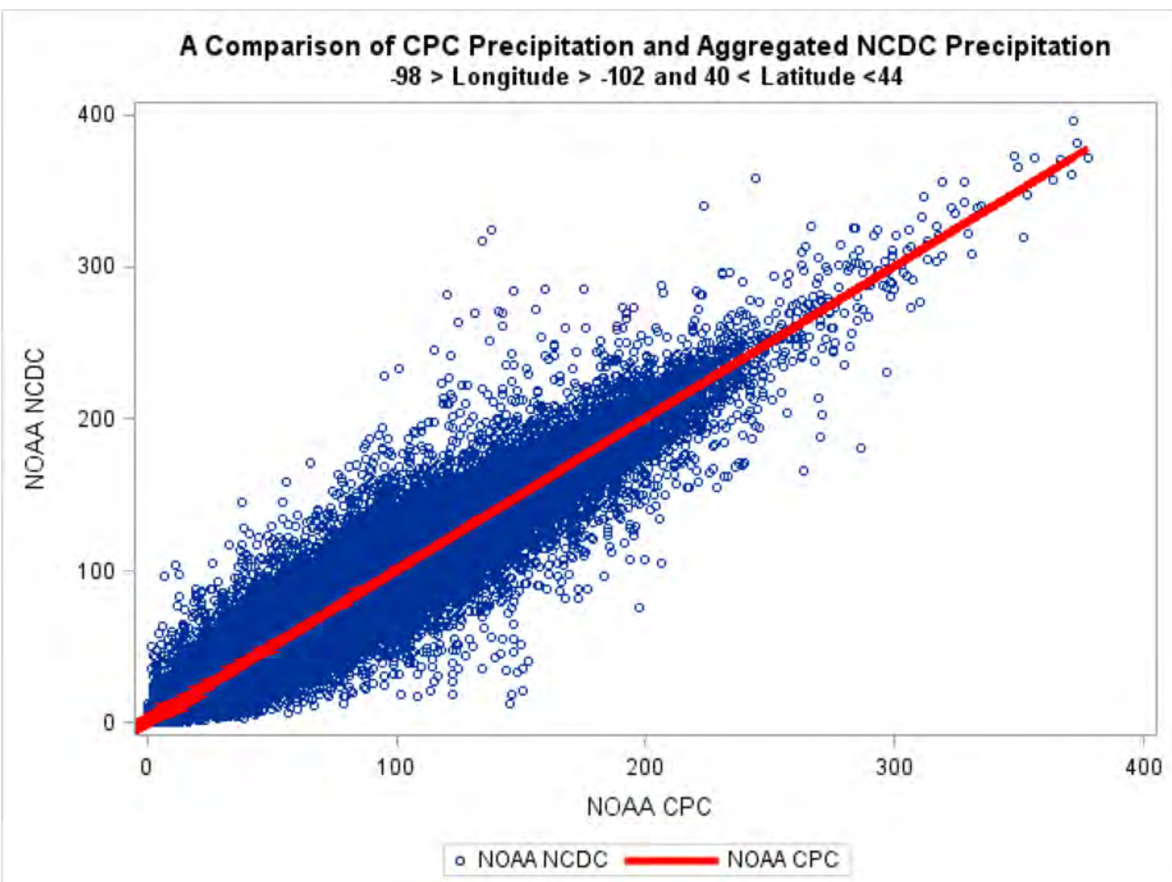


Figure 4-1

Comparison of NCDC and CPC NOAA Data

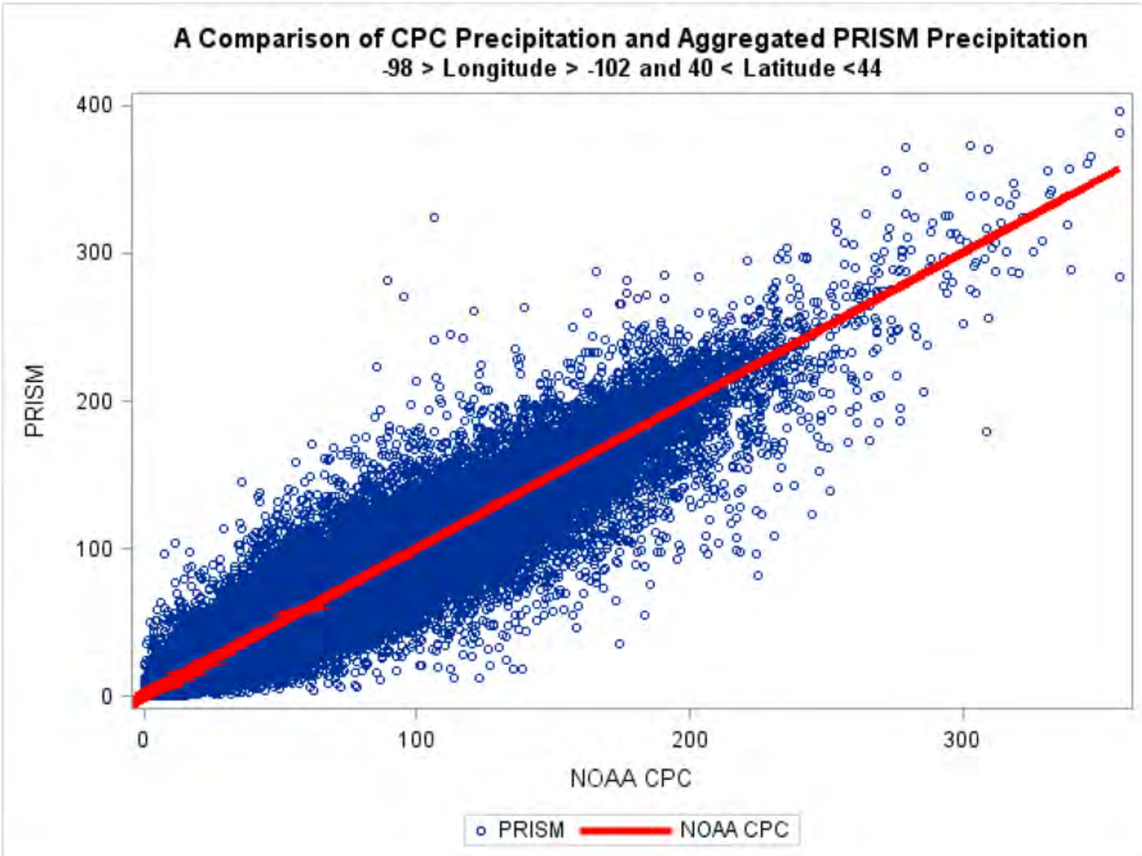


Figure 4-2

Comparison of PRISM and CPC NOAA Data

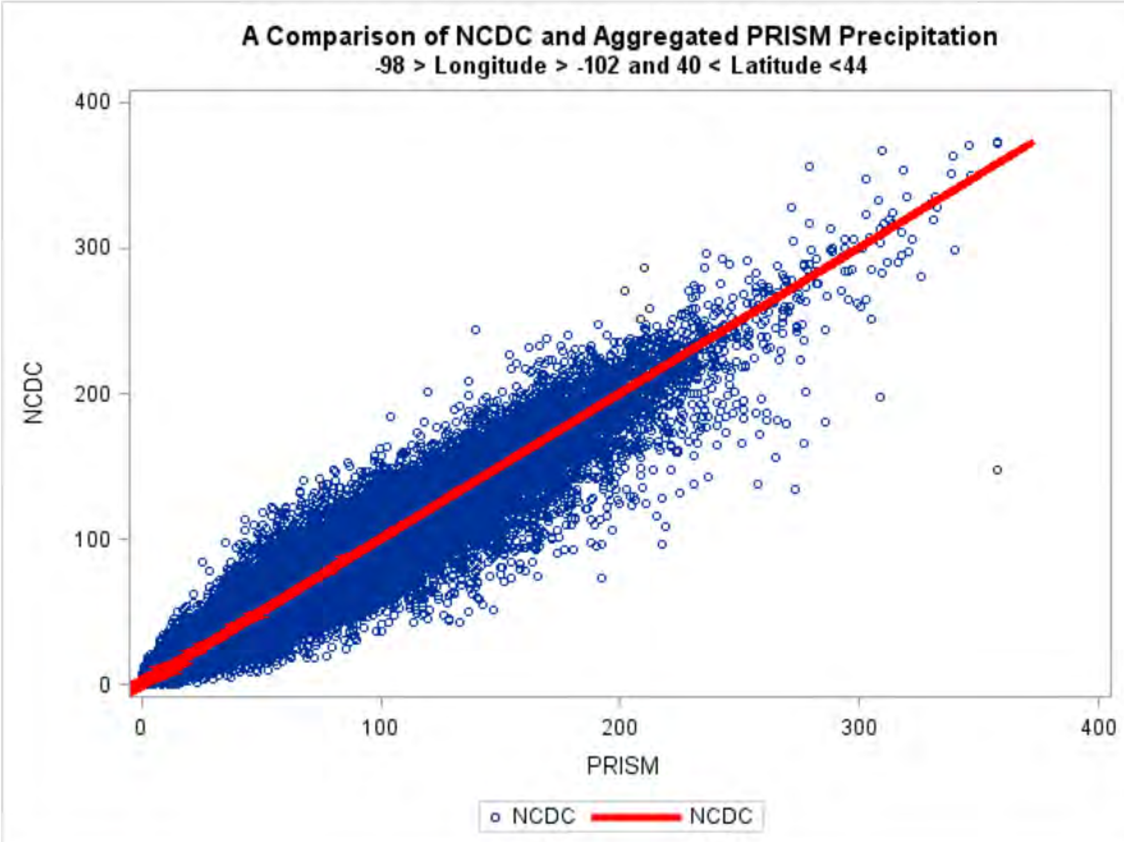


Figure 4-3

Comparison of PRISM and NCDC NOAA Data

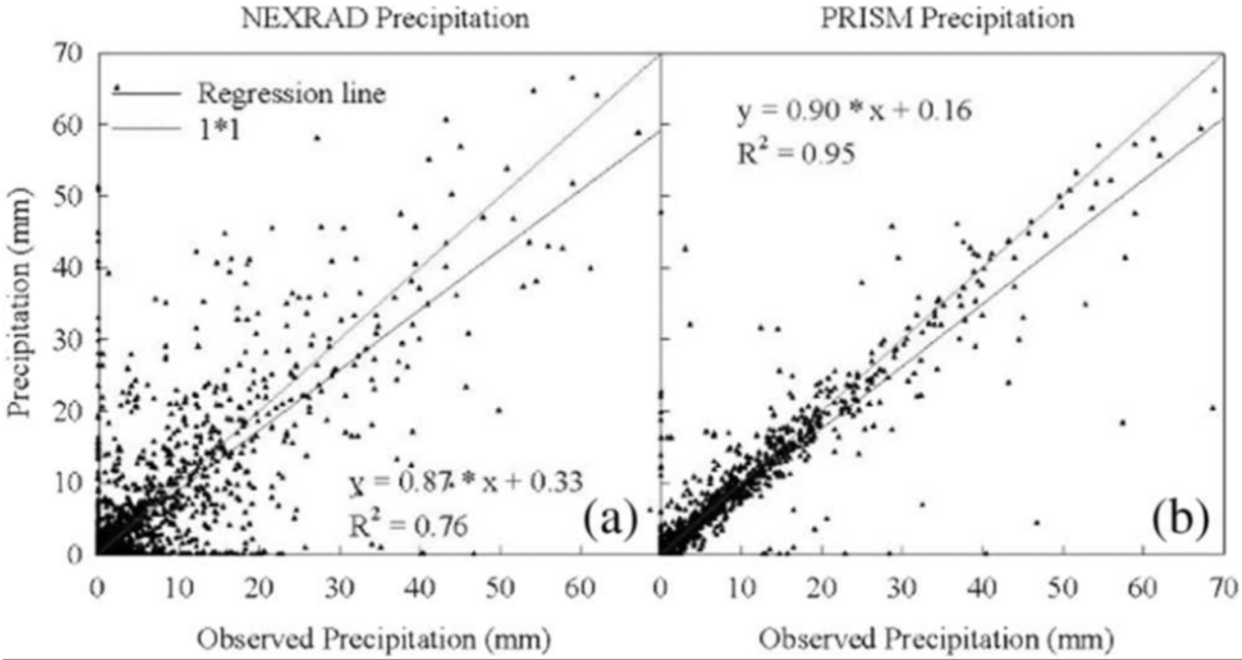


Figure 4-4

Comparison of NEXRAD and PRISM Precipitation Measures from Gao et al. (2017)

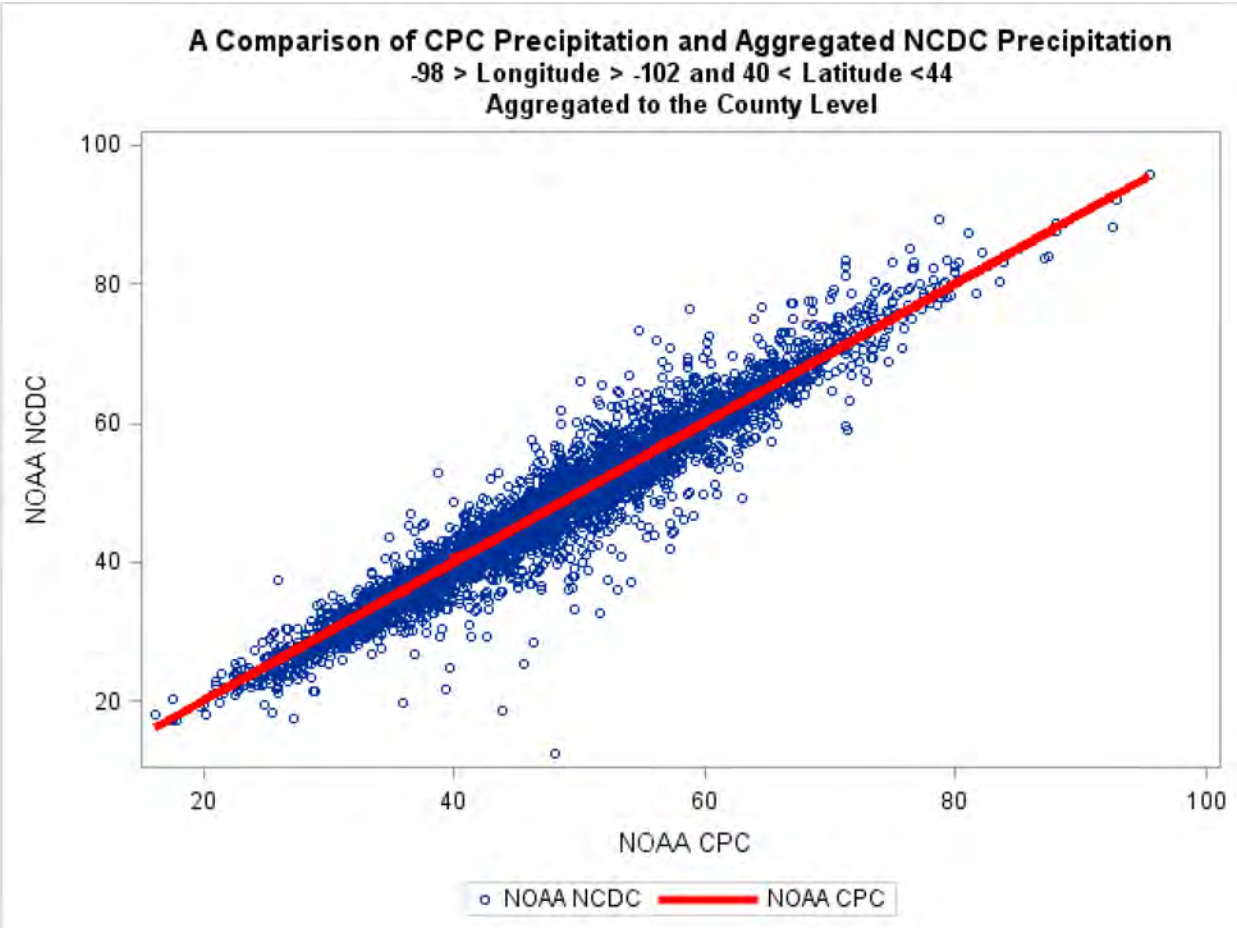


Figure 4-5

Comparison of NCDC and CPC NOAA Data at County Level

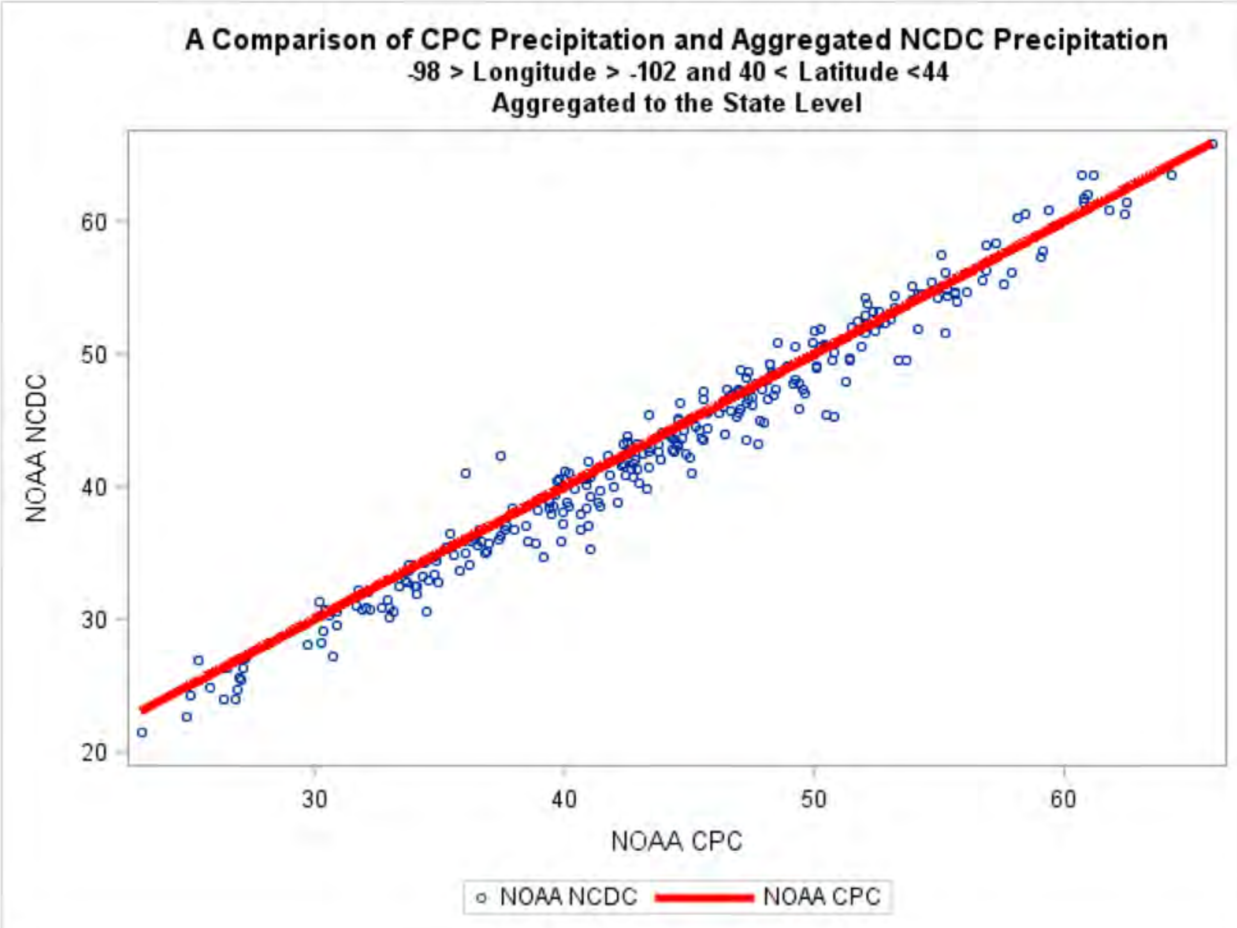


Figure 4-6

Comparison of NCDC and CPC NOAA Data at State Level

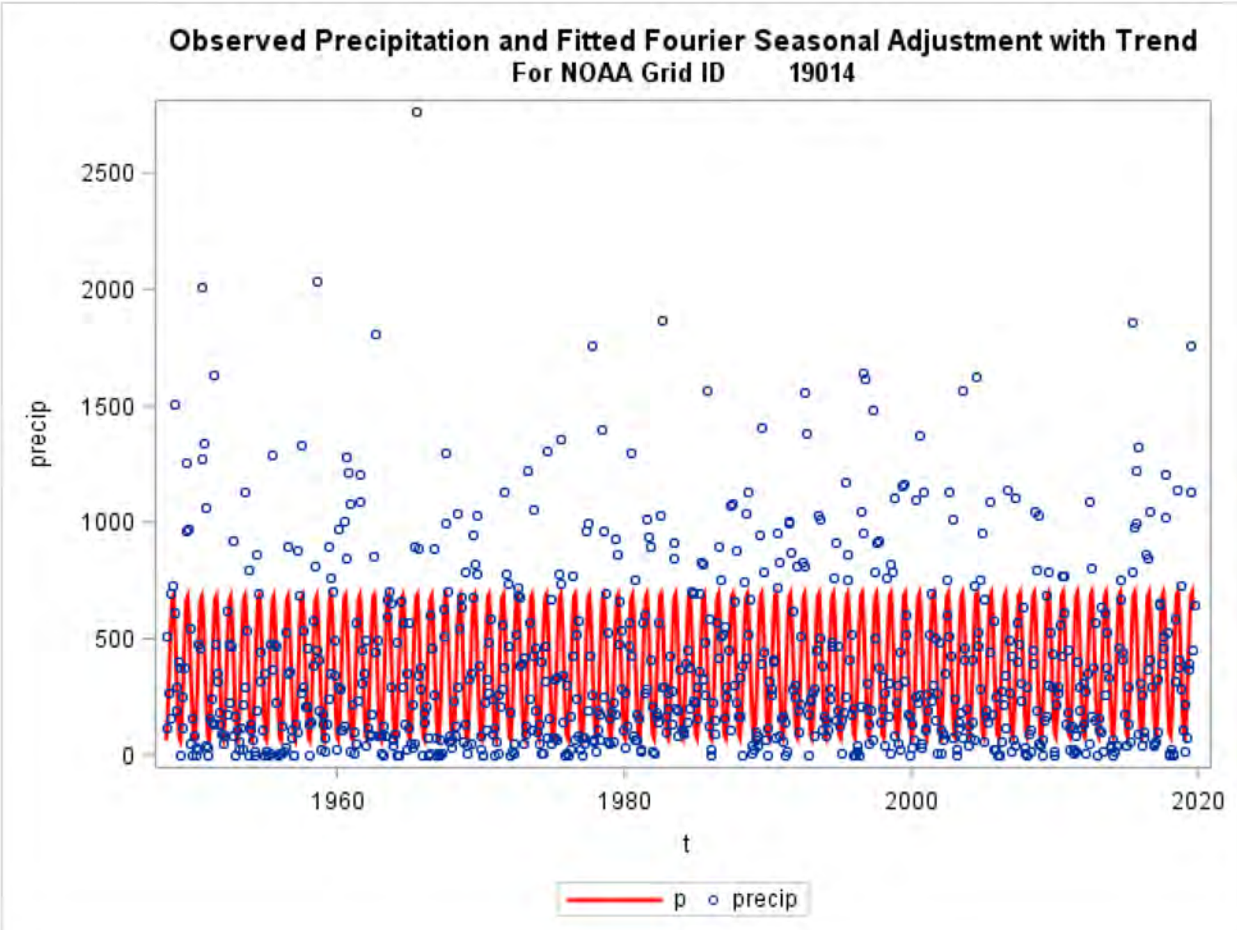


Figure 4-7

Estimated Trend and Seasonality for ID 19014

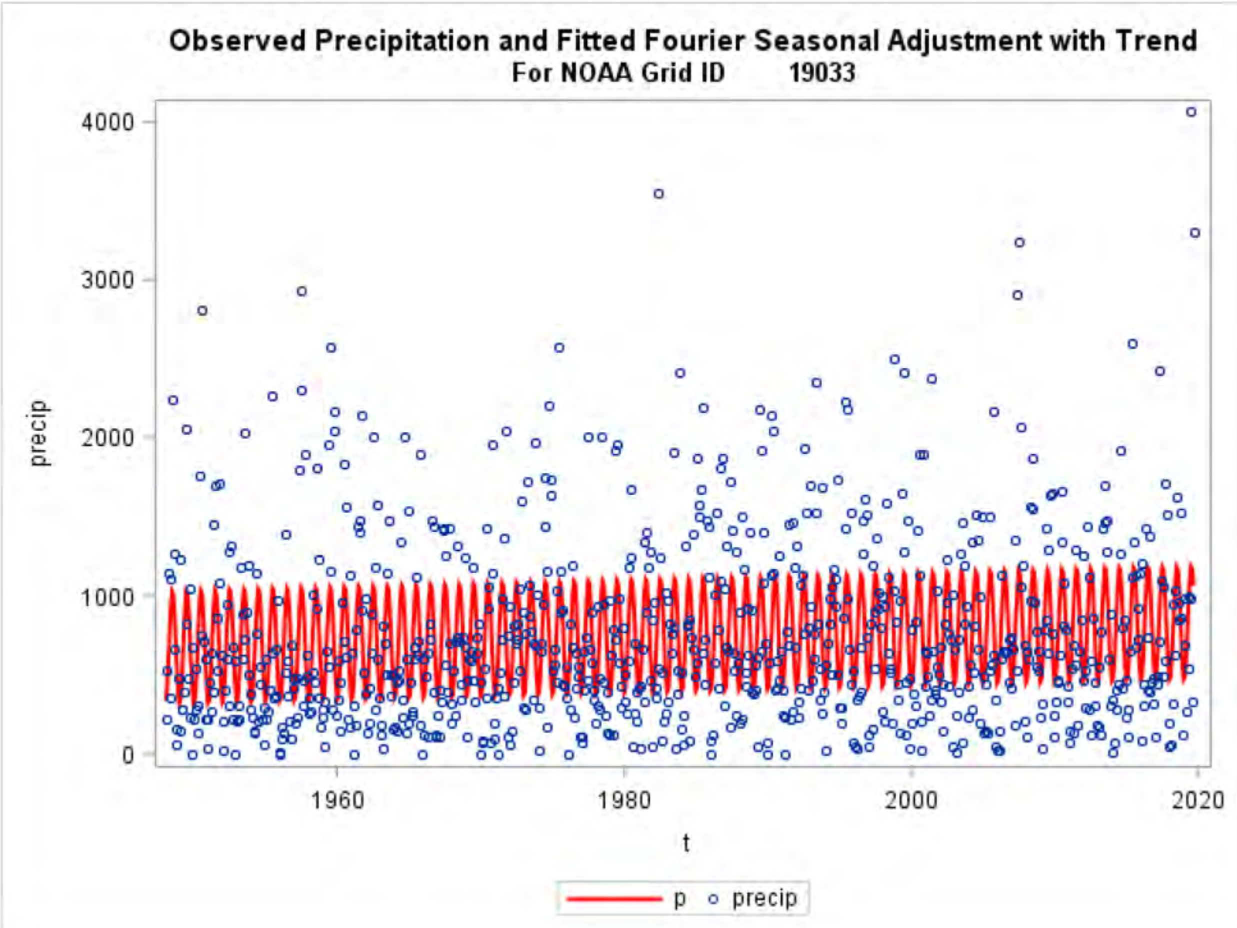


Figure 4-8

Estimated Trend and Seasonality for ID 19033

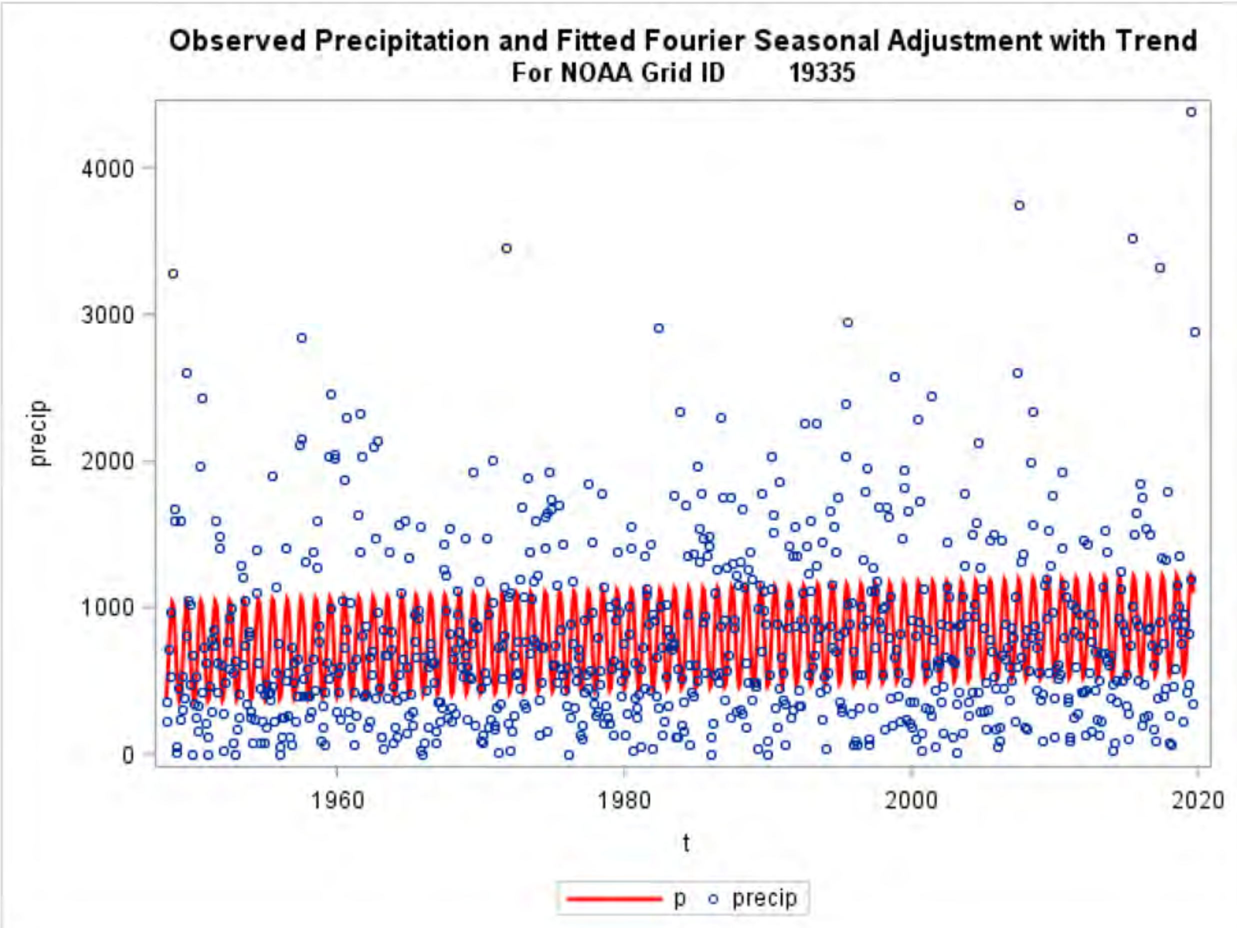


Figure 4-9

Estimated Trend and Seasonality for ID 19335

Rating Review

The current procedure used in rating the PRF product utilizes a nonparametric empirical burn rate and parametric distributions derived from the log-normal and the truncated normal. Because there are currently only 70 years of rainfall data available (in the CPC data currently used by RMA), the use of an empirical burn rate might be questionable. One would typically hope to have a longer range of data if departing from any specific parametric distribution in rating coverage. The fact that RMA's process includes a comparison of the burn rates to rates taken from the lognormal, truncated normal, and a Gram Charlier (GC) expansion distribution in order to bound the final rate serves to mitigate this concern. One would expect that parametric distributions would tend to smooth rates and result in slightly higher rates in high-risk cases. An alternative approach could consider smoothing rates and adding a modest amount of structure by applying nonparametric kernel density estimation methods.

The specific bounding undertaken by RMA is the rating process involves the following steps.

1. Calculate the burn rate and rates implied by the BS/lognormal, GC, and truncated normal.[9]
2. If the burn rate is less than the maximum of the truncated normal, the BS/log-normal, and the GC rates, the raw rate is set to the lowest of the three different parametric rates.
3. If the burn rate is higher than the maximum of the three parametric rates, the raw rate is set to the maximum of the parametric rates.
4. If the burn rate is between the minimum and maximum of the parametric rates, the raw rate is set to the burn rate.
5. The raw rate is then loaded by dividing by 0.88.

After a final raw rate is derived, a spatial smoothing algorithm that takes a weighted average of the raw rate and surrounding raw rates is used to determine a final rate. It should be noted that this weighting scheme is reasonable though it is of an ad hoc nature. One could combine the neighboring grids before estimating a final raw rate, though there is no reason to prefer such over the present method. The spatial smoothing practice is entirely reasonable and we do not recommend any changes to current smoothing practices. However, it may be relevant to consider how rates might differ if the pooling was done before the specific rates were calculated.

The bounding of rates through a comparison of the burn rate with the three parametric alternatives is a sensible approach. However, it is ad hoc and lacks any real justification. An alternative that may have merit would be to use specific criteria that reflect the goodness of

[9] The developers use a Black Scholes (BS) option pricing model formula to calculate a distribution analogous to a lognormal. As we note below, we believe an error exists in the coding of the BS estimates. The developers also use a Gramm Chatalier.

fit of the parametric alternatives as a means of selecting a final parametric rate. We discuss the application of such an approach next.

We broadened the consideration of parametric distributions to include the Weibull, Normal, Inverse Gaussian (Wald), and the Gamma distributions. We calculated various measures of standard goodness of fit tests of each of these distributions. Specifically, we considered the Anderson-Darling, Cramer von Mises, and Kolmogorov distributional tests. Not every test is available for every distribution considered, though each candidate is tested using at least two goodness of fit tests.

We considered the following alternative distributions:

$$PDF('WEIBULL', x, a, \lambda) = \begin{cases} 0 & x < 0 \\ exp(-(\frac{x}{\lambda})^a)\frac{a}{\lambda}(\frac{x}{\lambda})^{a-1} & x \geq 0 \end{cases}$$

$$PDF('GAMMA', x, a, \lambda) = \begin{cases} 0 & x < 0 \\ \frac{1}{\lambda^a \Gamma(a)} x^{a-1} exp(-\frac{x}{\lambda}) & x \geq 0 \end{cases}$$

$$PDF('INVERSE\ GAUSSIAN) = [\frac{\lambda}{2\pi x^3}]^{1/2} \exp\{-\frac{\lambda}{2\mu^2 x}(x-\mu)^2\}, \quad x > 0$$

$$PDF('LOGN', x, \theta, \lambda) = \begin{cases} 0 & x \leq 0 \\ \frac{1}{x\lambda\ \sqrt{2\pi}} exp(-\frac{(log(x)-\theta)^2}{2\lambda^2}) & x > 0 \end{cases}.$$

A selection of 8 randomly chosen grids and intervals is presented in Figures 4-10 to 4-12. The range of densities illustrates that the density is quite similar, except for the normal density. The densities that admit a greater degree of negative skewness will tend to generate higher rates. This is illustrated by the shape of the distribution, with the mode falling closer to zero than is the case for other distributions. The highest rates would be expected to be observed for the inverse Gaussian distribution---a result that is confirmed below. The top diagram in Figure 4-12 illustrates the problems associated with fitting the parameter distribution to counties that typically have very dry climates.

The tests were calculated for every grid code and interval combination (149,866 cases). The tests provide strong support for the truncated normal distribution, which is rejected at the 5 percent level only in 3-10 percent of the cases. However, a similar degree of fit is offered by the Gamma distribution, which is rejected in only about 8-10 percent of the cases. Rather than using an ad hoc procedure to select the distribution for parametric rates, we recommend that RMA consider using an alternative approach that can be justified on statistical grounds. The goodness of fit tests could be compared to one another to select the best fitting distribution. Table 4-3 presents a summary of the test results for all grids and intervals. Table 4-4 reports results by interval and distribution.

Table 4-3

Goodness of Fit Tests Calculated from All Grid Codes and Intervals

			Proportion Rejected		
Distribution	**Test**	**N**	**10%**	**5%**	**1%**
Gamma	Anderson-Darling	142,165	0.1666	0.1000	0.0322
Gamma	Cramer-von Mises	142,165	0.1579	0.0929	0.0280
Gamma	Kolmogorov-Smirnov	142,165	0.1478	0.0834	0.0228
Inverse Gaussian	Anderson-Darling	149,875	0.6353	0.5643	0.4168
Inverse Gaussian	Cramer-von Mises	149,875	0.6264	0.5432	0.4123
Inverse Gaussian	Kolmogorov-Smirnov	149,875	0.5850	0.5010	0.3459
Lognormal	Anderson-Darling	149,875	0.5401	0.4521	0.3080
Lognormal	Cramer-von Mises	149,875	0.5048	0.4180	0.2750
Lognormal	Kolmogorov-Smirnov	149,875	0.4575	0.3568	0.0000
Normal	Anderson-Darling	149,875	0.7214	0.6361	0.4651
Normal	Cramer-von Mises	149,875	0.6738	0.5835	0.4117
Normal	Kolmogorov-Smirnov	149,875	0.6055	0.4925	0.0000
Truncated Normal	Cramer-von-Mises	149,886	0.1826	0.1084	0.0427
Truncated Normal	Kolmogorov-Smirnov	149,886	0.0369	0.0304	0.0272
Weibull	Anderson-Darling	149,875	0.3357	0.2479	0.0000
Weibull	Cramer-von Mises	149,875	0.3063	0.2163	0.0000

Table 4-4

Goodness of Fit Results by Interval and Distribution

			Proportion Rejected		
Interval	**Distribution**	**N**	**10%**	**5%**	**1%**
625	Gamma	39,501	0.1686	0.1014	0.0327
625	InverseGaussian	40,875	0.6067	0.5232	0.3796
625	Lognormal	40,875	0.4878	0.4007	0.1885
625	Normal	40,875	0.7025	0.6153	0.3350
625	Truncated_Normal	27,252	0.1088	0.0620	0.0182
625	Weibull	27,250	0.3207	0.2352	0.0000
626	Gamma	39,348	0.1797	0.1089	0.0367
626	InverseGaussian	40,875	0.6025	0.5172	0.3621
626	Lognormal	40,875	0.4885	0.3897	0.1773
626	Normal	40,875	0.6803	0.5866	0.3091
626	Truncated_Normal	27,252	0.1168	0.0724	0.0265
626	Weibull	27,250	0.3507	0.2659	0.0000
627	Gamma	39,075	0.1424	0.0801	0.0225
627	InverseGaussian	40,875	0.5439	0.4607	0.3213
627	Lognormal	40,875	0.4380	0.3477	0.1580
627	Normal	40,875	0.6589	0.5670	0.2870
627	Truncated_Normal	27,252	0.1025	0.0611	0.0242
627	Weibull	27,250	0.3388	0.2462	0.0000
628	Gamma	38,916	0.1285	0.0686	0.0163
628	InverseGaussian	40,875	0.5051	0.4248	0.2889
628	Lognormal	40,875	0.4097	0.3226	0.1444
628	Normal	40,875	0.6537	0.5502	0.2734
628	Truncated_Normal	27,252	0.1188	0.0737	0.0349
628	Weibull	27,250	0.3657	0.2665	0.0000
629	Gamma	37,875	0.1269	0.0706	0.0198
629	InverseGaussian	40,875	0.5330	0.4451	0.3045
629	Lognormal	40,875	0.4335	0.3402	0.1525
629	Normal	40,875	0.6064	0.5085	0.2514
629	Truncated_Normal	27,252	0.1293	0.0897	0.0556
629	Weibull	27,250	0.3388	0.2406	0.0000
630	Gamma	38,946	0.1440	0.0825	0.0230
630	InverseGaussian	40,875	0.5707	0.4851	0.3289
630	Lognormal	40,875	0.4658	0.3700	0.1634
630	Normal	40,875	0.6024	0.4980	0.2363
630	Truncated_Normal	27,252	0.1091	0.0712	0.0430
630	Weibull	27,250	0.3444	0.2515	0.0000
631	Gamma	38,178	0.1395	0.0771	0.0199

Interval	Distribution	N	Proportion Rejected 10%	5%	1%
631	InverseGaussian	40,875	0.5816	0.4977	0.3502
631	Lognormal	40,875	0.4742	0.3794	0.1744
631	Normal	40,875	0.5983	0.4996	0.2467
631	Truncated_Normal	27,252	0.1196	0.0838	0.0549
631	Weibull	27,250	0.3300	0.2397	0.0000
632	Gamma	38,535	0.1548	0.0873	0.0227
632	InverseGaussian	40,875	0.6297	0.5492	0.4035
632	Lognormal	40,875	0.5169	0.4205	0.2004
632	Normal	40,875	0.6777	0.5804	0.2967
632	Truncated_Normal	27,252	0.1358	0.0918	0.0514
632	Weibull	27,250	0.3315	0.2472	0.0000
633	Gamma	38,919	0.1968	0.1211	0.0393
633	InverseGaussian	40,875	0.7822	0.7184	0.5705
633	Lognormal	40,875	0.6443	0.5545	0.2843
633	Normal	40,875	0.6862	0.5829	0.2929
633	Truncated_Normal	27,252	0.0873	0.0542	0.0286
633	Weibull	27,250	0.2284	0.1522	0.0000
634	Gamma	39,150	0.1747	0.1049	0.0342
634	InverseGaussian	40,875	0.7071	0.6401	0.5022
634	Lognormal	40,875	0.5763	0.4841	0.2446
634	Normal	40,875	0.7342	0.6428	0.3380
634	Truncated_Normal	27,252	0.0819	0.0461	0.0208
634	Weibull	27,250	0.2680	0.1793	0.0000
635	Gamma	38,052	0.1743	0.1097	0.0371
635	InverseGaussian	40,875	0.7087	0.6364	0.4967
635	Lognormal	40,875	0.5739	0.4893	0.2498
635	Normal	40,875	0.7355	0.6467	0.3481
635	Truncated_Normal	27,252	0.0976	0.0574	0.0264
635	Weibull	27,250	0.3141	0.2287	0.0000

We utilized standard maximum likelihood estimation techniques to estimate the truncated normal distribution for each grid code and interval combination. An important limitation of this approach merits discussion here. The truncated normal distribution can prove difficult to estimate by standard nonlinear estimation procedures when the variance of the relevant data is very large or when data are concentrated at levels close to the truncation point (zero in our case). Both conditions characterize very dry and high-risk grid locations. We were unable to estimate parameters to maximize the likelihood function for the truncated normal distribution in a few cases. Such grids typically have a very negative mean/scale parameter, which also leads to difficulties in rate estimation. We utilized rejection/acceptance sampling (one-million replications) and in the cases of a very large in magnitude negative mean parameter, it is difficult to use rejection sampling methods because the relevant portion of the normal distribution that lies above the truncation point (zero) is very small. The lognormal distribution encounters similar problems in cases where a grid/interval has very low recorded rainfall and very high variance. In such a case, the distribution has an extreme mode close to zero and a very long right tail, reflecting the positive skew of the lognormal.

We also believe that there is an error in the formula used to derive the BS/lognormal rates in the RMA rating program. The rating program uses the following coding

```
        std(log(index+0.0001)) as vol…
        d1=( log(1/coveragelevelpercent)+(vol**2)/2)/vol;
    d2=d1-vol;
    N_d1=cdf("normal",-d1,0,1);
    N_d2=cdf("normal",-d2,0,1);
            BS = N_d2 – N_d1/coveragelevelpercent;  * black scholes rate ;
```

We have examined the formula carefully and do not believe the calculation is correct given the log-normal distribution assumption. Empirically, we compared the original (incorrect) formula from the developer and the BS rates calculated using a corrected formula.

BS formulas for a put option:

$$p = Ke^{-rT}N(-d_2) - S_0N(-d_1) \qquad (1)$$

$$d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} \qquad (2)$$

$$d_2 = d_1 - \sigma\sqrt{T} \qquad (3).$$

<u>Application to PRF index</u>

Assumptions:

A1: K=c, where c=coverage level;

A2: r=0, the risk-free interest rate is zero, so no discounting;

A3: T=1;

A4: S_0=1, the initial price for the index equals 1.

With assumptions A1-A4, the formulas for the PRF index become

$$p = c\, N(-d_2) - N(-d_1) \qquad (4)$$

$$d_1 = \frac{\ln(1/c) + (\sigma^2/2)}{\sigma} \qquad (5)$$

$$d_2 = d_1 - \sigma \qquad (6)$$

where σ is the standard deviation of the ln(index).

The equivalent of (4) used by the developer to calculate the BS rate is:

$$p = \frac{1}{c}\left(c\, N(-d_2) - N(-d_1)\right) \qquad (7).$$

We believe the multiplication by 1/c in (7) is incorrect.

The comparison is based on the average BS rates for 2019 and all grids. The BS rates calculated using the corrected formula tend to be lower than the BS rates calculated using the original formula. The average difference between the two rates is from a high of 4.2 percentage points for the 70% coverage level to a low of 2.1 percentage points for the 90% coverage level. Also, the corrected BS rates are very similar to the BR rates

As a further analysis, we randomly chose 500 grid codes from the collection of 13,626 total from the focus area illustrated in Figure 4-10. We calculated premium rates for coverage levels between 70-100 percent using each of the alternative distributions and the truncated normal. A summary of the average values of the shape and scale parameters is presented in Table 4-5.

Table 4-5

Average Values of ML Parameter Estimates

Distribution	Threshold	Scale	Shape	Mean	Standard Deviation
Gamma	0.0000	0.3208	3.9286	1.0000	0.5492
Inverse Gaussian	1.0000	---	2.8412	1.0000	1.0155
Lognormal	0.0000	-0.1711	0.6283	1.0646	1.1474
Normal	---	---	---	1.0000	0.5333
Truncated Normal	---	0.6051	0.6771	---	---
Weibull	0.0000	1.1205	2.0979	1.0011	0.5297

We utilized one-million replicates in a rejection sampling framework to determine rates based on each parametric distribution.[10] Table 4-6 presents average rates across the entire sample of 500 grid codes (with 11 intervals each). Table 4-6 also includes RMA raw rates for the truncated normal (RMA's version and the developer's approximation). The results demonstrate that there is relative homogeneity among the alternative parametric and burn rates, at least at an aggregate level. The lognormal tends to generate rates that are considerably smaller than the BS rates. The inverse Gaussian distribution tends to produce the highest average rates.

Average Values of Rates Across Selected 500 Grid Codes

Table 4-6

		Coverage Level					
Distribution	N	70%	75.00%	80.00%	85.00%	90.00%	100%
Black_Scholes	5500	0.1319	0.1500	0.1686	0.1875	0.2066	---
Burn_Rate	5500	0.1082	0.1234	0.1393	0.1558	0.1729	---
Dev_Truncated_Normal	5500	0.1247	0.1361	0.1480	0.1609	0.1743	---
Gamma	5500	0.1102	0.1260	0.1424	0.1595	0.1769	0.2127
Gram Charlier	5500	0.1151	0.1279	0.1411	0.1556	0.1707	---
Inverse Gaussian	5500	0.1547	0.1728	0.1913	0.2099	0.2286	0.2657
Lognormal	5500	0.1191	0.1366	0.1547	0.1731	0.1917	0.2291
Normal	5500	0.1387	0.1491	0.1603	0.1724	0.1852	0.2127
RMA_Truncated_Normal	5500	0.1248	0.1362	0.1482	0.1610	0.1744	---
Truncated Normal	5387	0.1251	0.1382	0.1518	0.1660	0.1807	0.2113

[10] For a discussion of rejection sampling, see P. W. Laud, P. Damien, and T. S. Shively, (2010) "Sampling Some Truncated Distributions Via Rejection Algorithms." Communications in Statistics - Simulation and Computation, Pages 1111-1121; and Marsaglia, George (1964). "Generating a variable from the tail of the normal distribution". Technometrics. 6 (1): 101–102.

Weibull	5500	0.1169	0.1314	0.1464	0.1619	0.1778	0.2106

We compared our rejection-based simulated rates to the two alternatives of the truncated normal embedded in the RMA rating program. As noted, we found the truncated normal to be unstable and difficult to fit by maximum likelihood methods in cases of high risk and long right tails. Such cases typically generated a mean value for the truncated normal that is very negative. This makes the effective coverage of the density to the right of the truncation point (zero) very small relative to the overall normal. Our rejection method rate estimates were compared to those generated by the RMA rating procedures. Table 4-7 below presents average values across the two alternative methods of rating with the truncated normal distribution. The rates are very close on average and the average differences are very close to zero. However, a consideration of differences across different levels of coverage does reveal modest differences at very high rates—a finding that likely reflects the substantial difficulties associated with fitting the truncated normal in very high-risk cases (Table 4-8).

Comparison of Alternative Truncated Normal Rates

Table 4-7

Coverage Level	RMA Truncated Normal	Rejection Method Truncated Normal	Mean Difference
70%	0.1227	0.1251	-0.0024
75%	0.1340	0.1382	-0.0041
80%	0.1462	0.1518	-0.0057
85%	0.1590	0.1660	-0.0070
90%	0.1725	0.1807	-0.0082
100%	---	0.2113	---

Table 4-8

Truncated Normal Claim and Conditional Expected Indemnities

(Risk and Exposure)

	Probability of a Claim						Expected Indemnity Conditional on a Claim					
Distribution	**70%**	**75.00%**	**80.00%**	**85.00%**	**90.00%**	**100%**	**70%**	**75.00%**	**80.00%**	**85.00%**	**90.00%**	**100%**
Gamma	0.3258	0.3682	0.4108	0.4530	0.4944	0.5730	0.2244	0.2461	0.2688	0.2924	0.3169	0.3688
Inverse Gaussian	0.4047	0.4473	0.4885	0.5279	0.5652	0.6329	0.2330	0.2595	0.2870	0.3155	0.3449	0.4064
Lognormal	0.3595	0.4038	0.4470	0.4887	0.5284	0.6010	0.2169	0.2412	0.2666	0.2930	0.3205	0.3785
Normal	0.2784	0.3117	0.3469	0.3837	0.4218	0.5000	0.3338	0.3469	0.3608	0.3756	0.3912	0.4255
Truncated Normal	0.3041	0.3386	0.3744	0.4113	0.4489	0.5250	0.2777	0.2967	0.3161	0.3360	0.3565	0.3996
Weibull	0.3151	0.3525	0.3906	0.4292	0.4677	0.5438	0.2504	0.2711	0.2923	0.3142	0.3368	0.3842

Figure 4-10 shows the area of the U.S. where we conduct a more intensive comparison of rates. Using this sample of grids, figures 4-11 through 4-13 are examples of the distributions fit using alternative fitted distributions. Figure 4-14 shows a histogram for a representative period that reflects the relatively small range of rainfall values often fit.

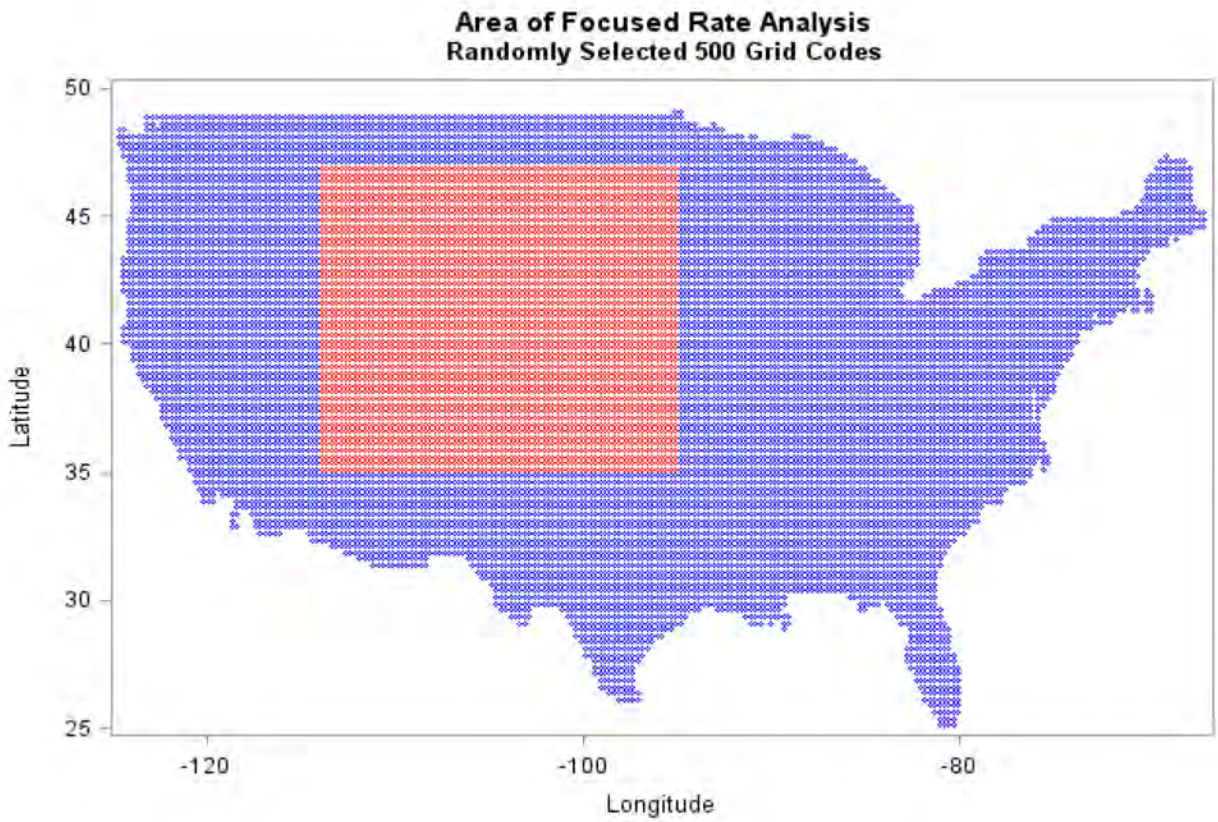


Figure 4-10

Area of Focused Analysis of Premium Rates

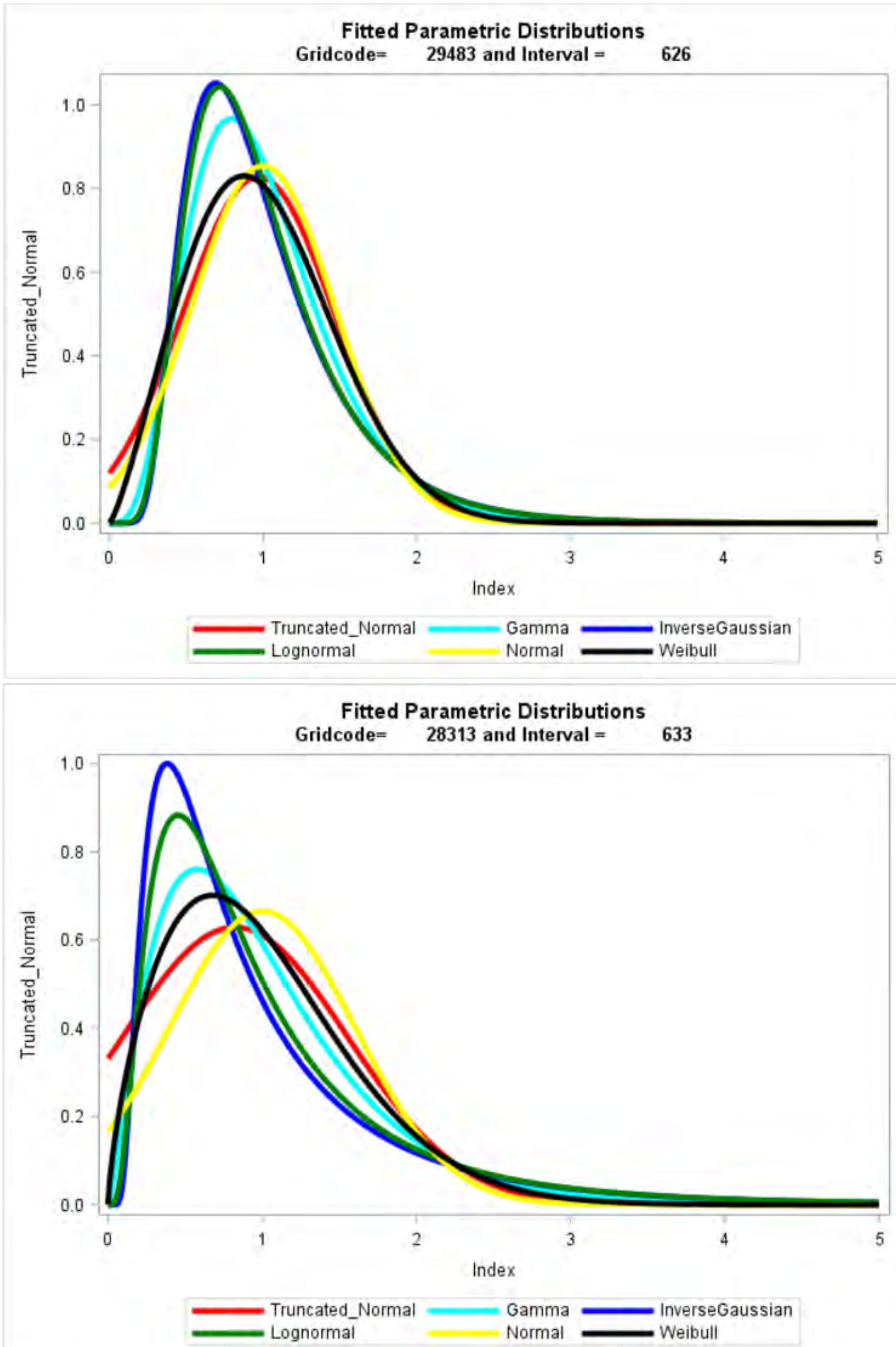


Figure 4-11

Examples of Fitted Densities

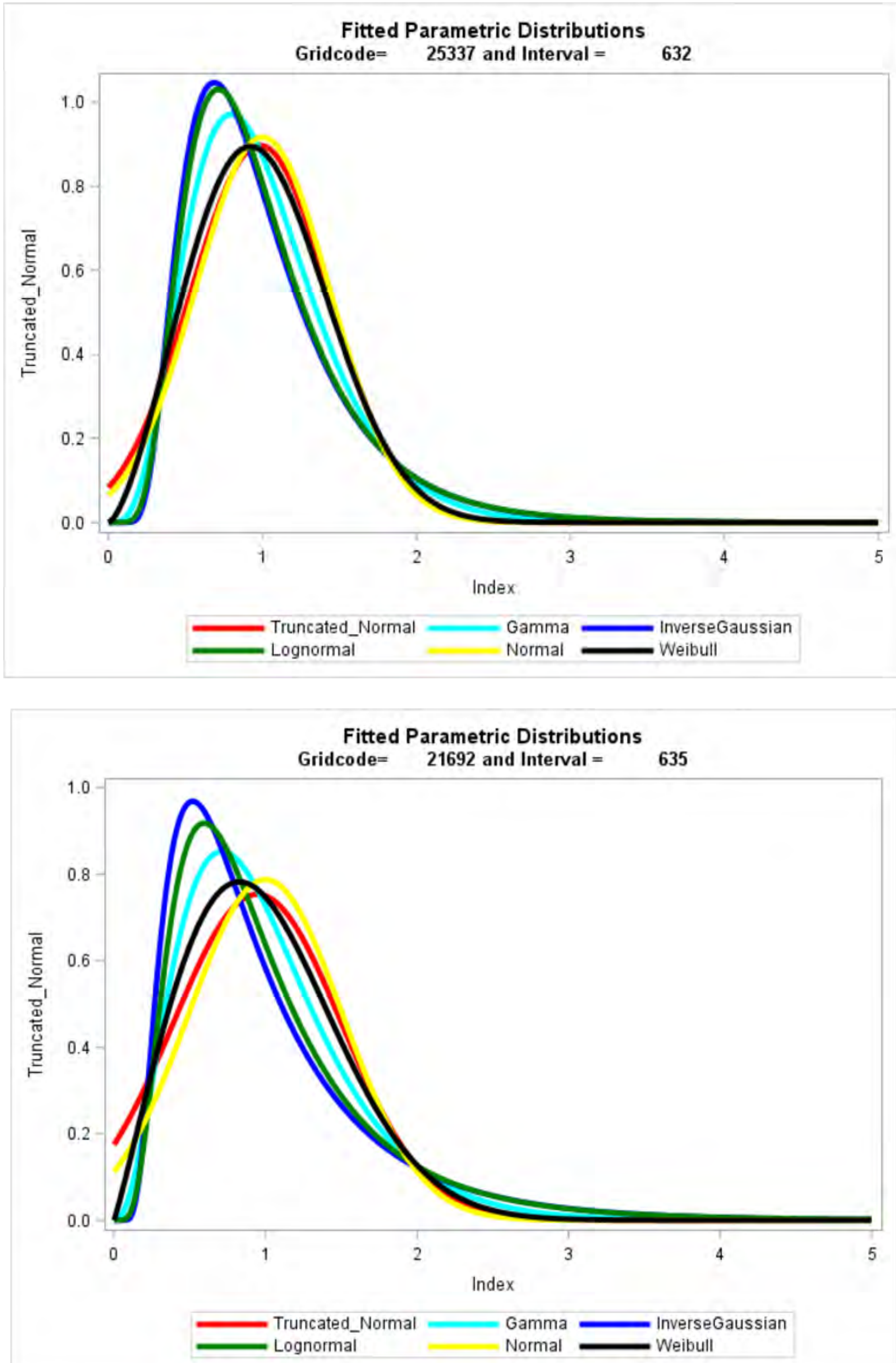


Figure 4-12

Examples of Fitted Densities

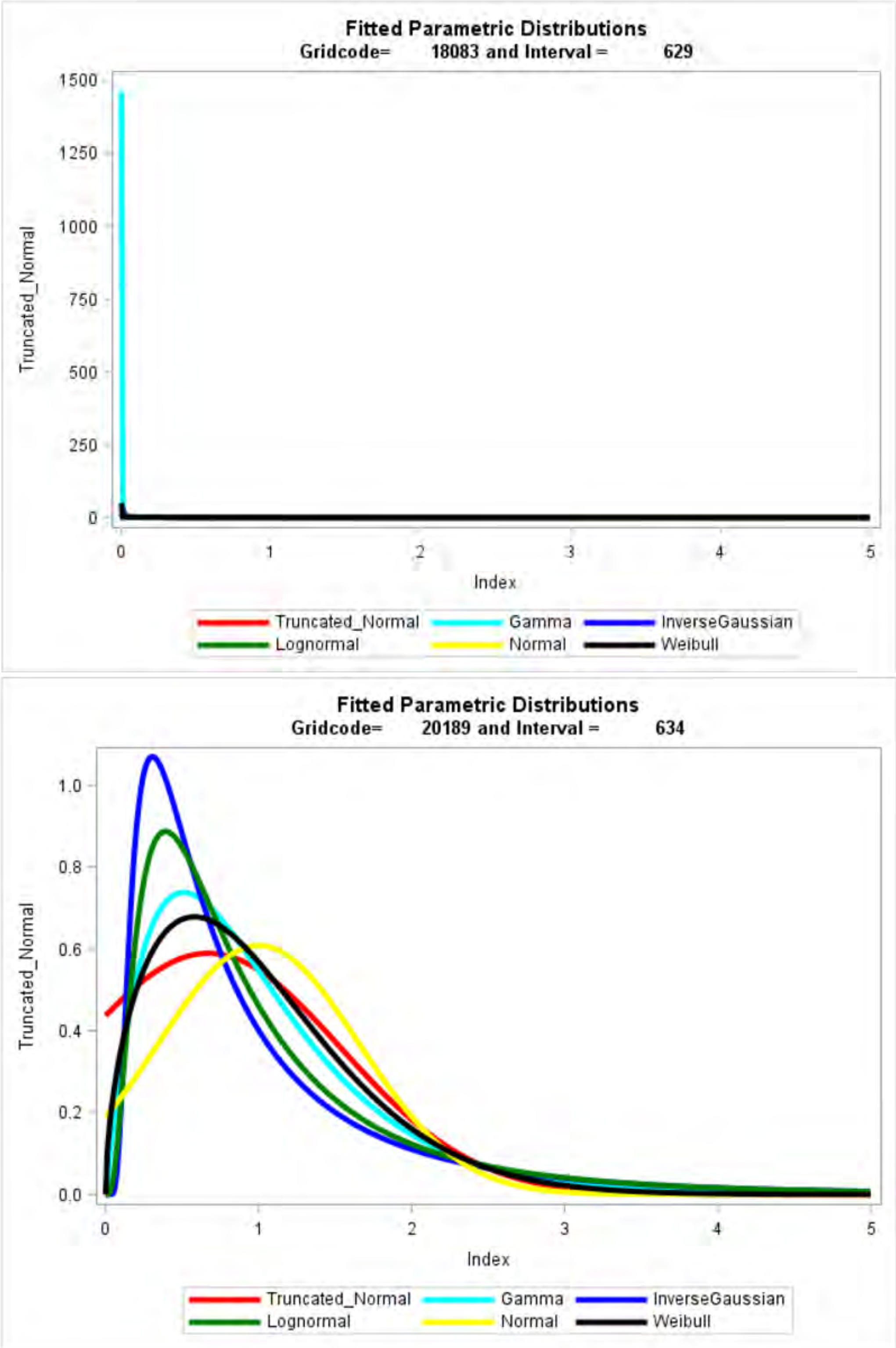


Figure 4-13

Examples of Fitted Densities

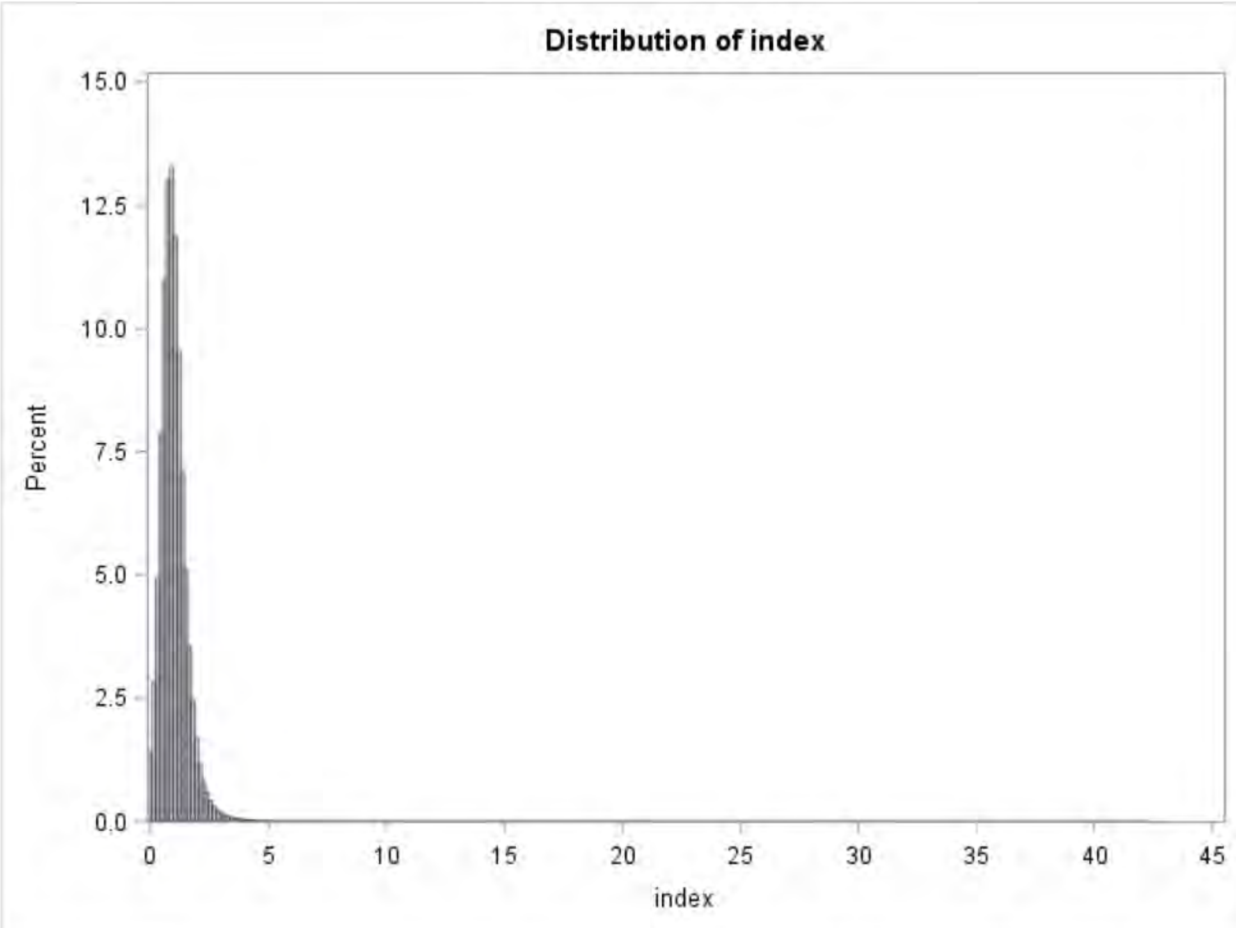


Figure 4-14

Histogram of data from Grid 18083 and Interval 629.

Figures 4-15 and 4-16 present rates derived from the truncated normal using the two alternative rating methods (our ML versions and those generated by the RMA rating program). The alternative rating methods track very closely at low to moderately high levels. However, a small but notable difference arises at higher rates, with our ML rejection sampling methods generating slightly higher rates. The differences are more notable at the higher 90 percent coverage level. The criteria for choosing one method over another are unclear and the underlying reasons for the differences are likewise uncertain. As noted, this likely reflects the difficulties associated with working with a truncated normal distribution when the scale (mean) parameter is very negative (i.e., in high-risk situations).

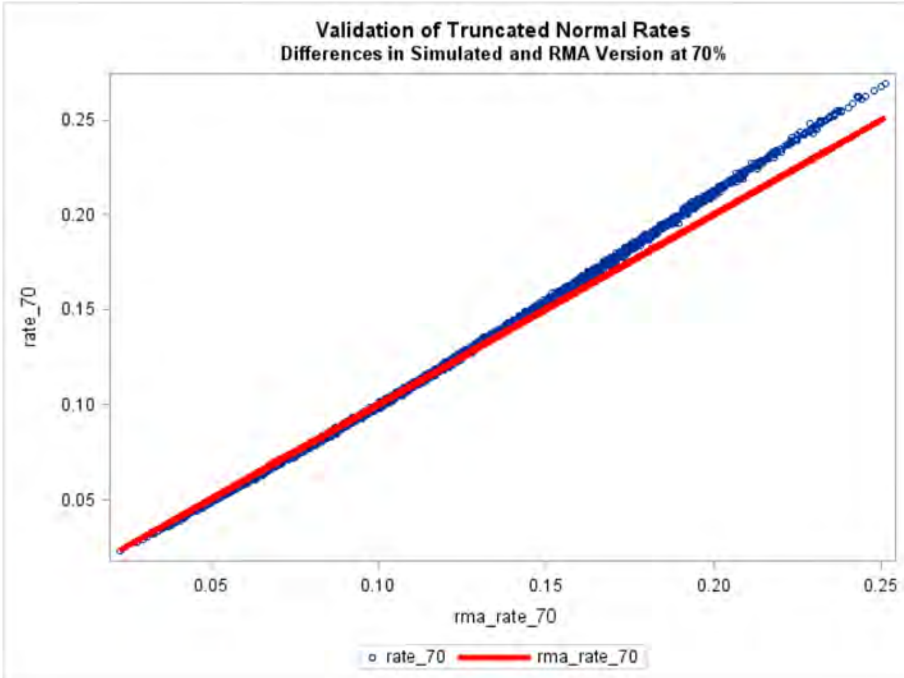


Figure 4-15

Seventy Percent Rate Comparison Rejection Method and RMA Truncated Normal

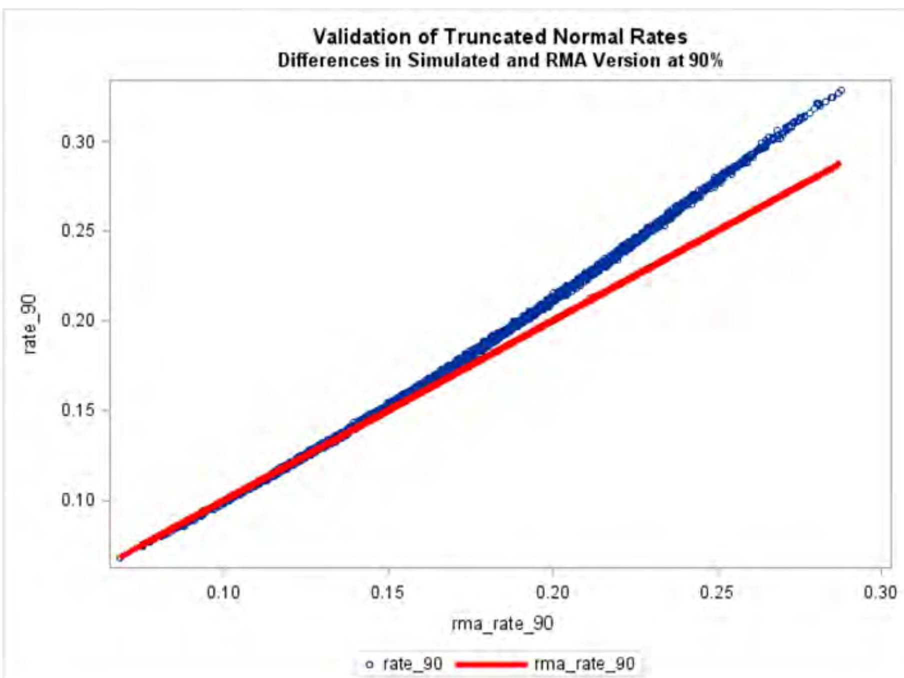


Figure 4-16

Ninety Percent Rate Comparison Rejection Method and RMA Truncated Normal

Actuarial Recommendations

Overall, this program is actuarially sound. Outside of a computation error in fitting the Black Scholes parameters, we find no significant shortcomings in the general approach used by RMA to estimate premium rates. Methods currently used to bound rates and to select the final rates from among the different rate estimates are ad hoc. We recommend that RMA consider the use of goodness-of-fit tests in the selection of the final parametric distribution used to estimate rates. Of course, rates derived from parametric distributions should be compared to empirical burn rates. In some cases with extremely high or low variance, convergence issues may make it difficult to adequately estimate parametric rates and thus any measure based on such rates needs a careful review. The truncated normal distribution is strongly supported in a majority of cases. Procedures currently used to spatially smooth rates are appropriate and we recommend no changes to these procedures.

Chapter 5 Evaluate the current program design

Assessment of the frequency of payments

The assessment of the frequency of payments is conducted using the rainfall index data at the national level, including all grids. The assessment is performed for the period 2002-2018. There are eleven two-month intervals, J-F, F-M, M-A, A-M, M-J, J-J, J-A, A-S, S-O, O-N, and N-D. Producers can select up to six non-overlapping intervals. When producers select more than one interval, there are at least two different ways to calculate payment frequencies. The first way would be to calculate payment frequencies at the "*producer level*". As an example, consider a producer who chooses five intervals. If at least one of the five intervals results in a payment, then the frequency of payment for this producer would be: 1/1 or 100 percent. A second way to calculate payment frequencies would be at the "*interval level*". Given that each interval is rated and indemnified independently of the other intervals when the producer chooses multiple intervals the producer is choosing different policies. Alternatively, when the producer chooses multiple intervals one can think as if the producer is choosing a single policy with multiple payments. For the example where the producer chooses five intervals, if one of the five intervals results in payment, then the frequency of payment for this producer would be 1/5 or 20 percent.

Figure 5-1 shows the payment frequencies by interval and coverage level for the period 2002-2018. Note that payment frequencies are very similar across the eleven intervals with only two intervals, J-F and F-M, where payment frequencies are slightly higher than the other intervals.

Figure 5-2 shows the payment frequencies by coverage level for the period 2002-2018. Payment frequencies increase with the coverage level.

Figures 5-3 and 5-4 show the payment frequencies for two combinations of the eleven intervals. The first combination consists of six non-overlapping two-month intervals, J-F, M-A, M-J, J-A, S-O, and N-D. This combination is referred to as "ODD" (the first month of each interval is odd). The second combination consists of five non-overlapping two-month intervals, F-M, A-M, J-J, A-S, and O-N referred to as "EVEN".

Figure 5-3 shows the payment frequencies calculated at the "*producer level*". Note that if at least one of the intervals in the combination results in a payment then the entire combination of five or six intervals also results in payment, and the frequency of payment for this producer would be 1/1 or 100 percent.

Figure 5-4 shows the payment frequencies calculated at the "*interval level*". The frequency of payment for each combination is calculated by dividing the number of intervals in the combination that result in a payment by the total number of intervals in the combination.

Payment frequency was also assessed for three-month intervals. The three-month intervals considered were J-F-M, F-M-A, M-A-M, A-M-J, M-J-J, J-J-A, J-A-S, A-S-O, S-O-N, and O-N-D.

Figure 5-5 shows the payment frequencies by three-month intervals and coverage level for the period 2002-2018. Note that payment frequencies for the two early in the year intervals J-F-M and F-M-A are again slightly higher than the other intervals.

Figure 5-6 shows the payment frequencies for three combinations of the ten 3-month intervals. The first combination consists of four non-overlapping three-month intervals, J-F-M, A-M-J, J-A-S, and O-N-D. This combination is referred to as "1st 3-Month". The second combination consists of three non-overlapping three-month intervals, F-M-A, M-J-J, and A-S-O and is referred to as "2nd 3-Month". The third combination consists of three non-overlapping three-month intervals, M-A-M, J-J-A, and S-O-N and is referred to as "3rd 3-Month ". Figure 5-6 shows the payment frequencies calculated at the "*producer level*". Note again that if at least one of the intervals in the combination results in a payment then the entire combination of five or six intervals also results in payment, and the frequency of payment for this producer would be: 1/1 or 100 percent.

Results of Figure 5-6 show that payment frequencies for the combination "1st 3-Month" are much higher than the payment frequencies for the other two combinations, "2nd 3-Month" and "3rd 3-Month". For example, for coverage level, 90 percent payment frequency for the "1st 3-Month" combination is 10 percentage points higher than payment frequency for the other two combinations. For coverage level, 70 percent the difference is about 13 percentage points. Note that combinations "2nd 3-Month" and "3rd 3-Month" do not include the months of January and December.

Figure 5-7 shows the payment frequencies for the three-month intervals by coverage level for the period 2002-2018. Payment frequencies increase with the coverage level.

A comparison of Figures 5-1 and 5-5 indicates a tendency for the lower frequency of payments for the three-month intervals compared to the two-month intervals. A more direct comparison of the frequency of payments between the two- and three-month intervals is provided by comparing Figures 5-2 and 5-7. The frequency of payments for each coverage level for the three-month intervals, as shown in Figure 5-7, is lower than the respective frequency of payments for the two-month intervals shown in Figure 5-2. For example, the frequency of payments for the 90% coverage level is 42.5% for the three-month intervals versus 46.1% for the two-month intervals. Similarly, the frequency of payments for the 85% coverage level is 37.6% for the three-month intervals versus 41.8% for the two-month intervals.

A combination of lowering the highest coverage level and/or the replacement of the two-month intervals with the three-month intervals would result in a lower frequency of small payments. For example, using two-month intervals but lowering the highest coverage level from 90% to 80% would lower the highest frequency of payments from 46.1% to 37.6%. Alternatively, replacing the two-month intervals with the three-month intervals and keeping the highest coverage level the same at 90% would lower the highest frequency of payments from 46.1% to 42.5%. As another alternative, a combination of lowering the highest coverage level from 90% to 85% and replacing the two-month intervals with the three-month intervals would lower the highest frequency of payments from 46.1% to 37.6%.

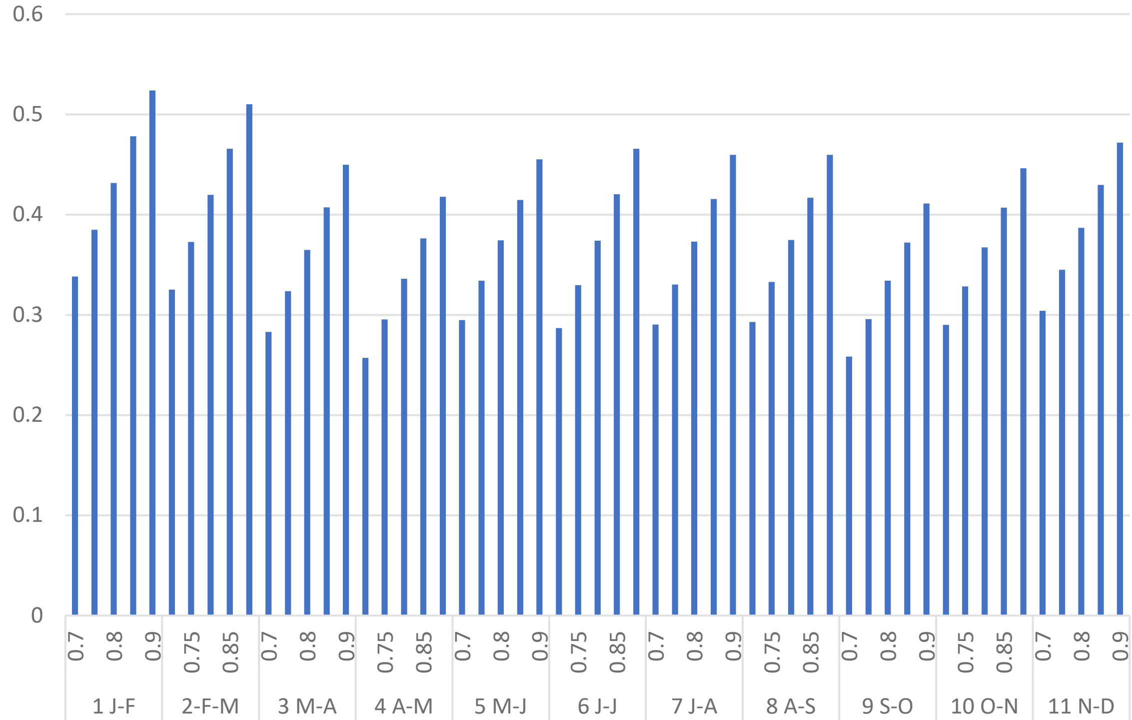


Figure 5.1. Payment Frequencies by Two-Month Interval and Coverage Level 2002-2018

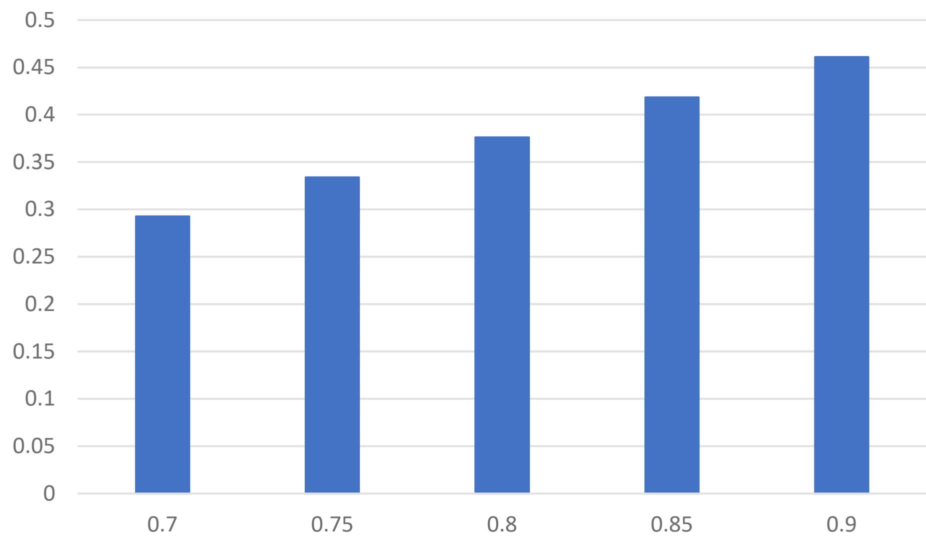


Figure 5.2. Payment Frequencies by Coverage Level for all Two-Month Intervals 2002-2018

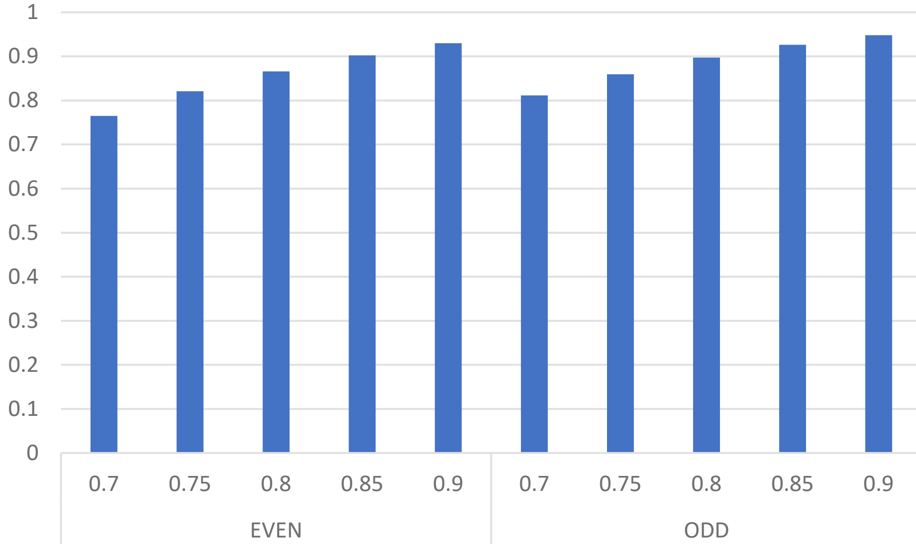


Figure 5.3. Payment Frequencies by Combinations of Two-Month Intervals and Coverage Level 2002-2018 (Frequencies are calculated at the "*producer level*" – see text for definition)

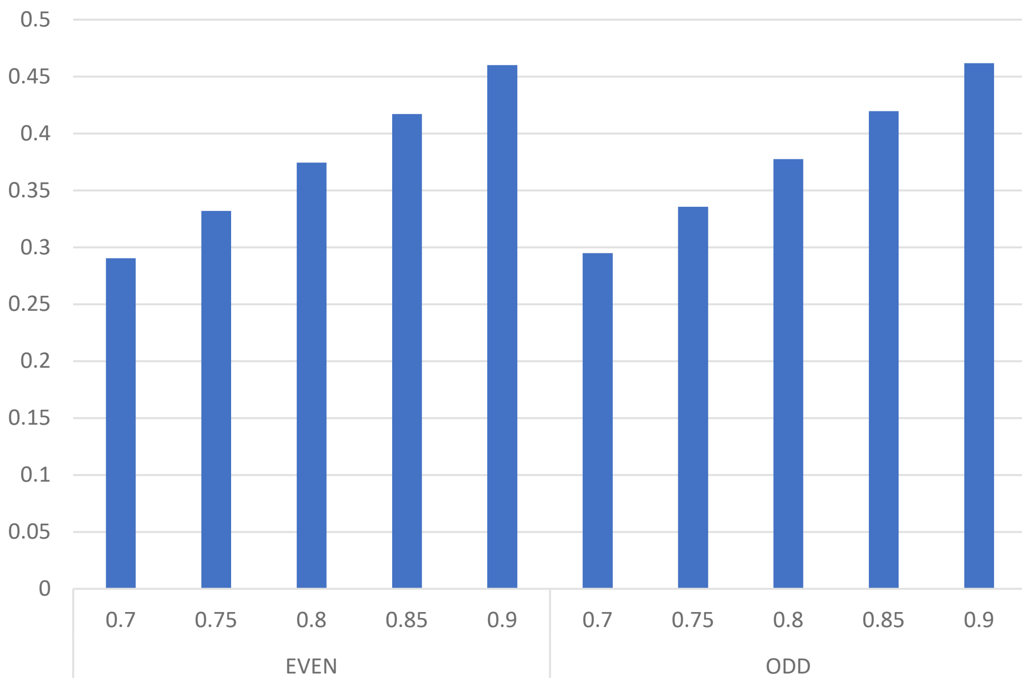


Figure 5.4. Payment Frequencies by Combinations of Intervals and Coverage Level 2002-2018 (Frequencies are calculated at the "*interval level*" – see text for definition)

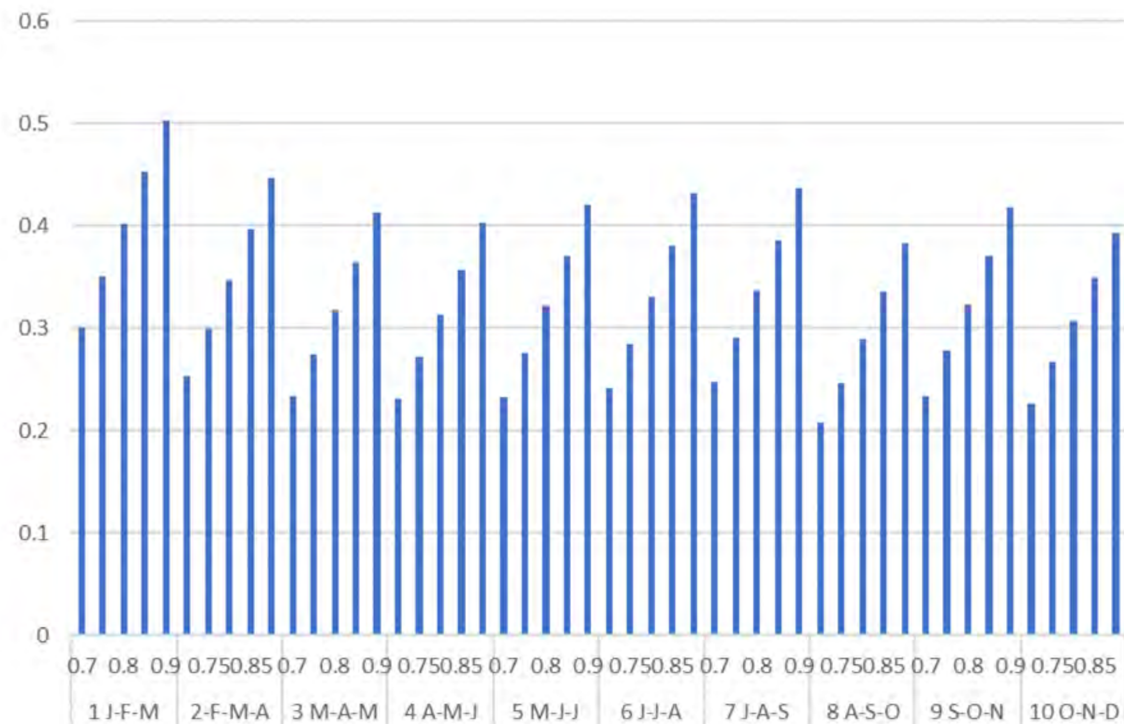


Figure 5.5. Payment Frequencies by Three-Month Interval and Coverage Level 2002-2018

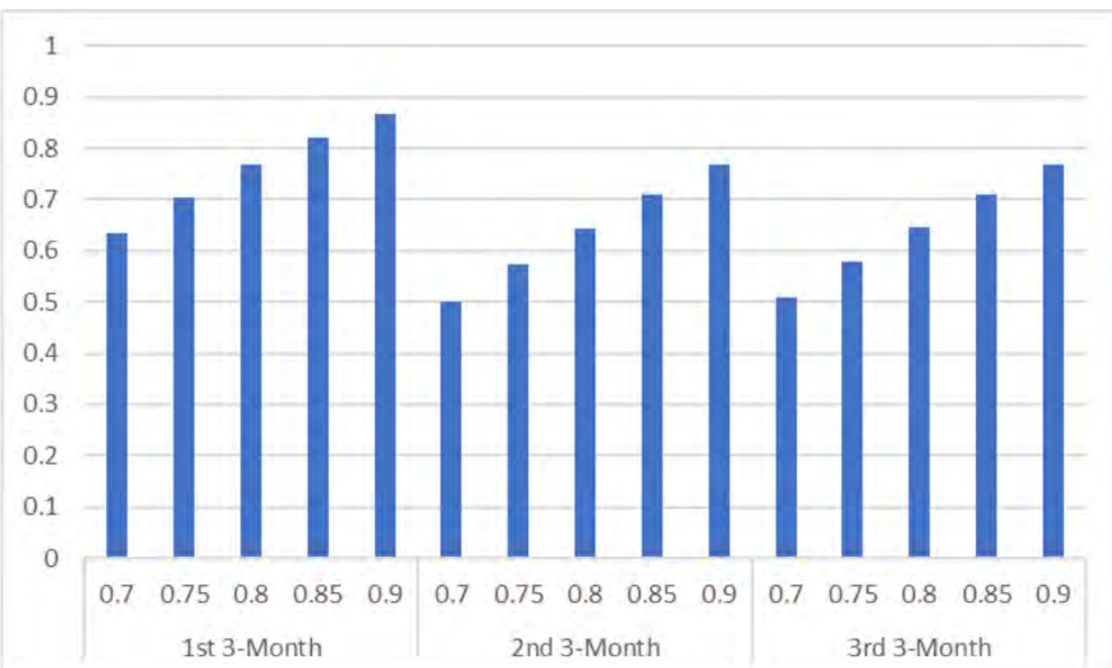


Figure 5.6. Payment Frequencies by Combinations of Three-Month Intervals and Coverage Level 2002-2018 (Frequencies are calculated at the "*producer level*" – see text for definition)

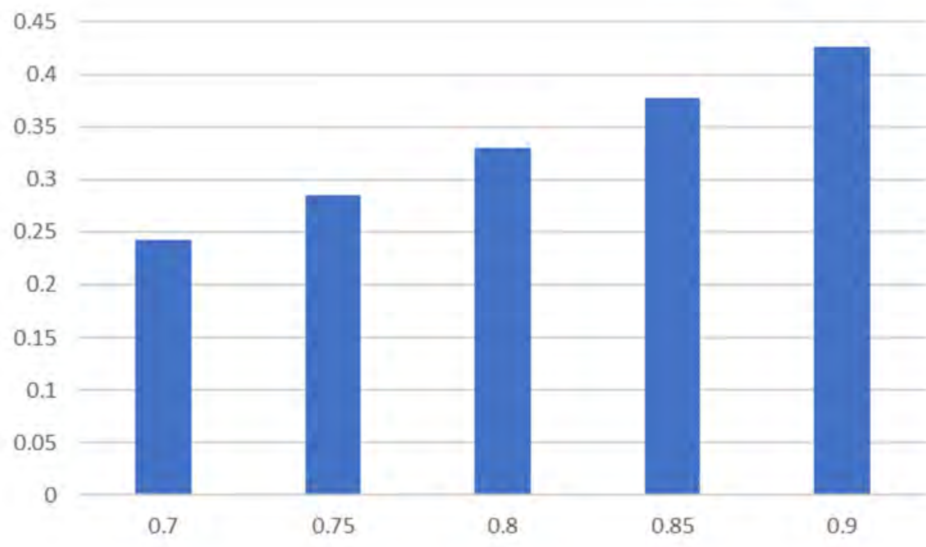


Figure 5.7. Payment Frequencies by Coverage Level for all Three-Month Intervals 2002-2018

Intervals contributing to forage production

Producers are given latitude to insure any period during the year. Given that some regions may have a mix of cool and warm-season grasses, defining a set period for a growing season may be difficult. Also, producers in arid regions may believe that pre-growing season rainfall is critical for growing season forage production. However, the Agrilytica report (2014 P 3.) states “While many producers allocate insurance to intervals that have the highest production risk, some select the intervals they think will yield the highest potential pay-out (based on several criteria). Others select all or several intervals to maximize the chances of an indemnity. For these producers, the interval selection incentives conflict with RMA’s view of the risk management objectives of the plans. In Texas, the uniform spreading of liability is not consistent with historical rainfall averages, which are much higher in summer months.”

As noted in the literature review, Diersen et al. (2015) suggest that the most risk efficient intervals are May-June and July-August and these choices are most consistent with the desire to have payments that offset the highest expected forage risk. Similarly, Westerhold et al. (2018) also find that intervals that coincide with the actual growing season in Nebraska are the ones where PRF provides the largest risk reductions. They go on to suggest dropping intervals in the PRF contract that do not coincide with the growing season since these intervals tend to be used as an income maximizing strategy rather than risk reduction.

Assessment of the relationship between hay yields and weather variables

Data for this part of the analysis consists of alfalfa other (excluding alfalfa) hay yields (ton/acre) from NASS, precipitation (mm), temperature (degree C), and Palmer Drought Severity Index (PDSI) (generally between -2 and 2) data. Data are observed annually at the state level. As an alternative to state-level data, county-level data are used to distinguish between different parts within a state that use irrigated or non-irrigated practice.

The dependent variable for this part of the analysis consists of alfalfa hay yield and other (excluding alfalfa) hay yield. The discussion here is for the case of other (excluding alfalfa) hay yield. Findings are similar for the case of the alfalfa hay yield. The dependent variable (hay yield) was modeled as a function of two sets of independent variables. The first set includes precipitation and temperature while the second set consists of PDSI. A trend variable is also included in both sets.

Several issues were investigated:

1. What is the effect of the monthly precipitation, temperature, and PDSI variables on hay yields?
2. What is the effect of the neighboring states' aggregate precipitation, temperature, and PDSI variables on the hay prices of a target state?
3. Is there a nonlinear (quadratic) relationship between precipitation, temperature, and PDSI and hay prices?

The results for each of these issues are discussed below.

1. What is the effect of the monthly precipitation, temperature, and PDSI variables on hay yields?

Two sets of regressions were estimated to address the first issue. First, hay yields were regressed against 12 monthly variables of precipitation and temperature. Second, monthly variables of precipitation and temperature were aggregated into two 6-month periods, one before the growing season from previous October to March and the other during the growing season from April to September. A trend variable was also added in both sets of regressions.

The same analysis was repeated to investigate the relationship between hay yields and PDSI.

Some general notation description for all the tables is provided here. P indicates precipitation, T indicates temperature, and PDSI indicates the Palmer Drought Severity Index. The numbers in parenthesis following P, T, and PDSI indicate lags, for example, P(3) indicates the value of precipitation lagged by three months. The numbers without parenthesis following P, T, and PDSI indicate the calendar month, for example, P3 indicates the value of precipitation for March. X^2 indicates the square term of the variable X while NB_X indicates the aggregate value from the neighboring states for the variable X.

The results of the stepwise regression of the relationship between hay yields and precipitation and temperature are reported in Table 5.1 for the case of monthly variables and Table 5.2 for the case of the two 6-month periods, respectively. The results of the relationship between hay yields and PDSI are reported in Table 5.3 and Table 5.4, respectively.

Table 5.5 presents the extends the analysis to include the effect of precipitation and temperature variables from the neighboring states. Table 5.6 presents similar results to table 5.5 for PDSI variables.

The results of Table 5.1 show that the maximum number of significant monthly variables for precipitation varies from zero to seven. For temperature the number of significant monthly variables varies from zero to six. Additionally, all monthly variables for both precipitation and temperature have a significant effect on hay yield for at least one state. Results of Table 5.1 also show that precipitation, temperature, and a trend variable explain from a low of 26% for the state of MI to a high of 97% for MT of the variation in hay yields.

The results of Table 5.3 show that the maximum number of monthly variables for PDSI varies from zero to four. Additionally, all monthly variables for PDSI, except for March, have a significant effect on hay yield for at least one state. Results of Table 5.3 show PDSI explains from a low of 0% for the states of IA, MI, and OH to a high of 84% for ND and CO of the variation in hay yields.

Table 5.2 presents the results of the regression of the hay yield on monthly precipitation and temperature variables aggregated into a prior to – and during the growing season. Table 5.4 presents the results of the similar regression of the hay yield on the aggregated monthly PDSI variables. Results of Table 5.2 show that while for a few states precipitation before the growing season has a significant effect on hay yield, for the majority of states (21 out of 29 states), it is the precipitation during the growing season that significantly affects hay yield. *This finding indicates that restricting interval selection to only during the growing season should not negatively affect the risk management offered by the program.*

Results of Table 5.4 similarly show that while for a few states PDSI before the growing season has a significant effect on hay yield, for the majority of states (21 out of 29 states), it is the PDSI during the growing season that significantly affects hay yield. *This finding again indicates that restricting interval selection to only during the growing season should not negatively affect the risk management offered by the program.*

As noted earlier, to distinguish between different parts within a state that use irrigated or non-irrigated practice, county-level data are used to derive state-level yield data as an alternative to the all-practice state-level data. NASS reports yield data for a limited number of counties. Agriculture Census data, available from NASS, were used to identify whether a county within a state is under a dominantly irrigated or non-irrigated practice. If the percentage of irrigated acres in hay production in a county is more than 50 percent of total acres in hay production, the county is designated as an irrigated county. Otherwise, the county is designated as the non-irrigated county. State-level yields for irrigated and non-irrigated practice were then calculated as a weighted average of the county yields with acreage being used as weights.

The results of the analysis using the yield data obtained as above are reported in Tables 5.7 through 5.12. The results from Tables 5.7 – 5.12 provide a similar picture as the earlier results using state-level data. While some differences were found in the relationship between yield and weather variables like precipitation, temperature, and PDSI for the irrigated versus non-irrigated practices within a state, these differences cannot be generalized across states.

Finally, we did the same analysis at the county level for 1,700 counties to further test whether the findings use state-level data are consistent at the county level. The story of Table 5.1 repeats here. Only 4 counties (0.24%) have 8 months of precipitation effect as significant. Another 17 counties (1%) have 7 months of significant precipitation effect. 41 counties (2.41%) have 6 months of significant precipitation effect. The rest of the counties, 1,638 of them (96.35%) have only 5 or fewer months of significant precipitation effect. For the Western states (CA, AZ, NM, and NV), 47 of the 56 counties (83.93%) have only 3 or fewer months of significant precipitation effect, or 39 of the 56 counties (69.64%) have only 2 or fewer months of significant precipitation effect.

The results for the case of the alfalfa hay yield are presented in tables 5-13 – 5.18. Findings for the case of the alfalfa hay yield are similar to findings for the case of other (excluding alfalfa) hay yield discussed above.

We believe this provides strong evidence of two things. First, there is little evidence in the forage literature or our analysis that producers suffer from significant rainfall risk in more than eight months per year. However, because production systems sometimes vary even within a county, we believe producers may need the flexibility to choose the periods that best fit their operation and reduce the basis risk for their farm. Ultimately, *we recommend increasing the minimum percentage of value in any one index interval to 25 percent if two-month intervals are used or 33 percent if three-month intervals are used. This will avoid the paperwork of additional indices and will require producers to focus participation in periods that most affect production.*

Table 5-1. Results of the stepwise regression of the hay (excluding alfalfa) yield on monthly precipitation and temperature

Prod_Pract	State	Constant	Trend	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	P_max	T_max	Rsq
All	AZ	10.582***	0.032***					0.009*					-0.008***										-0.248***		-0.035**			2	2	0.71
All	CA	3.955***	0.028***		-0.001*					-0.021**	-0.009*								-0.098***									3	1	0.76
All	CO	3.600***	0.007***										0.005***				0.048***		-0.037**				-0.103***					1	3	0.64
All	ID	1.869***	0.012***	-0.002**	0.003***			0.003**		0.009***											-0.047***				0.029**	0.038***		4	3	0.74
All	IL	1.384***	0.008**					0.003***		0.003**	0.002*																	3	0	0.5
All	IA	3.670***						0.003***						-0.002*			0.020*		0.042**			-0.085***						2	3	0.47
All	KS	4.526***					0.001**	0.002***				0.001**					0.020***	-0.023***				-0.067***	-0.033**		-0.023*	-0.029***		3	6	0.86
All	KY	1.172**		0.001*				0.001*	0.004***	0.002**	0.002***						0.026**		0.046***					-0.041*				5	3	0.74
All	MI	3.119***			-0.005**				0.003*													-0.057*						2	1	0.26
All	MN	1.695***	-0.012***									0.003**							-0.026*						0.051**			1	2	0.39
All	MO	2.729***					0.002***	0.002***	0.003***	0.001**				0.001*			0.030***						-0.047***		-0.056***		0.014**	5	4	0.8
All	MT	0.775***	0.008***						0.004***	0.002**				0.007***														3	0	0.7
All	NE	-0.299	0.010***					0.003***	0.002***				0.001*	0.003**						0.023**	0.024**					-0.023***		4	3	0.85
All	NV	1.777***	0.019***						0.006***															-0.036*			0.040**	1	2	0.69
All	NM	2.265**	0.018***																	0.051**		-0.146***	0.106***			-0.067***		0	4	0.62
All	NY	3.266***	-0.005**					0.001*															-0.071***					1	1	0.45
All	ND	0.922***	0.009***		0.011***			0.003***	0.004***	0.002**	-0.004***		0.004***											-0.030*				6	1	0.84
All	OH	4.862***		0.002*	-0.003***				0.002**									0.055***		-0.075***		-0.076***					-0.032***	3	4	0.68
All	OK	1.527**					0.001*		0.003***			0.001*				-0.043***							-0.043**	0.038**				3	3	0.7
All	OR	1.400***	0.017***					0.003***					0.001*		0.001*													3	0	0.72
All	PA	1.074***		-0.002*					0.003***	0.003***			0.002**													0.040*		4	1	0.6
All	SD	0.293	0.010***		0.008***			0.003***	0.002**				0.002***	0.003*		-0.015***					-0.020***			0.029**				5	3	0.86
All	TX	8.981***		0.005***																	-0.180***		-0.085*					1	2	0.59
All	UT	2.555***	0.013***		0.003***	-0.001*		0.004***		0.003***					-0.005***	-0.020***	-0.022**		-0.059***	0.025**			-0.034**					5	5	0.87
All	WI	2.062***								0.005***											-0.034***							1	1	0.3
Irrig	CO	1.748***	0.014***	0.004*	0.006**					0.004***			0.007***									-0.044*						4	1	0.83
Irrig	MT	1.294***	0.013***	0.003**	0.003*			-0.001**	0.004***	0.001**		-0.004***		0.005***				-0.027***								-0.029***		7	2	0.97
Non_Irrig	CO	0.792**						0.002*		0.007***	0.008***														-0.052*	-0.029**		3	2	0.74
Non_Irrig	MT	0.296**							0.006***	0.002*				0.012***													0.020**	3	1	0.75
Total				7	9	1	3	15	13	14	5	4	8	7	2	3	6	3	6	4	5	6	9	5	6	7	4			

Table 5-2. Results of the regression of the hay (excluding alfalfa) yield on precipitation and temperature prior to- and during the growing season

Prod_Pract	State	Constant	Trend	P_prior	P_during	T_prior	T_during	Rsq
All	AZ	4.692**	0.030***	-0.001	0.001	-0.032	-0.045	0.41
All	CA	3.04	0.038***	0	0.001	-0.158*	0.029	0.68
All	CO	1.464	0.008*	0.002	0.001	0.028	-0.045	0.36
All	ID	1.908**	0.007**	0	0.002**	0.051	-0.035	0.42
All	IL	1.711	0.006	-0.001	0.001**	0.004	0.006	0.35
All	IA	2.613**	-0.003	0	0.001	0.002	-0.036	0.09
All	KS	3.101***	-0.003	0	0.001***	-0.004	-0.092**	0.69
All	KY	2.561*	0.006	0	0.001***	0.039	-0.07	0.46
All	MI	3.171**	-0.002	-0.001	0.001	0.003	-0.074	0.12
All	MN	2.005**	-0.012***	0.001	0.001*	0.002	-0.026	0.28
All	MO	2.579***	0.004	0	0.001***	0.046**	-0.089**	0.57
All	MT	0.448	0.007**	0.001	0.002***	0.019	0.017	0.52
All	NE	-0.338	0.007***	0.001	0.002***	0.005	0.04	0.69
All	NV	1.731*	0.016***	0.001	0	0.057	-0.044	0.61
All	NM	2.423	0.016***	0	0	-0.069	-0.014	0.44
All	NY	2.945***	-0.006*	0	0.001*	0.017	-0.076	0.31
All	ND	0.248	0.007**	0.002**	0.002***	-0.002	0.007	0.59
All	OH	4.688***	-0.004	0	0.001*	0.042	-0.150**	0.33
All	OK	4.124***	0.002	0.001***	0.001**	-0.013	-0.135***	0.56
All	OR	0.715	0.018***	0.000**	0.001*	-0.012	0.04	0.67
All	PA	1.905	0.007	0	0.001***	-0.011	-0.025	0.34
All	SD	0.928***	0.010***	0.001*	0.002***	-0.018	-0.029**	0.66
All	TX	4.168*	-0.010*	0.001*	0.002**	0.083*	-0.157	0.62
All	UT	2.841***	0.011***	0	0.001	-0.017	-0.059*	0.58
All	WI	1.230*	-0.016***	0.001	0.002***	-0.001	-0.025	0.42
Irrig	CO	-0.828	0.012**	0.003***	0.003***	-0.055	0.08	0.69
Irrig	MT	0.763	0.017***	0.001	0.001*	-0.016	0.018	0.53
Non_Irrig	CO	-0.641	-0.003	0.001	0.003**	-0.116*	0.063	0.43
Non_Irrig	MT	-0.223	0.006	0.001	0.003***	0.034	0.017	0.49

Table 5-3. Results of the stepwise regression of the hay (excluding alfalfa) yield on monthly PDSI

Prod_Pract	State	Constant	Trend	PDSI1	PDSI2	PDSI3	PDSI4	PDSI5	PDSI6	PDSI7	PDSI8	PDSI9	PDSI10	PDSI11	PDSI12	PDSI_max	Rsq
All	AZ	3.486***	0.028***													0	0.36
All	CA	2.348***	0.032***													0	0.62
All	CO	1.429***	0.010***								0.055***					1	0.34
All	ID	1.861***	0.010***						-0.178*	0.216**						2	0.45
All	IL	2.103***	0.007**				-0.220***	0.205***		-0.147*	0.205**					4	0.57
All	IA	2.226***														0	0
All	KS	1.802***	-0.003*		-0.041***							0.089***				2	0.59
All	KY	2.071***						-0.105**	0.085*			0.068***				3	0.44
All	MI	2.003***														0	0
All	MN	2.149***	-0.014***							0.072***						1	0.48
All	MO	1.809***									0.072***				-0.028*	2	0.37
All	MT	1.326***	0.008***					-0.068***		0.106***						2	0.6
All	NE	1.127***	0.009***							0.043***						1	0.62
All	NV	1.264***	0.018***									0.029**				1	0.6
All	NM	1.703***	0.012***							0.072**		-0.091***				2	0.51
All	NY	1.980***	-0.005*										-0.021**			1	0.27
All	ND	1.389***		-0.400***					0.157***						0.336**	3	0.84
All	OH	2.253***														0	0
All	OK	1.595***									0.069***		-0.033**			2	0.38
All	OR	1.716***	0.019***					0.029**								1	0.66
All	PA	2.040***						-0.172***	0.145**	0.101***						3	0.51
All	SD	1.195***	0.009***						0.115***						-0.051***	2	0.78
All	TX	2.043***						-0.589***	0.679***					-0.071*		3	0.56
All	UT	1.899***	0.011***						-0.111**		0.121***					2	0.59
All	WI	2.343***	-0.021***								0.129***					1	0.46
Irrig	CO	1.556***	0.020***					0.054**	-0.149***	0.173***						3	0.84
Irrig	MT	1.627***	0.018***					-0.071**		0.101***						2	0.6
Non_Irrig	CO	1.287***					0.060*		-0.184***	0.192***						3	0.57
Non_Irrig	MT	0.949***	0.009**					-0.095***		0.135***						2	0.54
Total				1	1	0	2	9	9	11	6	4	2	1	3		

Table 5-4. Results of the regression of the hay (excluding alfalfa) yield on PDSI before- and during the growing season

Prod_Pract	State	Constant	Trend	PDSI_prior	PDSI_during	Rsq
All	AZ	3.463***	0.030***	0.003	0.008	0.36
All	CA	2.300***	0.035***	-0.034	0.061	0.65
All	CO	1.427***	0.010***	-0.003	0.060**	0.31
All	ID	1.913***	0.008***	-0.008	0.054**	0.39
All	IL	2.118***	0.007*	-0.041	0.085**	0.31
All	IA	2.251***	-0.002	-0.034	0.048	0.05
All	KS	1.758***	-0.002	-0.070***	0.112***	0.48
All	KY	1.923***	0.008**	-0.042	0.064**	0.33
All	MI	2.100***	-0.005	-0.059	0.063	0.07
All	MN	2.149***	-0.014***	-0.02	0.098***	0.49
All	MO	1.733***	0.004	-0.050**	0.088***	0.37
All	MT	1.329***	0.008***	-0.02	0.056***	0.47
All	NE	1.126***	0.008***	-0.032	0.073***	0.63
All	NV	1.274***	0.018***	-0.01	0.037	0.59
All	NM	1.737***	0.012***	-0.023	0.009	0.38
All	NY	2.001***	-0.006**	-0.036**	0.025	0.29
All	ND	1.321***	0.004	-0.068***	0.155***	0.75
All	OH	2.395***	-0.007	-0.083*	0.090*	0.14
All	OK	1.564***	0.001	-0.039*	0.083***	0.33
All	OR	1.709***	0.019***	0.003	0.026	0.65
All	PA	1.916***	0.008**	-0.044	0.105***	0.37
All	SD	1.203***	0.008***	-0.066***	0.132***	0.77
All	TX	2.220***	-0.009**	-0.173***	0.211***	0.52
All	UT	1.925***	0.009***	-0.035	0.047**	0.5
All	WI	2.351***	-0.022***	-0.015	0.153***	0.44
Irrig	CO	1.550***	0.019***	0.012	0.072***	0.66
Irrig	MT	1.632***	0.018***	-0.033	0.060**	0.49
Non_Irrig	CO	1.264***	0	0.008	0.065*	0.36
Non_Irrig	MT	0.954***	0.009*	-0.042	0.081**	0.33

Table 5-5. Results of the nonlinear regression of the hay (excluding alfalfa) yield on precipitation and temperature and neighboring states

Prod_Pract	State	Constant	Trend	P_prior	P_during	T_prior	T_during	P_prior^2	P_during^2	T_prior^2	T_during^2	NB_P	NB_T	Rsq
All	AZ	-16.34	0.037***	0.003	-0.038**	0.209	1.980*	0	0.000**	-0.007	-0.049*	0.001	0.110*	0.61
All	CA	-86.97*	0.040***	0.004**	-0.011*	0.663	8.670*	0.000**	0.000**	-0.041	-0.219*	-0.001	0.028	0.82
All	CO	-10.25	0.008*	0.02	-0.004	0.02	1.479	0	0	-0.008	-0.052	0.001	-0.026	0.44
All	ID	3.451	0.009***	-0.004	-0.015**	0.057	0.11	0	0.000**	0.009	-0.005	-0.001	-0.002	0.57
All	IL	24.771	0.008	-0.001	0.004	0.073	-2.461	0	0	-0.012	0.063	0	0.006	0.41
All	IA	-6.828	-0.004	-0.001	0.010***	-0.003	0.586	0	-0.000***	-0.005	-0.016	0.001	0.024	0.66
All	KS	12.923	-0.003	-0.002	0.002	0.034	-1.076	0	0	-0.003	0.024	0.001	0.003	0.72
All	KY	-5.756	0.009*	-0.002	0.004	0.293	0.611	0	0	-0.021	-0.016	-0.001	-0.012	0.52
All	MI	9.528	-0.002	0.012	0.030**	0.006	-2.262	0	-0.000**	0.006	0.074	-0.001	0.052	0.3
All	MN	-14.72	-0.015***	0.002	-0.003	-0.024	2.232	0	0	-0.003	-0.074	0.003*	0.014	0.44
All	MO	0.709	0.003	0.003	0.005**	0.008	-0.107	0	0.000*	0.004	0	0	0.013	0.66
All	MT	-0.708	0.006**	0	0.001	-0.017	0.204	0	0	-0.01	-0.007	0.001	0.019	0.55
All	NE	-1.67	0.007**	0	0.001	0.039	0.196	0	0	-0.012	-0.004	0	0	0.71
All	NV	-13.01	0.015***	-0.004	0.003	0.011	1.87	0	0	0.008	-0.058	0.001	-0.050**	0.78
All	NM	7.878	0.015***	0.002	-0.006	0.343	-0.67	0	0	-0.034	0.018	-0.001	-0.022	0.52
All	NY	-22.27*	-0.003	-0.001	0	0.026	3.148*	0	0	-0.002	-0.103*	-0.003***	0.036*	0.61
All	ND	-2.499	0.004	-0.002	0.009*	0.133	0.232	0	0	0.014	-0.007	0.002	0.016	0.7
All	OH	-2.744	-0.006	0.003	0.011**	0.127	0.158	0	-0.000**	-0.018	-0.006	-0.002	0.012	0.52
All	OK	-19.45	0.002	0.003	0.005***	-0.267	1.761	0	0.000**	0.015	-0.04	0.001	0.03	0.74
All	OR	-7.506	0.018***	0.002	-0.001	-0.102	1.25	0	0	0.016	-0.043	-0.001	-0.018	0.7
All	PA	-0.195	0.001	0.014**	0.003	-0.073	-0.263	-0.000**	0	0.011	0.006	0.003**	0.011	0.56
All	SD	-0.396	0.008**	0.003	0.002	-0.01	0.055	0	0	0.003	-0.002	0.002	0.028	0.72
All	TX	49.825	-0.016**	0.006*	0.001	-2.416**	-2.608	-0.000*	0	0.101**	0.05	-0.001	-0.055	0.74
All	UT	1.479	0.010***	-0.003	0.002	-0.017	0.107	0	0	-0.004	-0.005	0.003	0.018	0.64
All	WI	-3.785	-0.018***	0	0.007	0.061	0.422	0	0	0.008	-0.016	0.001	0.102**	0.64
Irrig	CO	-7.177	0.008	0.030*	0.001	0.034	0.813	-0.000*	0	-0.064	-0.026	0	-0.078*	0.81
Irrig	MT	-5.824	0.016***	-0.015	-0.004	-0.086	1.38	0	0	-0.027	-0.052	0.001	-0.011	0.61
Non_Irrig	CO	-17.64	-0.007	0.054**	-0.009	-0.06	2.185	-0.000**	0	-0.041	-0.074	0	-0.102*	0.69
Non_Irrig	MT	-5.356	0.006	-0.009	0	0.021	0.971	0	0	-0.008	-0.036	0.002	0.016	0.55

Table 5-6. Results of the nonlinear regression of the hay (excluding alfalfa) yield on PDSI and neighboring states

Prod_Pract	State	Constant	Trend	PDSI_prior	PDSI_during	PDSI_prior^2	PDSI_during^2	NB_PDSI	Rsq
All	AZ	3.352***	0.008***	-0.023	0.066	0.003	0.021	-0.041	0.4
All	CA	2.353***	0.000***	-0.025	0.061	-0.012	-0.003	-0.005	0.68
All	CO	1.529***	0.009***	-0.009	0.027	-0.003	-0.006	0.064**	0.45
All	ID	1.854***	0.003***	-0.017	0.041	-0.005	0.011	0.035	0.44
All	IL	2.126***	0.077***	-0.04	0.077*	0.013	-0.02	0.01	0.35
All	IA	2.350***	0.303***	-0.032	-0.016	0.009	-0.023**	0.084**	0.27
All	KS	1.704***	0.761***	-0.059***	0.060***	0.011**	-0.005	0.069***	0.73
All	KY	1.944***	0.058***	-0.059**	0.087***	0.020*	-0.024**	0.003	0.43
All	MI	2.123***	0.199***	-0.052	0.026	0.021	-0.02	0.068	0.21
All	MN	2.125***	0.000***	-0.031	0.090***	0.026***	-0.011	0.027	0.65
All	MO	1.710***	0.205***	-0.059**	0.098***	0.011	-0.007	-0.002	0.42
All	MT	1.334***	0.001***	-0.018	0.048**	0.006	-0.006	0.013	0.5
All	NE	1.130***	0.000***	-0.031	0.068**	-0.002	0	0.007	0.64
All	NV	1.265***	0.000***	-0.021	0.008	-0.002	-0.003	0.052**	0.65
All	NM	1.735***	0.003***	-0.024	0.02	-0.001	-0.001	-0.021	0.39
All	NY	2.042***	0.050***	-0.041**	0.023	-0.008	-0.001	0.008	0.35
All	ND	1.386***	0.052***	-0.087***	0.186***	-0.003	-0.014**	-0.034**	0.82
All	OH	2.386***	0.278***	-0.098**	0.098*	0.023**	-0.027*	-0.024	0.27
All	OK	1.629***	0.887***	-0.069***	0.099***	0.017**	-0.028***	0.03	0.57
All	OR	1.657***	0.000***	0.01	-0.007	0.014*	-0.007	0.036	0.73
All	PA	2.050***	0.484***	-0.060**	0.064	0	-0.02	0.045	0.47
All	SD	1.222***	0.000***	-0.048**	0.122***	0.014**	-0.018**	-0.011	0.81
All	TX	2.211***	0.085***	-0.183***	0.206***	0.012	-0.005	0.028	0.54
All	UT	1.891***	0.000***	-0.015	0.02	0.006	-0.004	0.021	0.55
All	WI	2.359***	0.000***	-0.026	0.162**	0.045**	-0.047**	0.007	0.54
Irrig	CO	1.543***	0.000***	0.01	0.072**	0.006	-0.003	0.002	0.68
Irrig	MT	1.614***	0.002***	-0.038	0.066	0.003	0.01	0.007	0.57
Non_Irrig	CO	1.312***	0.982***	-0.001	0.038	-0.006	-0.002	0.044	0.41
Non_Irrig	MT	0.960***	0.101***	-0.037	0.056	0.005	-0.004	0.025	0.35

Table 5-7. Results of the stepwise regression of the hay (excluding alfalfa) yield on monthly precipitation and temperature using county-level data

Prod_Pract	Irrigated	State	Constant	Trend	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	P_max	T_max	Rsq
All	No	AL	3.717***	0.024***	.	.	.	.	.	0.002***	0.001**	.	.	.	0.002***	.	-0.035***	-0.030*	.	0.055**	.	.	.	-0.111***	.	.	.	.	3	4	0.89
All	No	AZ	13.343**	.	-0.009***	.	.	.	.	.	.	.	.	.	.	.	.	.	0.111***	.	.	.	.	-0.367***	.	.	.	-0.131*	1	3	0.67
All	No	IL	2.227***	.	.	.	.	.	0.002**	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	-0.039**	.	1	1	0.3
All	No	KS	3.851***	.	.	.	.	.	0.002***	.	.	.	0.002**	.	.	.	.	0.019**	-0.018*	.	.	.	-0.085***	.	.	.	-0.025**	.	2	4	0.65
All	No	KY	2.108***	0.011***	.	.	.	.	.	0.003***	.	0.003***	.	.	.	.	.	0.025**	.	.	.	.	.	.	-0.044*	.	.	.	2	2	0.7
All	No	MN	1.875***	-0.013***	.	.	.	.	.	.	0.003**	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	0	0.41
All	No	NE	0.500***	0.011***	.	.	.	.	0.002***	0.002***	.	.	0.001*	.	.	.	-0.016***	0.015***	.	.	0.014*	.	.	.	.	.	-0.021***	.	3	4	0.89
All	No	NV	1.354***	0.058***	.	.	.	-0.009*	.	.	.	.	.	.	.	0.006*	.	.	.	.	.	.	.	.	.	.	-0.072**	0.127**	2	2	0.83
All	No	NJ	5.789***	-0.013***	.	.	-0.001**	.	.	.	.	.	.	.	.	0.001***	.	.	.	.	-0.029**	-0.079***	.	-0.080***	.	0.021	.	.	2	4	0.87
All	No	NM	-0.104	0.031***	.	0.022**	0.024**	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.147**	.	2	1	0.41
All	No	NY	2.459***	-0.010***	.	.	.	.	0.001	.	.	.	.	.	.	.	.	.	.	-0.034**	0.035**	.	.	-0.055**	.	0.038**	.	.	1	4	0.62
All	No	ND	0.391***	0.009***	.	0.009***	.	0.004***	0.003***	0.003***	0.002***	-0.002*	.	0.004***	.	.	.	.	.	.	.	.	.	.	.	.	.	.	7	0	0.86
All	No	OK	3.324***	.	.	.	.	0.002**	0.001***	0.002***	.	.	.	.	.	0.001*	-0.035***	.	.	.	.	-0.034*	.	-0.057***	0.035**	-0.031*	.	.	4	5	0.8
All	No	OR	1.930***	0.006**	.	.	.	-0.002*	0.004***	.	.	.	.	.	.	0.001**	.	.	.	.	.	.	.	.	.	.	-0.027*	.	3	1	0.44
All	No	PA	2.093***	.	.	.	.	.	.	0.003***	0.002**	.	.	0.003***	.	.	.	.	.	.	.	-0.058*	.	.	.	.	0.052**	.	3	2	0.58
All	No	SD	2.117***	.	0.008**	.	.	0.006***	0.004***	0.002***	.	0.004***	.	.	.	.	.	.	.	.	.	-0.055***	-0.043***	.	.	0.023**	.	.	5	3	0.93
All	No	TN	3.054***	.	.	.	.	0.001*	0.001**	0.001*	.	0.004***	.	.	.	-0.002***	.	.	.	.	.	.	.	-0.070***	.	.	0.036***	.	5	2	0.81
All	No	UT	2.367***	.	.	0.002***	.	.	.	.	0.003**	.	.	0.004***	-0.004***	-0.002**	.	.	.	-0.055***	.	.	-0.030***	.	.	0.043***	0.030***	.	5	4	0.92
All	No	VA	0.999***	.	.	.	-0.003***	0.004***	0.002***	.	0.007***	.	-0.001*	.	0.002**	.	.	.	.	.	.	.	.	.	.	.	.	.	6	0	0.81
All	No	WA	5.167***	.	0.003***	-0.003**	.	.	.	-0.012***	.	.	.	.	.	.	.	.	.	.	.	-0.149***	.	.	.	.	.	.	3	1	0.42
All	No	WV	2.873***	.	.	.	0.002*	.	.	0.003***	.	.	.	.	.	.	.	.	.	.	.	.	-0.072**	.	.	.	.	.	2	1	0.35
All	No	WI	1.598***	-0.019***	.	.	.	.	.	0.003**	0.004**	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	2	0	0.46
All	Yes	AZ	4.927***	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	-0.187*	0	1	0.13
All	Yes	CO	2.254***	.	.	.	.	.	.	.	.	0.005***	.	0.005***	-0.003**	.	.	0.049***	.	.	0.043**	.	-0.068**	.	.	.	.	.	3	3	0.6
All	Yes	KS	-1.039	.	.	.	.	.	.	.	0.004**	.	.	.	.	.	.	.	.	.	.	.	.	.	0.073	0.118**	.	.	1	2	0.35
All	Yes	MT	0.946***	0.008***	.	.	0.002*	0.003***	.	0.003***	0.003***	.	.	.	0.005***	.	.	.	.	0.035***	-0.035***	.	.	.	.	-0.024***	.	.	5	3	0.85
All	Yes	NE	0.233	0.018***	.	.	.	.	0.002*	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.046*	.	.	-0.048***	.	1	2	0.5
All	Yes	NV	2.066***	0.022***	.	.	.	-0.005**	.	.	.	.	.	.	.	.	.	.	.	-0.024*	-0.038**	.	.	.	.	.	.	0.071**	1	3	0.82
All	Yes	NM	1.783	0.015***	.	.	.	.	0.003*	.	.	.	.	.	.	.	.	.	.	.	0.074***	.	-0.152***	0.119***	.	.	-0.071***	-0.057*	1	5	0.67
All	Yes	OR	1.245***	0.021***	.	.	.	.	0.005***	.	.	.	.	.	.	0.002***	.	.	.	.	.	.	.	.	.	.	-0.036**	.	2	1	0.72
All	Yes	UT	4.098***	0.010***	.	0.003***	-0.002*	.	.	0.005**	.	.	.	.	.	.	.	.	.	.	.	.	.	-0.082***	.	-0.036**	.	.	3	2	0.78
All	Yes	WA	7.081***	0.073***	.	.	.	.	.	.	.	.	.	.	.	-0.004*	.	.	.	.	.	-0.240**	.	.	.	.	.	.	1	1	0.55
All	Yes	WY	0.701***	0.006***	.	.	.	0.003*	0.003***	0.003**	.	0.006***	.	.	.	.	.	.	0.024**	.	.	.	.	.	.	.	.	.	4	1	0.71
Irrig	Yes	CO	2.746***	0.016***	.	.	.	.	.	.	.	.	.	0.007***	.	.	.	.	.	.	.	.	-0.069**	.	.	.	.	.	1	1	0.64
Irrig	Yes	MT	1.114***	0.016***	.	.	.	0.005***	.	.	0.004***	.	.	.	0.002*	.	.	.	-0.014**	.	-0.037***	.	.	.	0.038***	.	-0.015**	.	3	4	0.93
Irrig	Yes	WY	1.652***	0.011***	.	.	.	.	0.002**	0.002*	.	0.009***	.	.	.	.	.	.	0.019	.	.	.	.	.	-0.045***	-0.037**	.	.	3	3	0.72
Non_Irrig	Yes	CO	2.701***	.	.	-0.013**	.	.	.	.	.	.	-0.010**	.	.	.	.	.	.	-0.107**	.	.	.	.	.	.	.	.	2	1	0.39
Non_Irrig	Yes	MT	1.041***	0.003	0.004**	.	.	0.003**	.	0.004***	0.003***	.	.	.	0.010***	-0.005***	.	.	.	.	.	-0.037***	.	.	.	-0.025**	-0.012**	0.019**	6	4	0.94
Non_Irrig	Yes	WY	0.058	.	.	.	.	0.005***	0.003**	0.007***	.	.	.	.	.	.	-0.021*	.	.	.	.	.	.	.	.	.	.	.	3	1	0.73
Total					4	6	6	13	16	17	11	7	4	5	7	9	4	5	5	6	8	7	7	9	5	10	14	6			

Table 5-8. Results of the regression of the hay (excluding alfalfa) yield on precipitation and temperature prior to- and during the growing season

Prod_Pract	Irrigated	State	Constant	Trend	P_prior	P_during	T_prior	T_during	Rsq
All	No	AL	4.319**	0.020***	0	0.001***	-0.08	-0.088	0.68
All	No	AZ	2.733	-0.014	-0.002**	0.003	-0.052	0.082	0.33
All	No	IL	2.181	0.003	-0.001*	0.001	-0.036	0.011	0.32
All	No	KS	3.364***	-0.005*	0	0.001***	-0.014	-0.099**	0.61
All	No	KY	1.66	0.007*	0	0.001***	0.032	-0.035	0.53
All	No	MN	1.690*	-0.015***	0	0.001*	-0.003	-0.001	0.38
All	No	NE	0.439	0.008***	0	0.001***	-0.003	0.006	0.76
All	No	NV	-1.92	0.053***	0.002	0.001	0.034	0.147	0.65
All	No	NJ	6.137***	-0.011**	0	0	0.05	-0.231***	0.55
All	No	NM	1.786	0.024	0.002	0	0.188	-0.068	0.19
All	No	NY	2.186***	-0.009***	0	0.001*	0.002	-0.032	0.37
All	No	ND	0.307	0.010***	0.001**	0.002***	-0.008	0	0.67
All	No	OK	3.011***	0	0.001***	0.001***	-0.024	-0.088**	0.61
All	No	OR	1.658*	0.005	0	0.001	-0.002	0.01	0.12
All	No	PA	2.219*	0.006	0	0.001**	0.008	-0.048	0.29
All	No	SD	1.563	-0.002	0	0.002***	0.008	-0.064	0.56
All	No	TN	2.512**	0.002	0	0.001***	0.023	-0.051	0.42
All	No	UT	2.612**	0.007	0	0.001	0.013	-0.06	0.34
All	No	VA	4.656**	0.015*	0	0.001**	0.018	-0.176*	0.5
All	No	WA	3.735**	0.003	0	0	-0.008	-0.083	0.04
All	No	WV	3.560***	0.010**	0	0.001	0.01	-0.132*	0.31
All	No	WI	1.605	-0.020***	0.001	0.002***	-0.011	-0.031	0.45
All	Yes	AZ	9.491	0.027	-0.001	-0.001	-0.063	-0.236	0.12
All	Yes	CO	1.469	0.004	0.001	0.001	-0.014	-0.036	0.26
All	Yes	KS	0.571	-0.001	-0.001	0.002	0.097	0.036	0.12
All	Yes	MT	0.848	0.007***	0	0.002***	0.013	-0.001	0.54
All	Yes	NE	0.266	0.014***	0	0.001	-0.043	0.047	0.36
All	Yes	NV	1.509	0.024***	0.001	0.001	0.035	-0.035	0.68
All	Yes	NM	0.642	0.008	0.001	0	-0.091	0.076	0.21
All	Yes	OR	1.777	0.021***	0	0.001	0.02	-0.046	0.55
All	Yes	UT	3.232***	0.011**	0	0.001	-0.007	-0.076	0.48
All	Yes	WA	5.639	0.082***	-0.001	0.004*	-0.107	-0.205	0.54
All	Yes	WY	0.368	0.008***	0	0.003***	0.009	0.012	0.66
Irrig	Yes	CO	-0.329	0.014***	0.003***	0.002**	-0.060**	0.052	0.7
Irrig	Yes	MT	1.016	0.018***	0	0.002*	-0.011	0.005	0.54
Irrig	Yes	WY	0.788	0.012***	0.001	0.002	-0.011	-0.006	0.48
Non_Irrig	Yes	CO	-0.462	0.002	0.001	0.002	-0.066	0.056	0.11
Non_Irrig	Yes	MT	0.111	0.009**	0	0.003***	0.018	0.005	0.46
Non_Irrig	Yes	WY	-0.607	-0.001	0	0.004***	-0.03	0.034	0.67

Table 5-9. Results of the stepwise regression of the hay (excluding alfalfa) yield on current and eleven lagged values of PDSI using county-level data

Prod_Pract	Irrigated	State	Constant	Trend	PDSI1	PDSI2	PDSI3	PDSI4	PDSI5	PDSI6	PDSI7	PDSI8	PDSI9	PDSI10	PDSI11	PDSI12	PDSI_max	Rsq
All	No	AL	1.891***	0.018***	.	.	.	.	.	.	.	0.091***	.	.	.	.	1	0.72
All	No	AZ	3.981***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
All	No	IL	2.272***	.	.	.	.	.	.	0.056**	.	.	.	.	.	.	1	0.18
All	No	KS	1.843***	-0.006**	-0.044**	.	.	.	.	.	.	.	0.089***	.	.	.	2	0.53
All	No	KY	1.945***	0.007**	.	.	.	.	.	.	.	.	0.070***	.	-0.027*	.	2	0.52
All	No	MN	2.180***	-0.017***	.	.	.	.	.	.	0.067***	.	.	.	.	.	1	0.53
All	No	NE	1.096***	0.010***	.	-0.068***	.	.	0.050**	0.043**	.	.	.	.	.	.	3	0.74
All	No	NV	1.005***	0.055***	.	.	.	.	.	.	.	.	.	.	.	.	0	0.62
All	No	NJ	2.204***	-0.020***	.	.	.	.	-0.181***	0.131***	.	.	0.042*	.	-0.139*	0.178**	5	0.74
All	No	NM	1.767***	0.026**	.	.	.	.	.	.	.	.	.	.	.	.	0	0.15
All	No	NY	2.018***	-0.008***	.	.	.	.	.	.	.	.	.	.	.	.	0	0.26
All	No	ND	1.319***	0.004*	-0.042**	.	.	.	.	0.140***	.	.	.	.	.	.	2	0.79
All	No	OK	1.593***	.	.	.	.	.	.	.	.	0.077***	.	-0.034**	.	.	2	0.47
All	No	OR	2.137***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
All	No	PA	2.061***	.	.	.	.	.	.	.	.	.	0.076***	.	.	.	1	0.31
All	No	SD	1.423***	.	.	.	-0.065**	.	.	.	0.120***	.	.	.	.	.	2	0.72
All	No	TN	2.098***	.	-0.071***	.	.	.	.	.	.	0.078***	.	0.183**	-0.141*	.	4	0.54
All	No	UT	1.789***	0.007**	.	.	.	.	.	.	.	0.034***	.	.	.	.	1	0.42
All	No	VA	2.108***	.	.	.	-0.133***	0.082	.	.	.	0.126***	.	.	.	.	3	0.76
All	No	WA	2.598***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
All	No	WV	1.605***	0.009**	.	.	.	.	.	.	.	.	.	.	.	.	0	0.14
All	No	WI	2.318***	-0.022***	.	.	.	.	.	.	.	0.111***	.	.	.	.	1	0.49
All	Yes	AZ	3.865***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
All	Yes	CO	1.604***	.	.	.	.	.	.	.	.	.	0.038**	.	.	.	1	0.14
All	Yes	KS	2.374***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
All	Yes	MT	1.338***	0.007***	.	.	.	.	-0.074***	.	0.109***	.	.	.	.	.	2	0.67
All	Yes	NE	1.375***	0.013***	-0.086*	.	.	.	0.107**	.	.	.	.	.	.	.	2	0.4
All	Yes	NV	1.168***	0.026***	.	.	.	.	.	.	.	.	0.035***	.	.	.	1	0.7
All	Yes	NM	1.868***	.	.	.	.	.	.	.	.	.	.	-0.042**	.	.	1	0.13
All	Yes	OR	1.607***	0.022***	.	.	.	-0.100**	0.136***	.	.	.	.	.	.	.	2	0.62
All	Yes	UT	2.113***	0.011***	.	.	.	.	-0.129***	.	.	0.135***	.	.	.	.	2	0.55
All	Yes	WA	2.980***	0.069***	.	.	.	.	.	.	.	.	.	.	.	.	0	0.41
All	Yes	WY	1.175***	0.010***	-0.029*	.	.	.	.	.	0.073***	.	.	.	.	.	2	0.7
Irrig	Yes	CO	1.540***	0.021***	.	.	.	.	.	-0.100**	0.146***	.	.	.	.	0.041***	3	0.82
Irrig	Yes	MT	1.649***	0.016***	.	.	.	.	-0.086***	.	0.149***	.	-0.048*	.	.	.	3	0.69
Irrig	Yes	WY	1.261***	0.013***	-0.036**	.	.	.	.	.	.	.	0.066***	.	.	.	2	0.55
Non_Irrig	Yes	CO	1.227***	.	.	.	.	.	.	.	.	.	.	.	.	.	0	0
Non_Irrig	Yes	MT	0.950***	0.009**	.	.	.	.	-0.083**	.	0.129***	.	.	.	.	.	2	0.55
Non_Irrig	Yes	WY	0.860***	.	.	.	.	.	.	.	.	0.102***	.	.	.	-0.051***	2	0.73
Total					6	1	2	2	8	5	7	7	8	3	3	3		

Table 5-10. Results of the regression of the hay (excluding alfalfa) yield on PDSI before- and during the growing season using county-level data

Prod_Pract	Irrigated	State	Constant	Trend	PDSI_prior	PDSI_during	Rsq
All	No	AL	1.878***	0.020***	-0.063**	0.143***	0.73
All	No	AZ	4.303***	-0.022	-0.04	-0.036	0.08
All	No	IL	2.280***	-0.001	-0.014	0.071	0.16
All	No	KS	1.818***	-0.005**	-0.068***	0.108***	0.42
All	No	KY	1.906***	0.010***	-0.039	0.073***	0.43
All	No	MN	2.184***	-0.017***	-0.021	0.088***	0.51
All	No	NE	1.110***	0.009***	-0.035**	0.065***	0.69
All	No	NV	0.929***	0.060***	0.092	-0.048	0.65
All	No	NJ	2.135***	-0.016***	-0.008	0.028	0.33
All	No	NM	1.733***	0.028**	-0.11	0.12	0.18
All	No	NY	2.022***	-0.009***	-0.024	0.024	0.31
All	No	ND	1.316***	0.005*	-0.047**	0.142***	0.76
All	No	OK	1.600***	0	-0.050**	0.095***	0.42
All	No	OR	2.057***	0.005*	-0.022	0.031*	0.14
All	No	PA	1.925***	0.007*	-0.037	0.094***	0.32
All	No	SD	1.422***	0	-0.072**	0.142***	0.67
All	No	TN	2.055***	0.005	-0.025	0.065***	0.34
All	No	UT	1.798***	0.007*	-0.023	0.056*	0.39
All	No	VA	2.015***	0.006	-0.096***	0.165***	0.67
All	No	WA	2.545***	0.003	-0.02	0.014	0.01
All	No	WV	1.634***	0.007*	-0.028	0.044	0.18
All	No	WI	2.320***	-0.022***	0.013	0.104**	0.44
All	Yes	AZ	3.132***	0.049**	0.227*	-0.082	0.22
All	Yes	CO	1.510***	0.005	-0.009	0.051*	0.16
All	Yes	KS	2.293***	0.005	-0.004	0.041	0.04
All	Yes	MT	1.342***	0.007***	-0.033**	0.064***	0.53
All	Yes	NE	1.378***	0.013***	-0.009	0.032	0.31
All	Yes	NV	1.173***	0.026***	0.008	0.031	0.69
All	Yes	NM	1.758***	0.006	-0.038	0.023	0.13
All	Yes	OR	1.625***	0.021***	-0.025	0.057**	0.57
All	Yes	UT	2.143***	0.009**	-0.070*	0.089**	0.44
All	Yes	WA	2.926***	0.073***	-0.312**	0.281**	0.52
All	Yes	WY	1.188***	0.009***	-0.026	0.076***	0.68
Irrig	Yes	CO	1.535***	0.021***	0.026	0.060**	0.69
Irrig	Yes	MT	1.633***	0.018***	-0.031	0.057**	0.51
Irrig	Yes	WY	1.303***	0.010***	-0.043**	0.070***	0.49
Non_Irrig	Yes	CO	1.109***	0.008	-0.028	0.072	0.07
Non_Irrig	Yes	MT	0.956***	0.009**	-0.042	0.086***	0.37
Non_Irrig	Yes	WY	0.885***	-0.002	-0.068***	0.120***	0.68

Table 5-11. Results of the nonlinear regression of the hay (excluding alfalfa) yield on precipitation and temperature and neighboring states

Prod_Pract	Irrigated	State	Constant	Trend	P_prior	P_during	T_prior	T_during	P_prior^2	P_during^2	T_prior^2	T_during^2	NB_P	NB_T	Rsq
All	No	AL	-95.47*	0.017***	0.005	0.004*	-2.515**	9.391**	0	0	0.108**	-0.203**	-0.001	0.007	0.82
All	No	AZ	-191.8**	-0.025*	-0.004	-0.023	0.174	17.520**	0	0.000*	-0.01	-0.395**	0.014**	0.261***	0.71
All	No	IL	19.015	0.006	0.012	0.003	0.015	-2.054	0	0	-0.008	0.053	-0.002	-0.003	0.43
All	No	KS	18.348	-0.005*	-0.002	0.004	0.041	-1.632	0	0	-0.005	0.037	0.001	-0.004	0.66
All	No	KY	-16.62	0.010**	-0.002	0.005*	0.365	1.568	0	0	-0.027	-0.038	-0.002*	-0.002	0.62
All	No	MN	-16.37	-0.016***	-0.001	-0.003	-0.019	2.493	0	0	-0.002	-0.082	0.002	0.029	0.49
All	No	NE	8.025	0.010***	-0.002	0.005*	0.015	-0.938	0	0	-0.009	0.027	0.001	0.017	0.81
All	No	NV	4.28	0.062***	0.023	0.007	0.644	-0.867	0	0	-0.113	0.028	0.011*	-0.033	0.8
All	No	NJ	60.805*	-0.011**	-0.004*	0.001	0.984**	-6.310*	0.000*	0	-0.107**	0.166*	-0.001	-0.038*	0.79
All	No	NM	-134.5	0.036	-0.007	-0.024	-3.812*	16.561	0	0	0.329*	-0.451	0.005	-0.092	0.35
All	No	NY	-6.791	-0.007**	-0.003	0.002	-0.008	1.1	0	0	-0.013	-0.035	-0.002***	0.02	0.61
All	No	ND	-3.397	0.006**	0.004***	0.005	0.136**	0.4	-0.000**	0	0.013*	-0.013	0.003**	0.006	0.8
All	No	OK	-21.15	-0.003	0.002	0.003**	-0.35	1.904	0	0	0.021	-0.042	0.002**	0.089***	0.81
All	No	OR	-12.75	0.002	0.001	-0.009	0.18	2.101	0	0.000*	-0.029	-0.073	0.002	0.007	0.29
All	No	PA	-11.08	0.003	0.012*	0.003	0.045	1.045	-0.000*	0	-0.012	-0.032	0.001	0.015	0.46
All	No	SD	16.001	0	-0.01	0.017*	0.025	-2.119	0	0	0.01	0.062	0.001	0.044	0.77
All	No	TN	-41.82**	0.004	0.004	0.009***	0.615*	3.501*	0.000*	-0.000***	-0.039*	-0.084*	-0.001	0.032	0.75
All	No	UT	17.706	0.005	0.003	0.002	0.046	-1.974	0	0	-0.012	0.057	0.003	0.031	0.46
All	No	VA	-58.66	0.015	0.003	-0.002	-0.03	6.141	0	0	0.002	-0.155	-0.002	-0.011	0.61
All	No	WA	6.107	0.003	0.001	0.004	0.427	-0.517	0	0	-0.068	0.015	-0.001	-0.08	0.24
All	No	WV	-16.77	0.013**	-0.002	0.005	0.596*	1.829	0	0	-0.071*	-0.053	-0.002	0.017	0.48
All	No	WI	-9.488	-0.021***	0.004	0.01	0.066	0.933	0	0	0.016	-0.03	0	0.087**	0.64
All	Yes	AZ	-69.46	0.023	-0.006	-0.022	0.96	6.642	0	0	-0.062	-0.158	0.014	0.19	0.22
All	Yes	CO	-11.31	0.003	0.027*	-0.007	0.002	1.596	-0.000*	0	-0.005	-0.055	0.001	-0.049	0.4
All	Yes	KS	-19.23	0	0	-0.011	0.699	1.984	0	0	-0.066	-0.047	0.004	0.089	0.27
All	Yes	MT	1.51	0.006**	0.003	0.002	0.002	-0.163	0	0	-0.006	0.006	0.001	0.019	0.58
All	Yes	NE	21.658	0.016***	-0.008	0.006	0.001	-2.503	0	0	-0.023	0.071	0.001	0.067	0.49
All	Yes	NV	-8.207	0.026***	0	0.002	0.032	1.258	0	0	0	-0.04	0	-0.059*	0.79
All	Yes	NM	25.983	0.007	0.006	-0.003	0.572	-2.883	0	0	-0.056	0.081	-0.002	-0.022	0.35
All	Yes	OR	-27.53	0.020***	0.003	-0.004	0.108	4.137	0	0	-0.008	-0.15	0.002	-0.027	0.68
All	Yes	UT	-7.659	0.013***	-0.004	0.002	-0.035	1.194	0	0	-0.001	-0.039	0.007**	0.074**	0.76
All	Yes	WA	-51.12	0.084***	0.009*	0.019	1.229**	6.858	-0.000*	0	-0.228*	-0.252	-0.004	-0.086	0.76
All	Yes	WY	-0.904	0.006***	0.014***	0.002	0.154***	-0.035	-0.000***	0	0.040***	0.003	0	0.043***	0.84
Irrig	Yes	CO	-18.67	0.018***	0.028*	-0.005	-0.102*	2.528	-0.000*	0	0.011	-0.086	0.001	-0.071	0.8
Irrig	Yes	MT	-5.05	0.018***	-0.006	-0.002	-0.115	1.058	0	0	-0.031	-0.039	0	0.006	0.59
Irrig	Yes	WY	3.59	0.009**	0.01	0.007	0.054	-0.744	0	0	0.02	0.029	0.002	0.059*	0.65
Non_Irrig	Yes	CO	14.575	0.014	0.036	-0.004	-0.281	-2.284	0	0	0.063*	0.078	-0.002	0.032	0.33
Non_Irrig	Yes	MT	-13.74	0.007	0.002	-0.003	-0.012	2.088	0	0	-0.014	-0.076	0.002	0.02	0.55
Non_Irrig	Yes	WY	9.693	-0.004	0.014*	0.008	0.036	-1.877	-0.000*	0	0.014	0.076	-0.002	0.013	0.8

Table 5-12. Results of the nonlinear regression of the hay (excluding alfalfa) yield on PDSI and neighboring states using county-level data

Prod_Pract	Irrigated	State	Constant	Trend	PDSI_prior	PDSI_during	PDSI_prior^2	PDSI_during^2	NB_PDSI	Rsq
All	No	AL	1.893***	0.000***	-0.067**	0.117***	0.01	-0.006	0.033	0.76
All	No	AZ	4.268***	0.164***	-0.026	-0.034	0.022	-0.007	-0.057	0.15
All	No	IL	2.309***	0.944***	-0.013	0.072	0.012	-0.026	0.018	0.22
All	No	KS	1.738***	0.072***	-0.062***	0.060**	0.013**	-0.003	0.068***	0.63
All	No	KY	1.945***	0.086***	-0.044*	0.033	0.019*	-0.011	0.089*	0.55
All	No	MN	2.167***	0.000***	-0.03	0.079**	0.024**	-0.015	0.025	0.59
All	No	NE	1.100***	0.000***	-0.023	0.045*	0.004	-0.003	0.016	0.7
All	No	NV	0.762***	0.000***	0.044	-0.187***	-0.005	0.005	0.214***	0.79
All	No	NJ	2.239***	0.004***	0.01	-0.019	0.025	-0.021	0.052*	0.44
All	No	NM	1.955***	0.085***	-0.113	0.168	0.013	-0.054*	-0.091	0.29
All	No	NY	2.037***	0.003***	-0.025	0.043*	-0.004	0.003	-0.026	0.35
All	No	ND	1.380***	0.037***	-0.062***	0.172***	-0.001	-0.013**	-0.03	0.81
All	No	OK	1.648***	0.847***	-0.080***	0.117***	0.018***	-0.031***	0.025	0.7
All	No	OR	2.042***	0.032***	-0.019	-0.02	0.015*	-0.013	0.065**	0.38
All	No	PA	2.016***	0.355***	-0.041	0.045	-0.005	-0.019	0.046	0.43
All	No	SD	1.417***	0.554***	-0.025	0.124***	0.022*	-0.026*	-0.035	0.74
All	No	TN	2.032***	0.266***	-0.03	0.065**	0.014*	-0.011	0.018	0.46
All	No	UT	1.837***	0.086***	-0.009	0.024	-0.002	-0.01	0.02	0.5
All	No	VA	1.951***	0.073***	-0.132***	0.225***	0	0.009	-0.054	0.75
All	No	WA	2.449***	0.457***	-0.013	-0.002	0.009	0.005	0.024	0.06
All	No	WV	1.601***	0.214***	-0.037	0.04	0.034***	-0.018	0.029	0.44
All	No	WI	2.318***	0.000***	0.015	0.077	0.005	-0.021	0.035	0.51
All	Yes	AZ	2.944***	0.059***	0.197	-0.062	-0.003	0.047	-0.003	0.31
All	Yes	CO	1.582***	0.280***	-0.014	0.027	0.001	-0.009	0.045	0.25
All	Yes	KS	2.260***	0.416***	0	0.001	-0.008	0.006	0.064	0.06
All	Yes	MT	1.346***	0.000***	-0.032*	0.058***	0.004	-0.005	0.01	0.55
All	Yes	NE	1.372***	0.007***	0.021	-0.001	0.019*	-0.017	0.009	0.39
All	Yes	NV	1.145***	0.000***	-0.01	-0.007	-0.002	-0.003	0.067**	0.77
All	Yes	NM	1.772***	0.385***	-0.039	0.046	0.005	-0.002	-0.056	0.19
All	Yes	OR	1.606***	0.000***	-0.029	-0.007	0.012	-0.011	0.096***	0.7
All	Yes	UT	2.089***	0.009***	-0.037	0.055	0.015*	-0.008	0.018	0.57
All	Yes	WA	2.913***	0.000***	-0.297**	0.263*	0.034	-0.032	0.001	0.54
All	Yes	WY	1.237***	0.000***	-0.026	0.082***	0	-0.008	-0.013	0.72
Irrig	Yes	CO	1.527***	0.000***	0.027	0.067**	0.004	-0.002	-0.011	0.7
Irrig	Yes	MT	1.619***	0.001***	-0.038	0.069*	0.001	0.01	0	0.55
Irrig	Yes	WY	1.318***	0.001***	-0.058**	0.068***	0.012	-0.015**	0.033	0.63
Non_Irrig	Yes	CO	1.168***	0.476***	-0.023	0.083	-0.011	-0.01	-0.04	0.15
Non_Irrig	Yes	MT	0.961***	0.050***	-0.035	0.068	0.004	-0.006	0.013	0.39
Non_Irrig	Yes	WY	0.918***	0.874***	-0.054**	0.127***	-0.009	-0.003	-0.024	0.73

Table 5-13. Results of the stepwise regression of the alfalfa hay yield on monthly precipitation and temperature

Prod_Pract	State	Constant	Trend	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	P_max	T_max	Rsq
All	AZ	7.196***	0.035***						0.017**																			1	0	0.71
All	CA	8.743***	0.009**							-0.037***			-0.005***				-0.036			0.096***	-0.098***				-0.063**			2	4	0.72
All	CO	4.004***	0.013***	0.009***						0.004*		-0.004*	0.005***				0.053**			0.067**		-0.089**				-0.056**		4	4	0.72
All	ID	3.922***	0.014***	0.003***																	-0.029*							1	1	0.65
All	IL	4.575***						0.004***			0.004***								0.044				-0.091***					2	2	0.47
All	IA	5.633***																					-0.092**					0	1	0.13
All	KS	1.587**								0.005***			0.006***												0.106**			2	1	0.38
All	KY	1.033	-0.030***						0.006***	0.005***	0.007***	0.002*					0.063***				0.208***			-0.183**	-0.028*			4	4	0.73
All	MI	3.098***	-0.029***				0.006**		0.006**					0.004*	-0.006**													4	0	0.56
All	MN	2.761***					0.006***			0.005***							0.032**											2	1	0.43
All	MO	5.964***						0.002**	0.003**								0.027**		0.064***		-0.065**	-0.120***						2	4	0.63
All	MT	2.289***	-0.009***				0.004**	0.001*	0.002**													-0.041***		0.032**				3	2	0.65
All	NE	3.597***	0.012***					0.003***	0.003***	0.002**			0.003**										-0.053***					4	1	0.85
All	NV	5.401***	0.021***					0.005**	0.006**			-0.009***					-0.053***							-0.086***			0.037*	3	3	0.7
All	NM	6.306***			-0.006**								-0.003**												-0.081***			2	1	0.35
All	NY	3.152***	-0.006*	-0.003**																						-0.070***		1	1	0.39
All	ND	0.22			0.016***			0.006***	0.004***	0.004***			0.004***														-0.022*	5	1	0.72
All	OH	6.607***	-0.012**												-0.004**							-0.116***						1	1	0.4
All	OK	12.809***					0.004**					0.003*	0.002*	0.003*							-0.152**	-0.241***						4	2	0.73
All	OR	1.801***	0.006***			0.001**		0.004***				0.002*	0.001*		0.001***						0.058***			0.062***				5	2	0.75
All	PA	4.589***		-0.002***		-0.002**	0.002***			0.003***		-0.001***			-0.001		-0.031***			-0.023*	.		-0.084***		0.038**			6	4	0.77
All	SD	1.701***			0.016***			0.007***	0.004***		0.003*		0.003***	0.014***							-0.068***							6	1	0.84
All	TX	4.005***	0.014**	0.007**																								1	0	0.23
All	UT	4.181***		0.005***														0.035*	-0.052***									1	2	0.47
All	WI	1.622***						0.006***				0.003*	0.005*															3	0	0.27
Irrig	CO	1.152		0.011***		0.007**	0.007***						0.010***							0.193***		-0.097***		0.059*			-0.095**	4	4	0.87
Irrig	ID	2.994***	0.009*	0.004***	0.004**					-0.004**			0.010***				0.026*								0.110***			4	2	0.86
Irrig	MT	2.588***	0.013***				0.004**						0.008***									-0.052***		0.076***				2	2	0.82
Irrig	NE	4.178***	0.021***																									0	0	0.51
Non_Irrig	CO	4.918***										-0.005**	0.007***									-0.187***						2	1	0.77
Non_Irrig	ID	4.529***		0.005***		0.001**		-0.004***				0.008***	-0.002***			-0.013*	-0.036***				-0.228***			-0.020**				5	4	0.99
Non_Irrig	MT	1.292***		0.005**		0.013***	0.004**						0.010***					0.054***	-0.058***			-0.076***		0.050***				4	4	0.91
Non_Irrig	NE	3.673***						0.003***	0.003**				0.005***							0.037		-0.082***				-0.036***		3	3	0.8
Total				10	4	5	8	11	10	9	3	9	17	3	4	1	9	2	4	5	8	10	4	8	6	3	3			

Table 5-14. Results of the regression of the alfalfa hay yield on precipitation and temperature prior to- and during the growing season

Prod_Pract	State	Constant	Trend	P_prior	P_during	T_prior	T_during	Rsq
All	AZ	9.497***	0.032***	-0.001	-0.002	0.074	-0.113	0.7
All	CA	5.574**	0.006	0	0	-0.164*	0.135	0.15
All	CO	1.442	0.008	0.003*	0.001	0.072	0.061	0.26
All	ID	4.078***	0.014***	0.001	0	0.036	-0.047	0.58
All	IL	4.004**	-0.006	0	0.001**	0.018	-0.051	0.19
All	IA	4.817**	0.003	0	0	0.048	-0.08	0.05
All	KS	1.835	-0.006	0.001	0.002**	0.056	0.021	0.26
All	KY	2.149	-0.019*	0	0.002***	-0.005	-0.003	0.27
All	MI	5.289***	-0.024***	-0.002	0.003**	0.025	-0.148	0.45
All	MN	2.973**	-0.006	0.001	0.002***	0.025	-0.044	0.24
All	MO	4.743***	0	0	0.001*	0.018	-0.115	0.22
All	MT	1.419*	-0.010***	0.001	0.002***	0.027	0.011	0.43
All	NE	2.731***	0.013***	0.001*	0.002***	0	-0.033	0.76
All	NV	3.223**	0.015***	0.001	-0.001	0.007	0.043	0.37
All	NM	5.364***	0.001	-0.001	0	-0.072*	0.017	0.15
All	NY	3.591***	-0.005	0	0	-0.067**	-0.056	0.28
All	ND	0.044	-0.005	0.003***	0.004***	-0.012	0.007	0.57
All	OH	6.881***	-0.009	-0.001	0	-0.019	-0.164*	0.39
All	OK	10.012***	-0.012**	0.002***	0.002***	-0.008	-0.350***	0.74
All	OR	1.641**	0.010***	0.001***	0.002***	0.03	0.111**	0.61
All	PA	5.269***	0	0	0	-0.029	-0.150**	0.28
All	SD	1.35	-0.005	0.003**	0.004***	0.031	-0.06	0.7
All	TX	10.457**	0.027**	0.001	-0.002	0.018	-0.255	0.23
All	UT	4.405***	0.007**	0.001	0.001	0.016	-0.054	0.38
All	WI	1.069	-0.004	0.001	0.003***	-0.002	-0.003	0.31
Irrig	CO	-2.073	-0.003	0.006**	0.003*?	-0.045	0.269*	0.36
Irrig	ID	3.976***	0.021**	0.001	0.001	0.001	0.002	0.44
Irrig	MT	0.868	0.015***	0.003**	0.003**	0.043	0.071	0.54
Irrig	NE	3.329***	0.020***	0.001	0	0.011	0.035	0.54
Non_Irrig	CO	0.527	-0.014	0.004*	0.002	-0.056	-0.025	0.63
Non_Irrig	ID	1.531	0	0.001*	0.002**	-0.081	-0.069	0.69
Non_Irrig	MT	-0.273	-0.006	0.004***	0.003**	0.044	0.005	0.54
Non_Irrig	NE	3.450**	-0.001	0.002*	0.002**	0.032	-0.096	0.61

Table 5-15. Results of the stepwise regression of the alfalfa hay yield on monthly PDSI

Prod_Pract	State	Constant	Trend	PDSI1	PDSI2	PDSI3	PDSI4	PDSI5	PDSI6	PDSI7	PDSI8	PDSI9	PDSI10	PDSI11	PDSI12	PDSI_max	Rsq
All	AZ	7.492***	0.023***										-0.068**			1	0.73
All	CA	6.795***														0	0
All	CO	3.231***	0.015***							0.066***						1	0.28
All	ID	3.808***	0.012***	0.057		0.050*							0.060*		-0.132***	4	0.69
All	IL	3.761***					-0.101***				0.132***					2	0.31
All	IA	3.612***														0	0
All	KS	3.814***										0.120***				1	0.32
All	KY	3.631***	-0.019***					-0.109***				0.198***				2	0.42
All	MI	3.764***	-0.023***													0	0.27
All	MN	3.374***	-0.008*?							0.119***						1	0.36
All	MO	2.830***														0	0
All	MT	2.321***	-0.007***							0.099***		-0.044*		-0.042**		3	0.45
All	NE	3.305***	0.012***		-0.218***					0.144***			0.128**			3	0.79
All	NV	4.002***	0.017***													0	0.35
All	NM	5.092***												-0.028**		1	0.12
All	NY	2.564***											-0.038**			1	0.17
All	ND	1.923***	-0.010**	-0.220***		0.172**				0.197***						3	0.75
All	OH	3.690***	-0.014**													0	0.17
All	OK	3.606***	-0.018***					-0.136**			0.271***					2	0.62
All	OR	4.111***	0.011***				0.033**									1	0.41
All	PA	2.898***						-0.063**			0.172***	-0.069*	-0.105**	0.074		5	0.53
All	SD	2.113***					-0.091***			0.199***						2	0.74
All	TX	4.287***	0.015**													0	0.12
All	UT	3.900***	0.009***	0.202*							0.077***			0.163**	-0.409***	4	0.54
All	WI	2.779***										0.118***				1	0.25
Irrig	CO	3.867***					0.094***									1	0.34
Irrig	ID	4.474***	0.021***			0.048***										1	0.54
Irrig	MT	2.888***	0.020***							0.050**						1	0.48
Irrig	NE	4.178***	0.021***													0	0.51
Non_Irrig	CO	1.235***								0.109***						1	0.58
Non_Irrig	ID	1.653***									0.088***					1	0.53
Non_Irrig	MT	1.231***								0.121***			-0.043*			2	0.6
Non_Irrig	NE	3.049***		-0.138**				0.095*		0.116***						3	0.61
Total				4	1	3	4	4	0	10	5	5	5	4	2		

Table 5-16. Results of the regression of the alfalfa hay yield on PDSI prior to- and during the growing season

Prod_Pract	State	Constant	Trend	PDSI_prior	PDSI_during	Rsq
All	AZ	7.481***	0.024***	-0.076*	0.01	0.72
All	CA	6.666***	0.007	0.041	-0.017	0.06
All	CO	3.242***	0.015***	0.006	0.062	0.26
All	ID	3.737***	0.015***	-0.003	0.034*	0.56
All	IL	3.860***	-0.005	-0.108**	0.141**	0.19
All	IA	3.517***	0.005	-0.051	0.031	0.04
All	KS	3.809***	-0.001	-0.046	0.155**	0.27
All	KY	3.465***	-0.009	-0.091*	0.137**	0.18
All	MI	3.863***	-0.028***	-0.096	0.133*	0.34
All	MN	3.365***	-0.008	-0.014	0.135**	0.32
All	MO	2.844***	0	-0.098**	0.097**	0.18
All	MT	2.311***	-0.007***	-0.044**	0.067***	0.33
All	NE	3.283***	0.013***	-0.105***	0.169***	0.73
All	NV	3.993***	0.017***	-0.003	0.014	0.35
All	NM	5.160***	-0.003	-0.03	-0.009	0.13
All	NY	2.702***	-0.007*	-0.028	0.016	0.15
All	ND	1.938***	-0.010**	-0.102***	0.254***	0.67
All	OH	3.646***	-0.013*	-0.076	0.058	0.22
All	OK	3.484***	-0.012*	-0.108**	0.234***	0.54
All	OR	4.098***	0.012***	0.015	0.021	0.41
All	PA	3.007***	-0.004	-0.050*	0.089***	0.26
All	SD	2.175***	-0.003	-0.093**	0.223***	0.68
All	TX	4.288***	0.015**	-0.033	0.055	0.14
All	UT	3.924***	0.008**	-0.057	0.095***	0.36
All	WI	2.892***	-0.006	-0.001	0.159**	0.26
Irrig	CO	3.680***	0.014	0.049	0.066	0.36
Irrig	ID	4.468***	0.021***	0.021	0.029	0.52
Irrig	MT	2.886***	0.020***	-0.01	0.054	0.43
Irrig	NE	4.185***	0.021***	-0.036	0.033	0.54
Non_Irrig	CO	1.377***	-0.011	-0.025	0.119***	0.58
Non_Irrig	ID	1.734***	-0.008	-0.042	0.120***	0.52
Non_Irrig	MT	1.239***	0	-0.048	0.131***	0.49
Non_Irrig	NE	3.060***	-0.001	-0.120***	0.200***	0.56

Table 5-17. Results of the nonlinear regression of the alfalfa hay yield on precipitation and temperature and neighboring states

Prod_Pract	State	Constant	Trend	P_prior	P_during	T_prior	T_during	P_prior^2	P_during^2	T_prior^2	T_during^2	NB_P	NB_T	Rsq
All	AZ	-32.92	0.037***	0.003	0.003	1.36	2.874	0	0	-0.065	-0.065	0.004	0.099**	0.8
All	CA	25.953	0.003	0.002	-0.001	2.671***	-3.281	0	0	-0.142***	0.085	0.001	-0.053	0.58
All	CO	-17.48	0.008	0.060***	-0.009	-0.018	2.232	-0.000***	0	0.033	-0.075	0.003	-0.038	0.47
All	ID	-7.895	0.017***	-0.001	-0.009	0.002	2.020*	0	0	-0.018	-0.079*	-0.001	-0.003	0.69
All	IL	12.43	-0.002	-0.005	0.012***	0.26	-1.212	0	-0.000**	-0.043*	0.031	0.001	0.015	0.49
All	IA	-13.36	0.001	0.002	0.017***	0.025	1.196	0	-0.000***	0.008	-0.033	0	0.036	0.69
All	KS	29.118	-0.012	-0.004	0.018**	-1.037*	-2.851	0	-0.000**	0.126*	0.07	0.005	0.048	0.43
All	KY	-85.14	-0.019*	0.001	0.008	0.01	8.281	0	0	-0.001	-0.2	-0.002	-0.005	0.35
All	MI	-5.146	-0.022***	0.017	0.022	0.036	0.1	0	0	0.004	-0.007	-0.003	0.054	0.53
All	MN	-11.26	-0.009	-0.004	0.015	0.105	1.412	0	0	0.009	-0.047	-0.001	0.034	0.35
All	MO	-31.21	0.001	0.002	0.009**	0.195	3.006	0	-0.000*	-0.017	-0.075	0	-0.003	0.43
All	MT	-1.552	-0.011***	-0.008	0	-0.037	0.604	0	0	-0.023	-0.022	0.002	0.006	0.52
All	NE	-25.35	0.016***	0.007	-0.001	0.077	3.159	0	0	-0.035*	-0.09	-0.001	0.021	0.83
All	NV	-39.47*	0.012*	-0.005	-0.013	-0.118	5.508*	0	0	0.022	-0.166*	0	-0.049	0.52
All	NM	4.261	0.001	-0.006*	0	0.115	0.177	0	0	-0.015	-0.005	0	-0.025	0.27
All	NY	-51.19***	-0.002	-0.003	0.001	-0.057*	7.004***	0	0	0.009	-0.226***	-0.003**	0.035	0.59
All	ND	-2.058	-0.007	0.001	0.016**	0.11	-0.024	0	-0.000*	0.012	0.001	0.002	0.05	0.69
All	OH	-22.37	-0.01	0.005	0.010*	0.229	2.426	0	-0.000*	-0.044	-0.069	-0.002	0.042	0.56
All	OK	-50.64	-0.007	0.004	0.002	-0.229	4.713	0	0	0.015	-0.108	0.001	0.111**	0.83
All	OR	-12.54	0.015***	-0.001	0.005	-0.017	2.142	0	0	0.006	-0.074	0	0.031	0.68
All	PA	-14.86	-0.003	0.004	0.006**	0.005	1.782	0	0.000**	-0.014	-0.055	0	0.038	0.49
All	SD	-8.677	-0.007	-0.001	0.012	0.059	0.925	0	0	0.011	-0.029	0.001	0.024	0.74
All	TX	-124.2	0.032**	0.002	-0.01	2.001	9.857	0	0	-0.08	-0.205	0.001	-0.068	0.32
All	UT	12.438	0.008**	0.010**	0.009	-0.062	-1.174	-0.000*	0	0.028	0.034	-0.004	-0.039*	0.53
All	WI	-6.856	-0.006	-0.001	0.013	0.104	0.684	0	0	0.02	-0.023	0.002	0.04	0.49
Irrig	CO	-39.93	-0.007	0.027	0.004	-0.245	5.218	0	0	0.174	-0.17	0.006*	-0.045	0.65
Irrig	ID	-5.268	0.020*	0.003	-0.001	0.041	1.582	0	0	0.019	-0.063	0.002	-0.091	0.65
Irrig	MT	-23.74*	0.014**	-0.021	-0.008	-0.077	4.209*	0.000*	0	-0.043*	-0.153*	0.003	0.01	0.71
Irrig	NE	13.857	0.025***	-0.007	0.013*	0.032	-1.424	0	-0.000*	-0.016	0.04	-0.001	0.048	0.75
Non_Irrig	CO	21.583	-0.014	0.032	0.004	-0.068	-3.34	0	0	-0.042	0.112	0.005*	0.036	0.74
Non_Irrig	ID	-12.4	-0.003	0.004	-0.017	-0.045	2.259	0	0	0.062	-0.088	0.002	0.009	0.81
Non_Irrig	MT	-21.75*	-0.008*	-0.024**	-0.017**	-0.121*	3.922**	0.000**	0.000**	-0.060***	-0.145**	0.005**	0.029	0.83
Non_Irrig	NE	-3.253	0.001	0.002	0.013	0.023	0.371	0	0	0.005	-0.014	0.001	0.033	0.71

Table 5-18. Results of the nonlinear regression of the alfalfa hay yield on PDSI and neighboring states

State	Constant	Trend	P	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)	P(8)	P(9)	P(10)	P(11)	T	T(1)	T(2)	T(3)	T(4)	T(5)	T(6)	T(7)	T(8)	T(9)	T(10)	T(11)	P_max	T_max	Rsq
AZ	1.438***	0.001***							-0.001**														0.010***	0.006**			1	2	0.3
AR	1.076***	0.000**																		0.002**							0	1	0.05
CA	1.892***	0.001***															-0.008***										0	1	0.16
CO	2.021***	0.002***				-0.001*	-0.001**	-0.002**	-0.002***	-0.002**	-0.002***	-0.002***	-0.002***	-0.002**		-0.005***											9	1	0.54
ID	1.506***	0.001***															-0.008**						-0.012***				0	2	0.32
IL	1.459***	0.001***																				0.004***					0	1	0.12
IN	1.681***	0.002***								-0.001**	-0.002***	-0.001**	-0.001**									0.013***					4	1	0.27
IA	2.499***	0.001***				-0.001*			-0.001**	-0.001*		-0.001**	-0.001***	-0.001*	-0.011**	-0.010*	-0.012**		-0.017***		-0.013***		-0.013***		-0.013***		6	7	0.2
KS	2.331***	0.001***		-0.001**	-0.001*	-0.001**	-0.001*	-0.001**	-0.001***	-0.001***	-0.001***	-0.001*	-0.001*	-0.001**	-0.011**					-0.009*	-0.008*					-0.012***	11	4	0.23
KY	1.629***	-0.000**							-0.000*	-0.001**																	2	0	0.06
MI	1.830***	0.001***			-0.001*		-0.001*	-0.001*	-0.001*	-0.001*	-0.001**	-0.001***			-0.012***												7	1	0.29
MN	2.533***	-0.000**				-0.001**	-0.001***	-0.001*	-0.001***	-0.001***	-0.001**	-0.001**	-0.001**	-0.001**	-0.014***	-0.014***		-0.009**	-0.012**	-0.011**			-0.008*	-0.008*?	-0.010**		9	8	0.26
MO	1.261***	-0.001***														0.005**						0.008***					0	2	0.21
MT	1.780***	0.000**							-0.001	-0.002**	-0.002***	-0.002***	-0.002***	-0.002***			-0.007***										6	1	0.14
NE	2.302***	0.001***		-0.001***	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***		-0.011***		-0.009**						-0.013***			11	3	0.38
NV	1.711***	0.001***																									0	0	0.15
NM	1.843***	0.001***								-0.001**	-0.001**			-0.001**						0.010***					0.016***		3	2	0.26
NY	1.775***	0.000***				-0.001*					-0.001*																2	0	0.04
ND	1.015***	-0.000***													-0.005***				0.004***							0.010***	0	3	0.08
OH	1.551***	-0.001***																	0.020***			0.003			0.016***		0	3	0.07
OK	1.745***	-0.001***				-0.001**	-0.000*	-0.001***		-0.001***	-0.001***	-0.001**	-0.000*								0.010***	.					7	1	0.24
OR	1.722***	0.002***														-0.007*						-0.013***					0	2	0.42
PA	2.061***	0.000***			-0.001**																						1	0	0.04
SD	1.044***	0.001***																						0.002*			0	1	0.08
TX	1.423***	-0.000**						-0.001*	-0.001**	-0.001**	.	-0.001**	-0.001**	-0.001**	0.014***							0.009**					6	2	0.16
UT	1.376***	0.001***																				-0.003**					0	1	0.27
WA	2.633***	0.002***															-0.022***	-0.019***			-0.022***	-0.022***			-0.017**	-0.020***	0	6	0.35
WI	2.038***						-0.001**	-0.001***			-0.001*	-0.002***	-0.002***	-0.001**			-0.014***										6	1	0.14
WY	1.713***	0.001***			-0.002***			-0.001**		-0.001*	-0.002**		-0.001*	-0.002**													6	0	0.16
Total			0	2	5	7	7	9	10	13	12	11	11	10	6	6	6	3	4	4	4	8	4	4	5	3			

Chapter 6 Targeting PRF to Viable Regions

At present, the PRF plan is offered across a geography that largely covers the entire coterminous United States. Not all areas where the PRF plan is offered are suitable for forage production. We have investigated two distinct measures of the suitability of land for the production of forage with the intent of formulating recommendations for restricting the PRF offering to areas that have the potential for viable forage and hay production.

The National Resources Inventory (NRI) is a periodic survey that catalogs the stock of US natural resources, including land capability and usage. The survey includes a measure of the suitability of non-irrigated soils for most kinds of field crops—the land capability classification (LCC). The Natural Resources Conservation Service (NRCS) has constructed quantitative measures of land characteristics to formulate the LCC system. Soils are grouped according to their limitations, their response to management, and the potential for damage if the land is cropped. The LCC ranges from scores of 1 to 8, with 1 being of the highest quality for agronomic uses and 8 corresponding to the lowest quality. An LCC of 1 corresponds to soils that have few limitations that restrict their use. The lowest quality of land has an LCC score of 8. This corresponds to "soils and miscellaneous areas that have limitations that preclude commercial plant production and that restrict their use to recreational purposes, wildlife habitat, watershed, or esthetic purposes."

The LCC system also has a set of four subclasses that correspond to additional hazards that affect their use. We believe that subclass C characterizes hazards that are likely to limit the suitability of the land for cultivation or forage production. Subclass C consists of soils for which the climate (based on temperature or lack of moisture) is the major limitation affecting their use.

We used the 2015 NRI survey (the most recent available) to consider the suitability of individual counties for inclusion in the PRF plan. The NRI data are not geographically identifiable at a resolution any finer than the county level due to non-disclosure considerations and the sampling procedures used in collecting the data.

We considered various aggregations of land area in each county according to the LCC metrics. Figure 6-1 illustrates the proportions of land area that falls into LCC class 8 and/or subclass C (which we denote as LCC 8/C). This represents the land least suitable for cultivation because of soil and climate conditions. As would be expected, the lowest quality of land is generally in the western states. Some coastal regions also have land that is not designated as being useful for cultivation.

We investigated the extent of the usage of land area in the production of hay and forage. Specifically, we considered the proportion of total area in a county, as reported in the 2017 Agricultural Census, that was harvested for forage, defined as "all hay and haylage, grass silage, and green-chop," (Agricultural Census Variable No. y17-M159). This was converted to a proportion of total area in a county by using the proportions of cropland harvested and land in farms as a proportion of total land area. We considered three different thresholds for the proportion of land in LCC 8 or C—counties with more than 10%, 25%, and 50% of land so designated. We identified such counties and examined the proportion of land in each county that was harvested for forage.

Figures 6-2 – 6-4 illustrate the proportion of land in each category of LCC rating 8/C used in producing forage. In each figure, the shorter bar reflects the proportion of LCC 8/U land exceeding each threshold in a county used in forage production. It is notable that counties having 10% or 25% of land area in LCC 8/C still have notable acreage devoted to the production of forage. In the case of those counties having more than 50% of land area in LCC 8/C, less than 1% of land area is harvested for forage or hay.

Figures 6-5 – 6-7 identify the counties exceeding each threshold (10%, 25%, and 50%) of land in LCC 8/U. We believe that the LCC measure of land quality could be used to limit the offering of the PRF plan in counties having a large proportion of land that is unsuitable for forage production. If RMA intends to limit entire counties, we would recommend eliminating those counties with 50% or more land area that falls into the lowest capability classes, either because of its suitability for cultivation or its unfavorable weather conditions. Our analysis demonstrates that such counties generally do not have very much land area (only about 0.95%) involved in forage production. This would serve to drop areas with unfavorable growing conditions and would have a minimal impact on forage producers that may have PRF coverage.

An important limitation of such a proposal lies in its relative lack of resolution. That is, entire counties would be eliminated based on average growing conditions. To the extent that land quality is highly heterogeneous in such counties, this would have the potential of eliminating small portions of land that could be amenable to forage production. We, therefore, considered an alternative measure of land viability for forage production. The US Forest Service has calculated an annual measure (1984-2018) of rangeland productivity. Rangeland productivity, in terms of rangeland vegetation in pounds per acre, is calculated for the non-forest domain of the coterminous US using the Normalized Difference Vegetation Index (NDVI) from the Thematic Mapper Suite at the 250 m^2 level of resolution.[11]

We collected the average level of rangeland production over the 1984-2018 period. Figure 6-8 illustrates the data at the 250 m^2 level of resolution. These data were reprojected on the wgs84 latitude and longitude coordinates and were aggregated by a factor of 40-times to allow the data to be managed in concert with the NOAA NCPC gridded data. The reprojected and aggregated data are presented in Figure 6-9. The data were then put on a latitude/longitude grid that was considerably finer than the NOAA NCPC precipitation data and nearest-neighbor averaging

[11] The USFS data can be downloaded from https://data.fs.usda.gov/geodata/rastergateway/rangelands/index.php.

further aggregated the data to match the grid points of the NCPC grid. Neighbors were defined as all points within a 15 km radius of the NCPC grid centroid.

Figure 6-10 illustrates average precipitation (from 1948-2017) and rangeland production. The figure demonstrates a strong relationship between precipitation and rangeland production. Figure 6-11 presents county-level aggregates of rangeland production. When compared to the LCC 8/U maps, very similar patterns of land quality and forage production are implied. We do not recommend using such a level of aggregation in light of the vast loss in resolution.

We then considered benchmarks defined by the distribution of rangeland output across the entire non-forested US. We considered the elimination of grid points from the PRF plan that alternatively had rangeland production that fell below the tenth, fifth, and first percentiles. Figures 6-12 – 6-14 illustrate the grid points that would be eliminated from the plan under each threshold. If a tenth percentile was to be used as a threshold, 970 of the 13,626 grid points would be eliminated. If the threshold is dropped to the fifth percentile, 484 grid points would be eliminated. Dropping the threshold to the first percentile leads to 96 grid points be dropped from the program.

PRF Viable Regions Recommendations

If RMA prefers to eliminate whole counties from the program based on the suitability of soil and climate conditions for forage production, we recommend consideration of the land capability classification. Specifically, we recommend dropping counties having more than 50% of the total area that falls into land capability class 8 and/or subclass C. Such land has been designated by NRCS to be unsuitable for cultivation. A review of the 2017 census indicates that only a very small proportion of land in such counties is used to harvest forage or hay. This recommendation comes with two caveats. First, eliminating entire counties may not be appropriate in areas where land quality is very heterogeneous. This reflects the lack of resolution in a county aggregate. Second, as is likely to be the case with any threshold criteria, the choice of 50% is admittedly arbitrary but is justified in light of the very limited acreage devoted to hay in forage in such areas. Appendix Table 2 presents the relevant FIPS codes.

If RMA is willing to consider a higher degree of resolution and instead eliminate individual grid points rather than entire counties, we believe that the USFS measures of forage production provide an ideal metric for selecting areas to drop from coverage. We have obtained a direct measure of average forage production for each grid point and have also demonstrated the strong correspondence between precipitation and forage production. Again, one can infer that, depending on the threshold selected, this would impact few producers of forage and rangeland. This is again demonstrated by the fact that forage production is low, both in terms of output and acreage, in such areas. Once again, the threshold of rangeland production that defines dropping a grid point from the PRF plan is arbitrary but is directly justified by the very low level of forage production and concomitantly low allocation of acreage to forage in such areas.

In summary, we recommend that RMA drop any grid point and its relevant 0.25-degree surrounding area that corresponds to the lowest 1-percentile of the distribution of forage production from eligibility for PRF coverage. This would eliminate 96 of the 13,626 grid points currently in the program. We have outlined alternative thresholds that could be used to eliminate marginal forage producing areas and believe that these may form the basis for future program revisions. A less drastic step would be to allow insurance in these areas, but with a reduced CBV and to allow irrigated acres to insure. We note that we also considered eliminating intervals with extremely high rates. This is an actuarial approach, but we believe that it is also a practical approach to the problem.

Figure 6-1: Land in LCC 8 and/or Subclass C

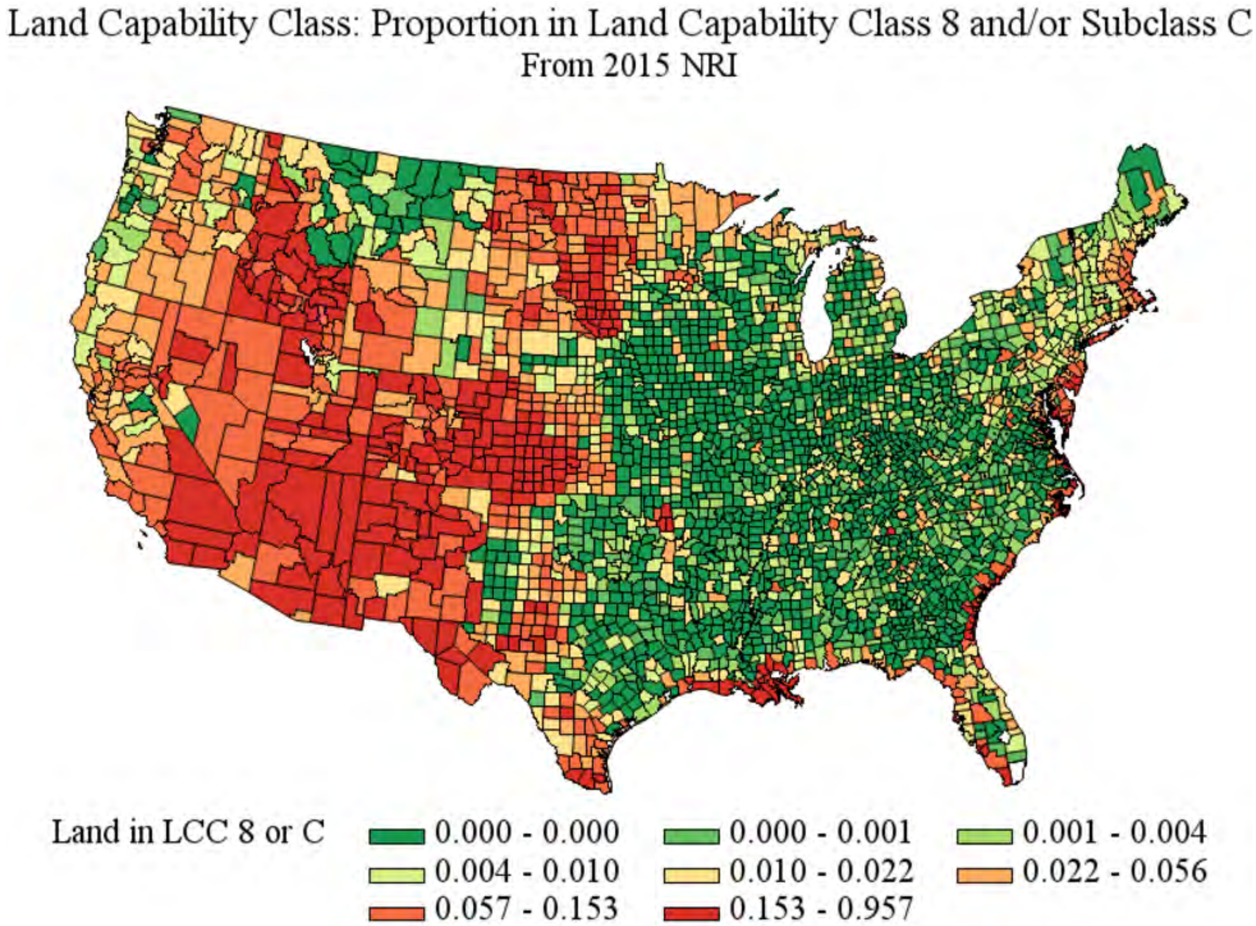


Figure 6-2: Forage and Hay Production in Counties

With LCC 8/C > 10% of Land Area

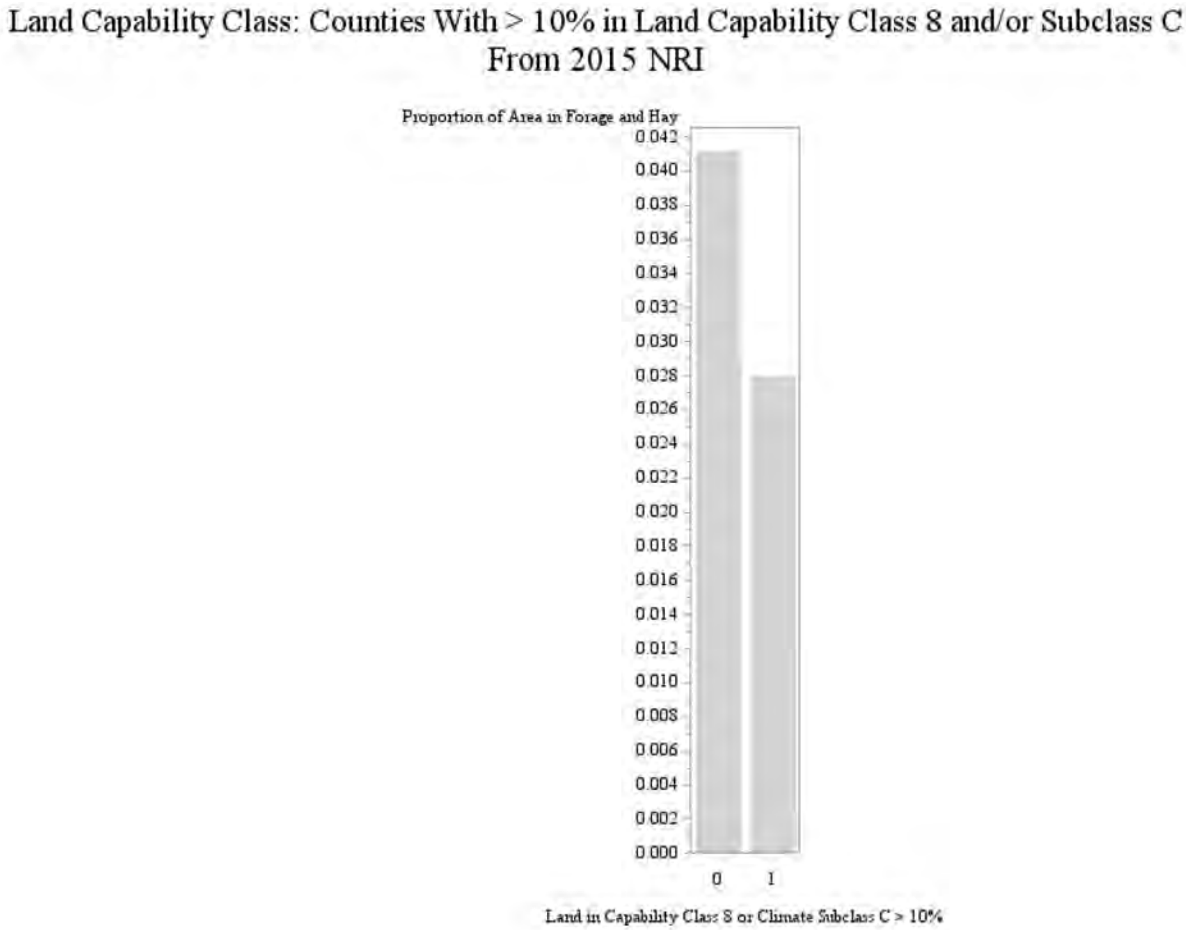


Figure 6-3: Forage and Hay Production in Counties

With LCC 8/C > 25% of Land Area

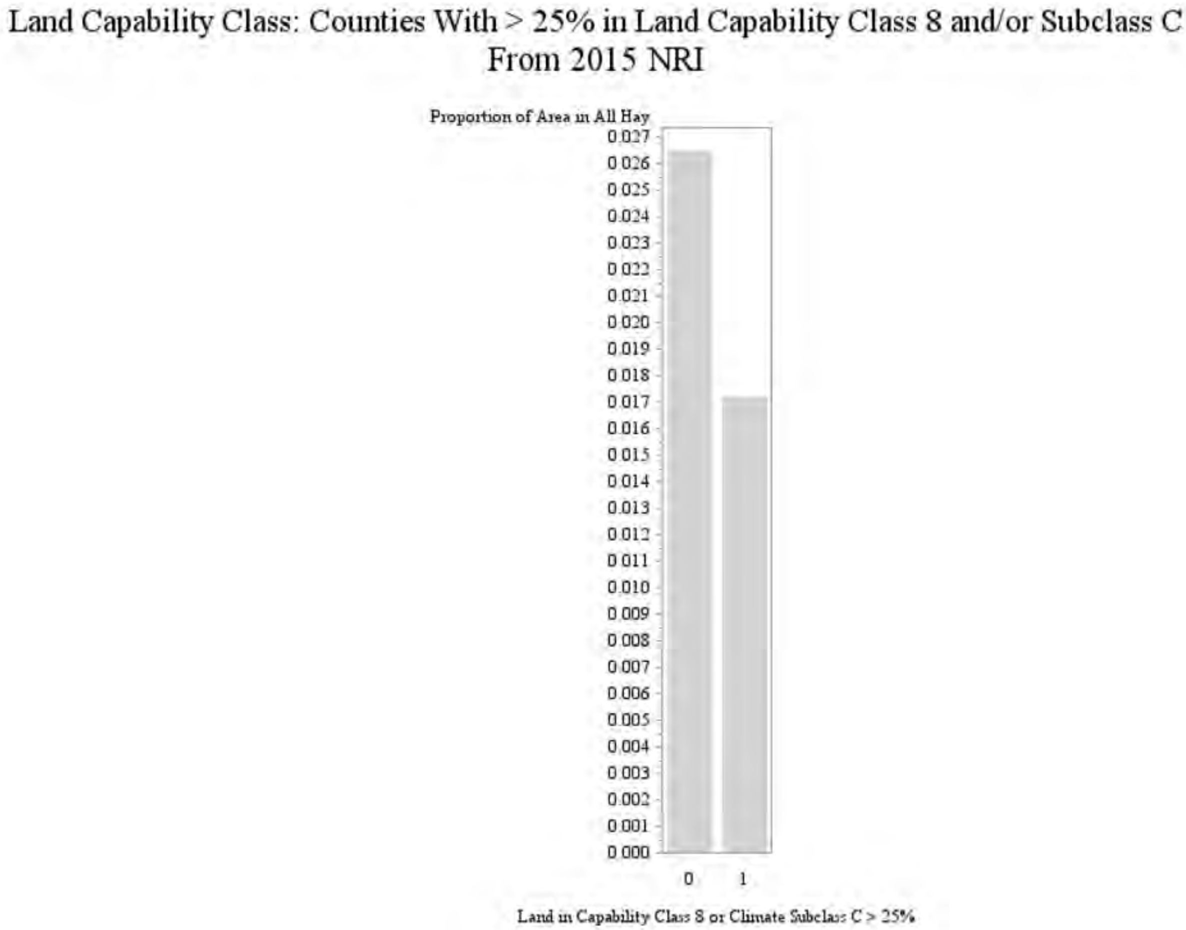


Figure 6-4: Forage and Hay Production in Counties

With LCC 8/C > 50% of Land Area

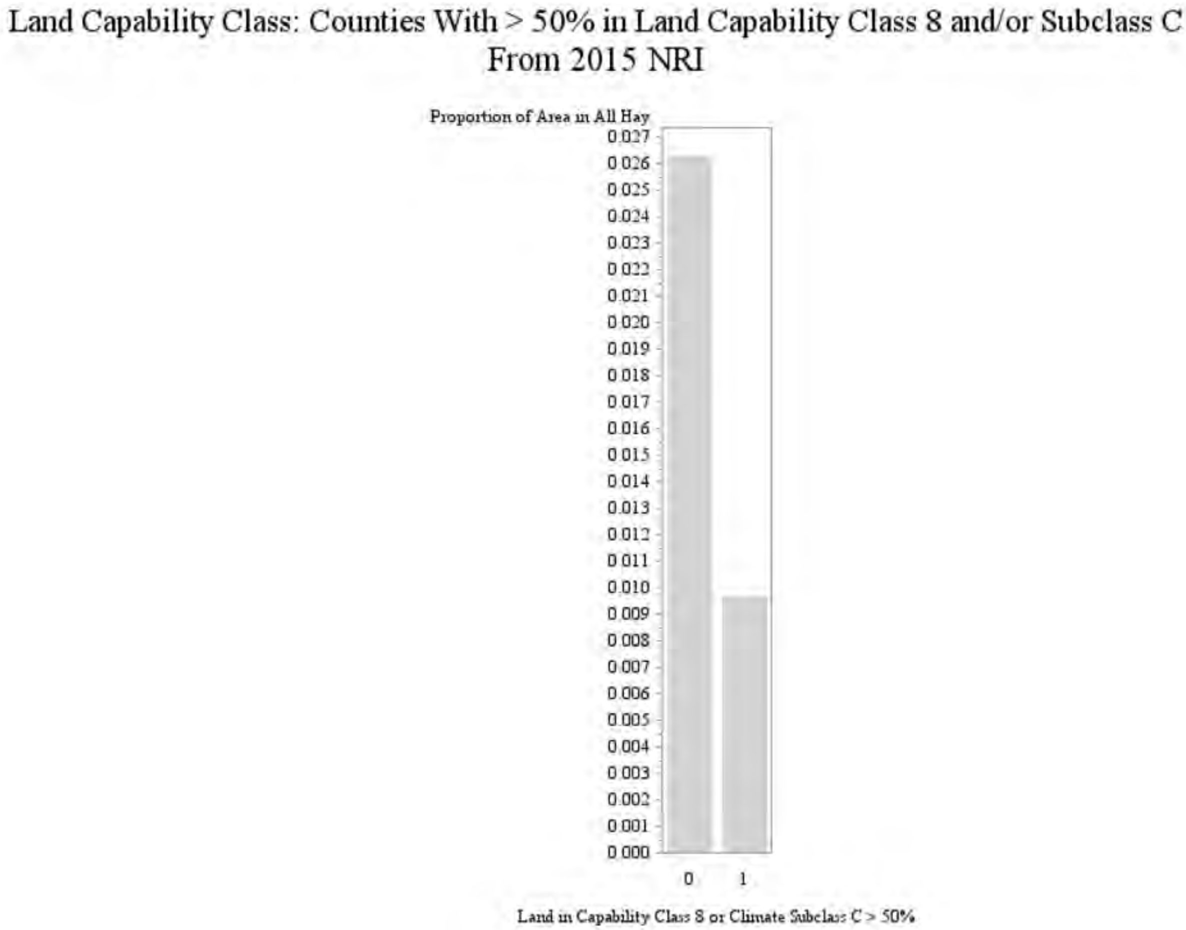


Figure 6-5: Counties with LCC 8/C > 10% of Land Area

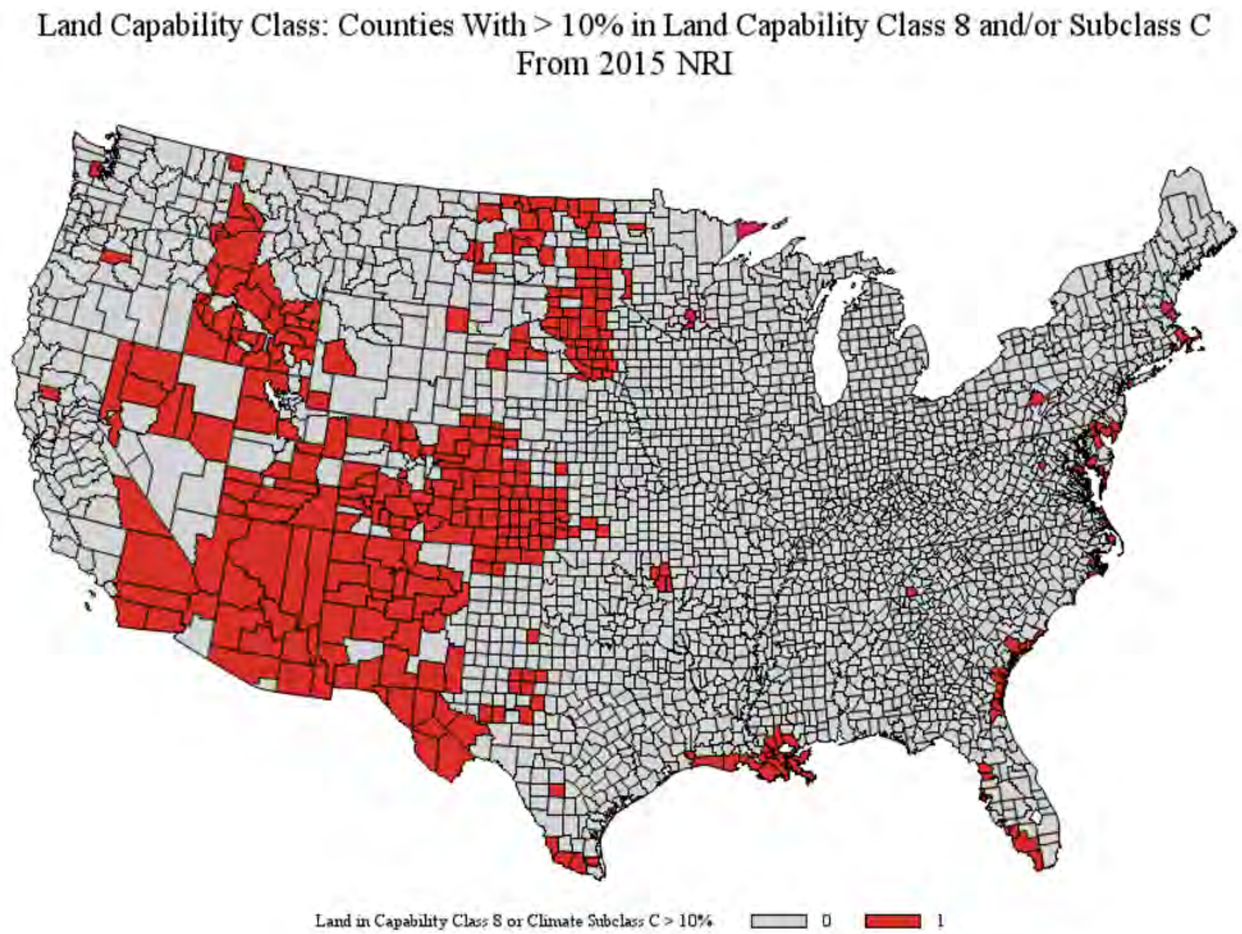


Figure 6-6: Counties with LCC 8/C > 25% of Land Area

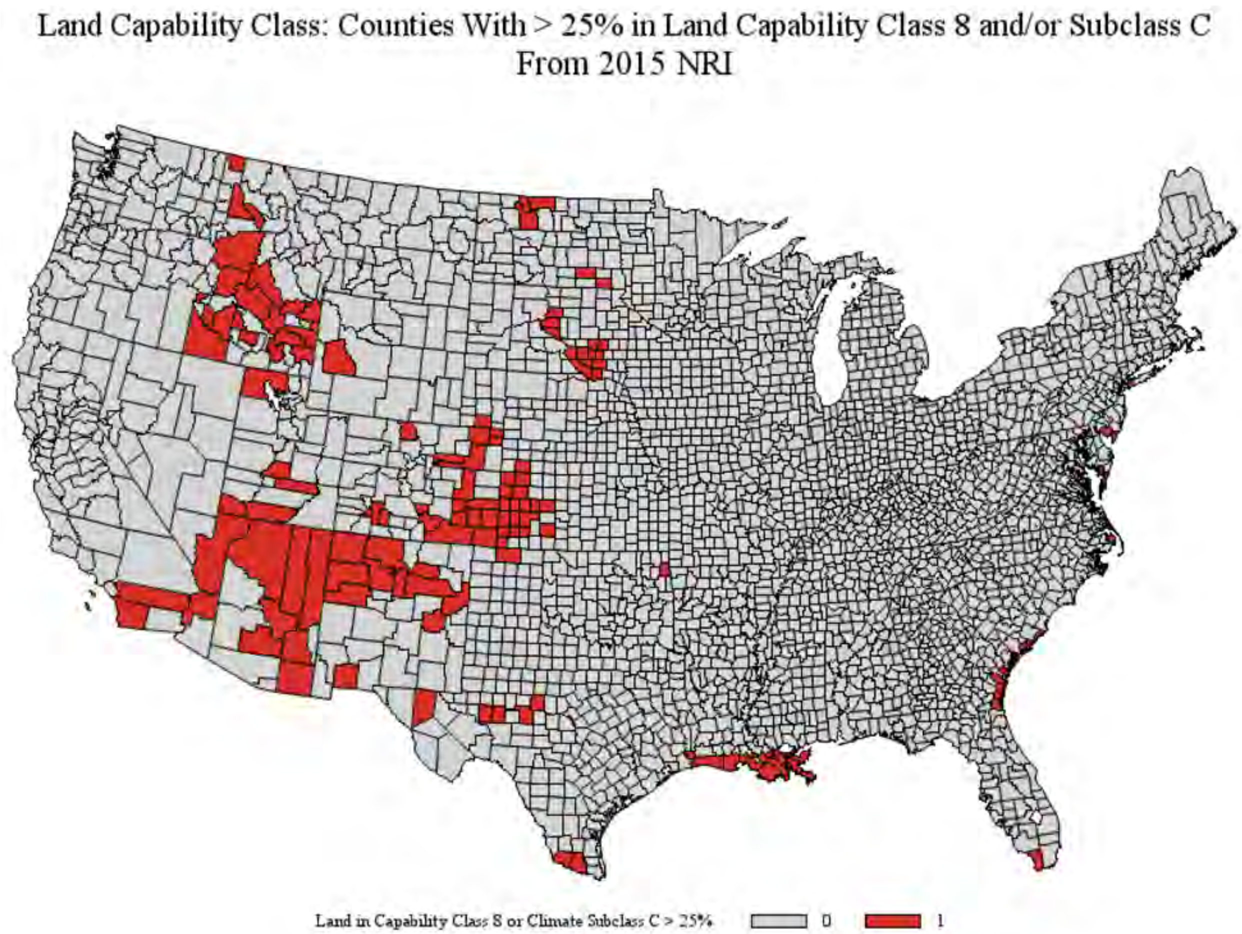


Figure 6-7: Counties with LCC 8/C > 50% of Land Area

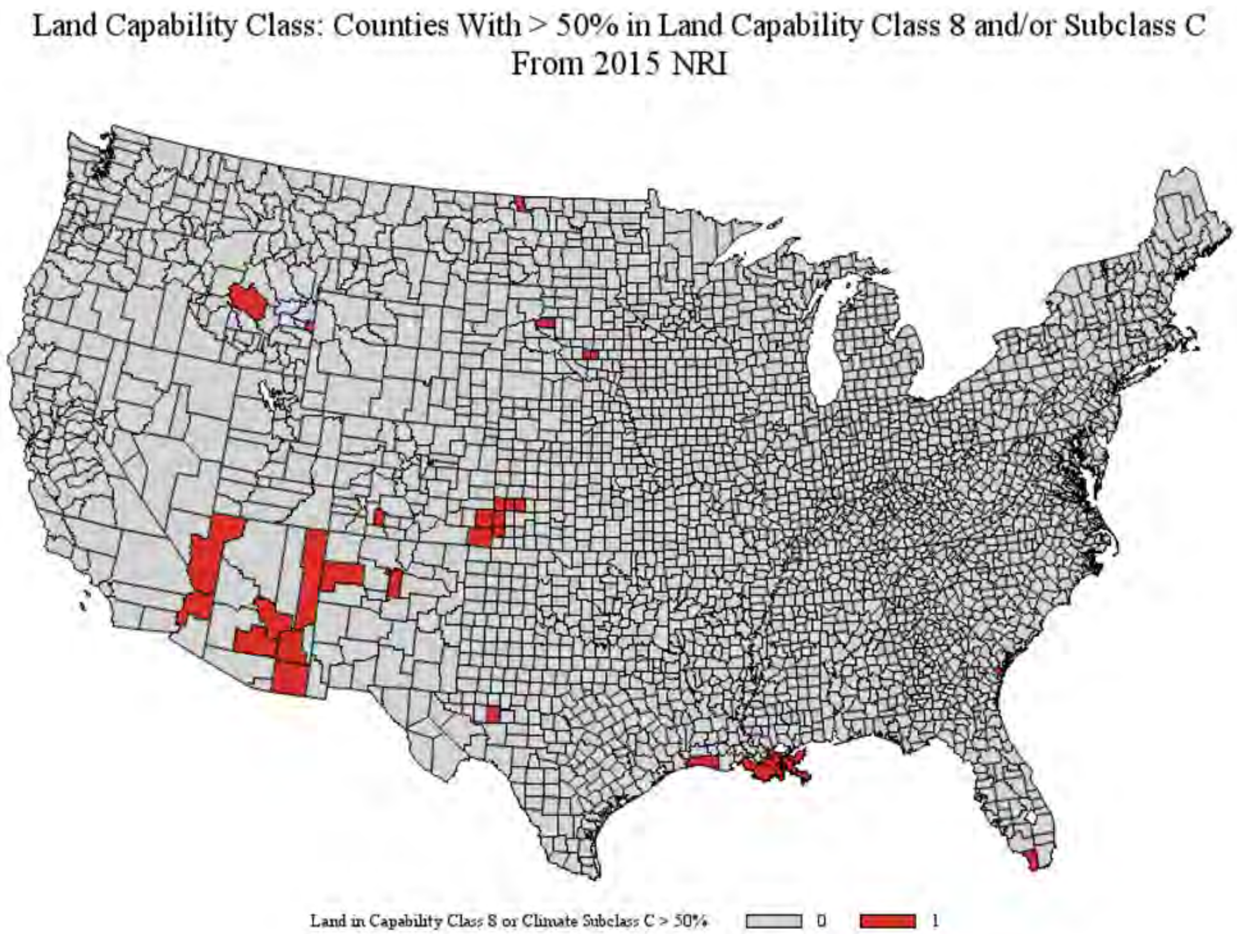


Figure 6-8: Raw USFS Rangeland Average (1984-2018) Production

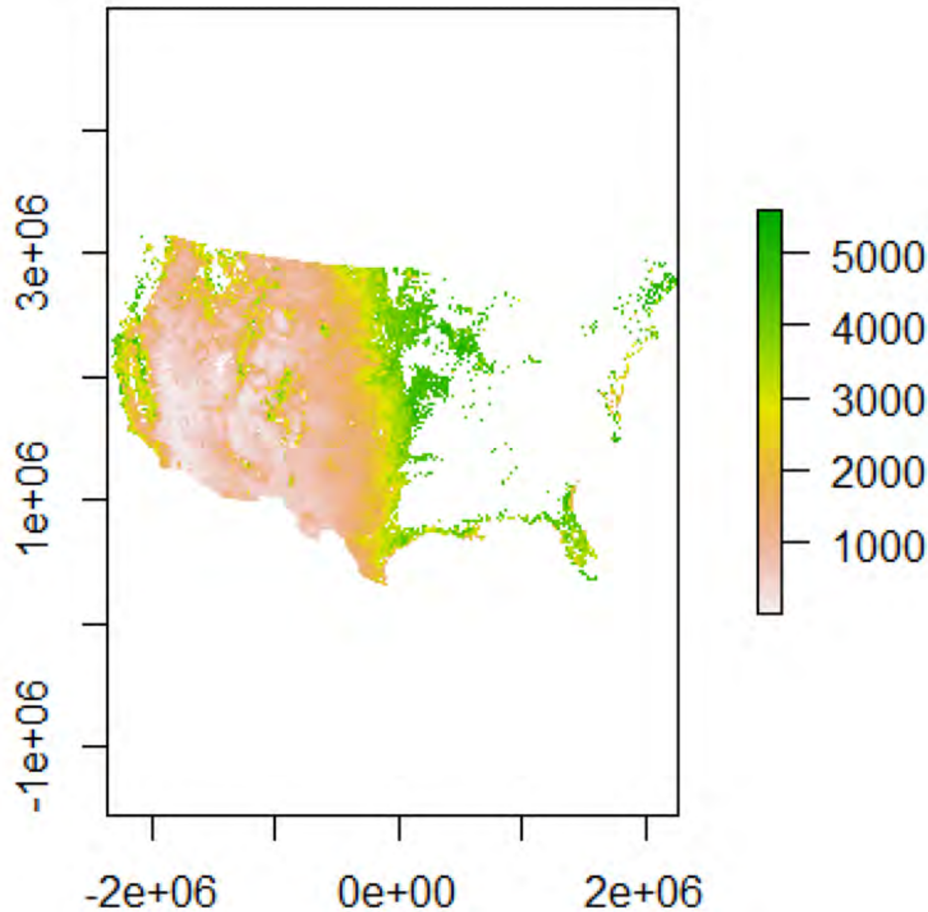


Figure 6-9: Aggregated and Reprojected USFS Rangeland

Average (1984-2018) Production

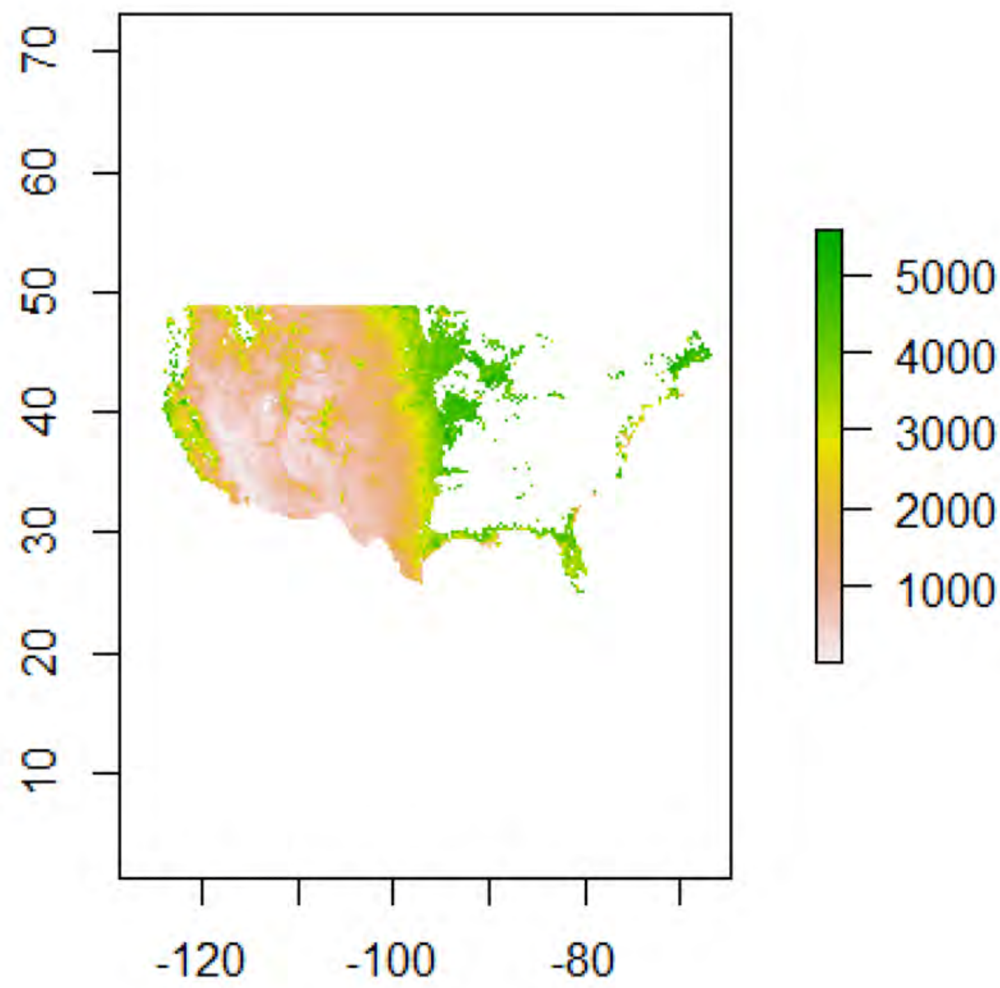


Figure 6-10: NCPC Average Precipitation and Forage Production

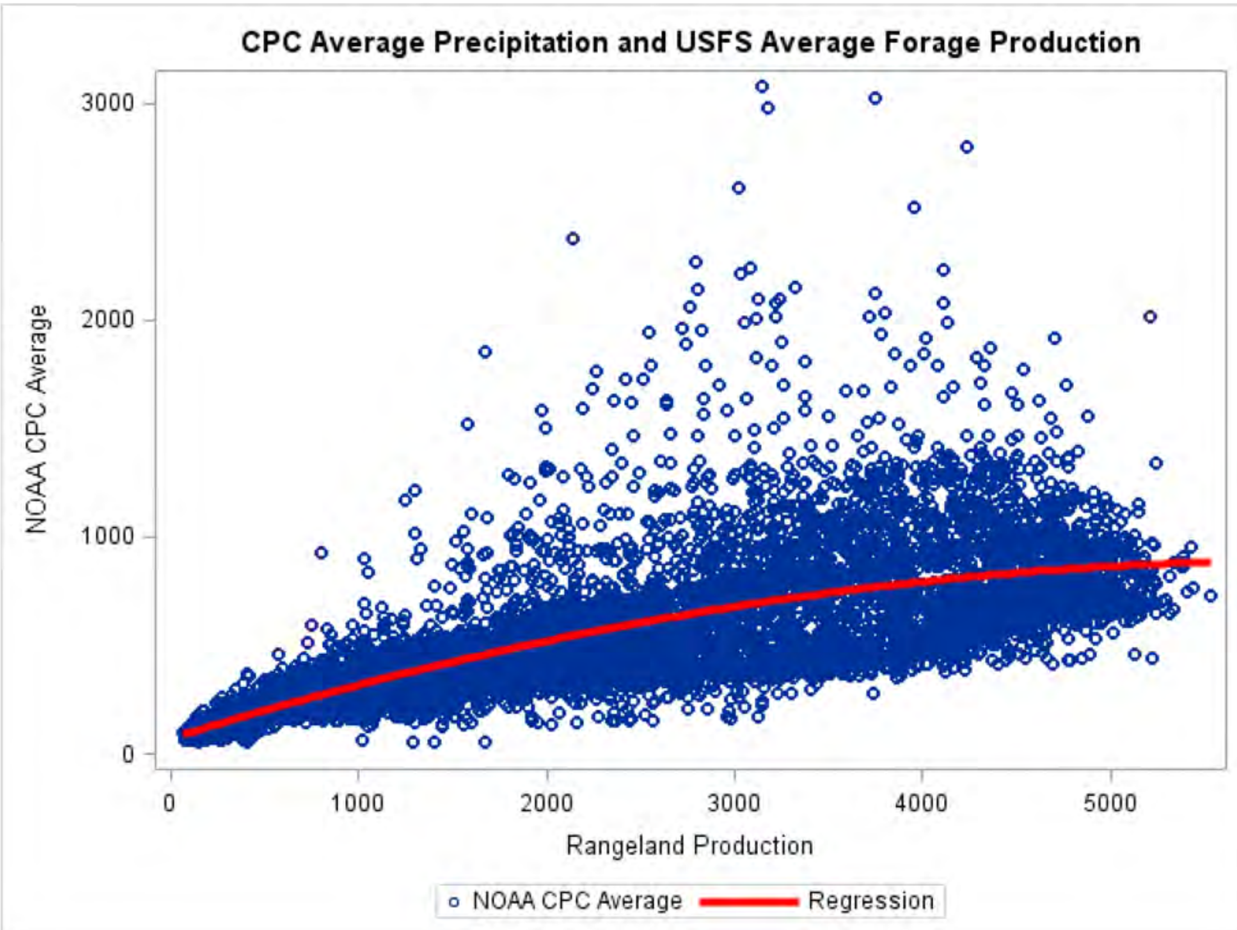


Figure 6-11: USFS Rangeland Average (1984-2018) Production

Aggregated to County Averages

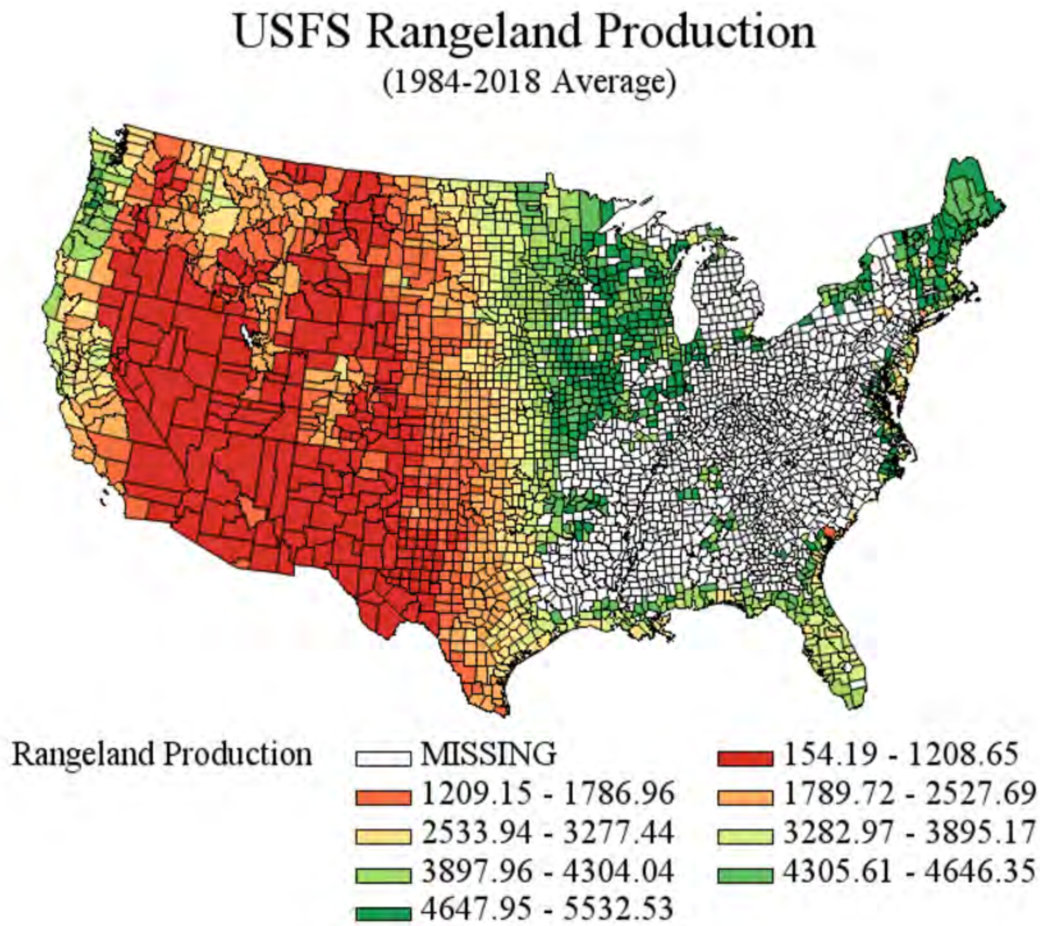


Figure 6- 12: Grid Points Dropped from PRF

Based on the 10th Percentile

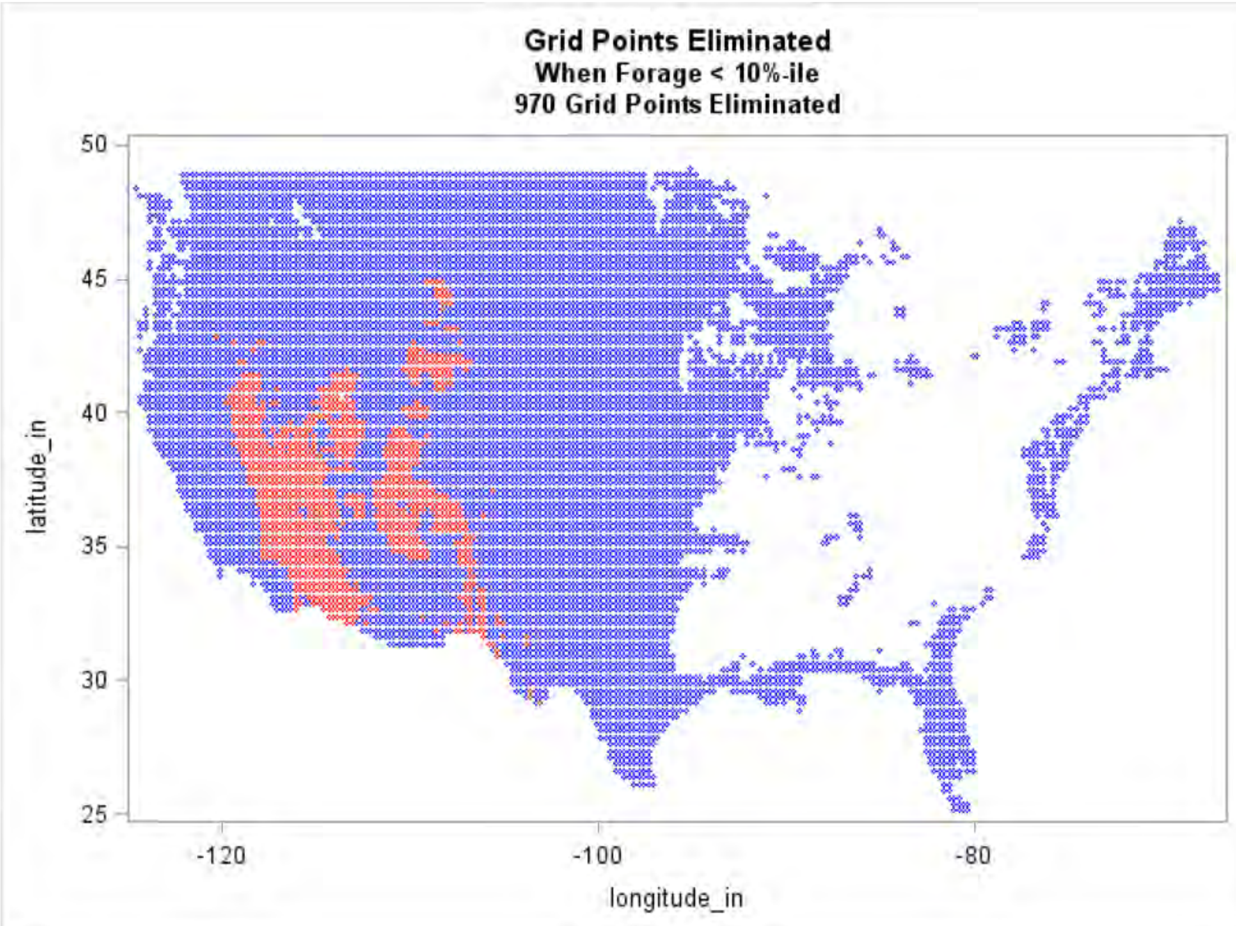


Figure 6-13: Grid Points Dropped from PRF

Based on the 5th Percentile

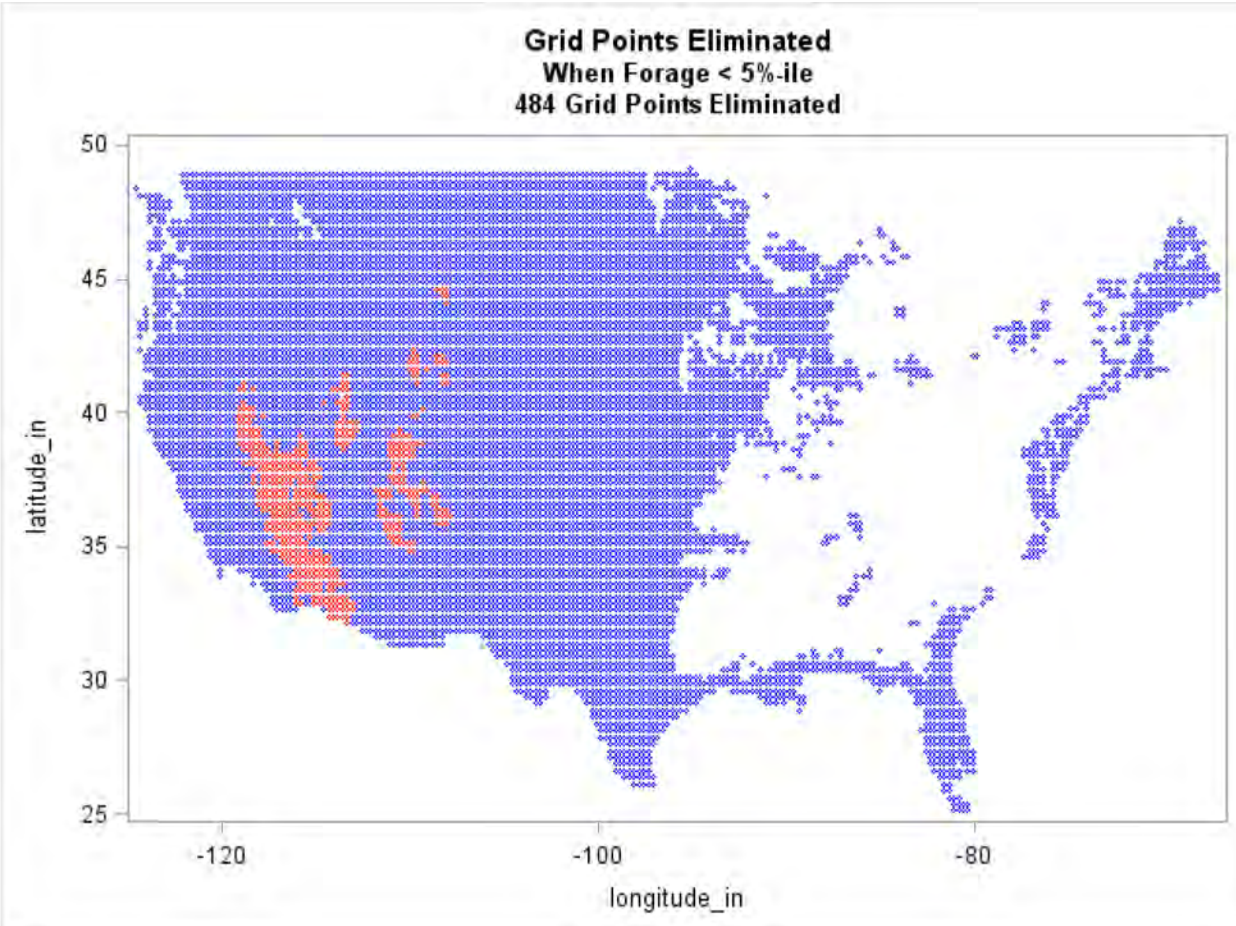
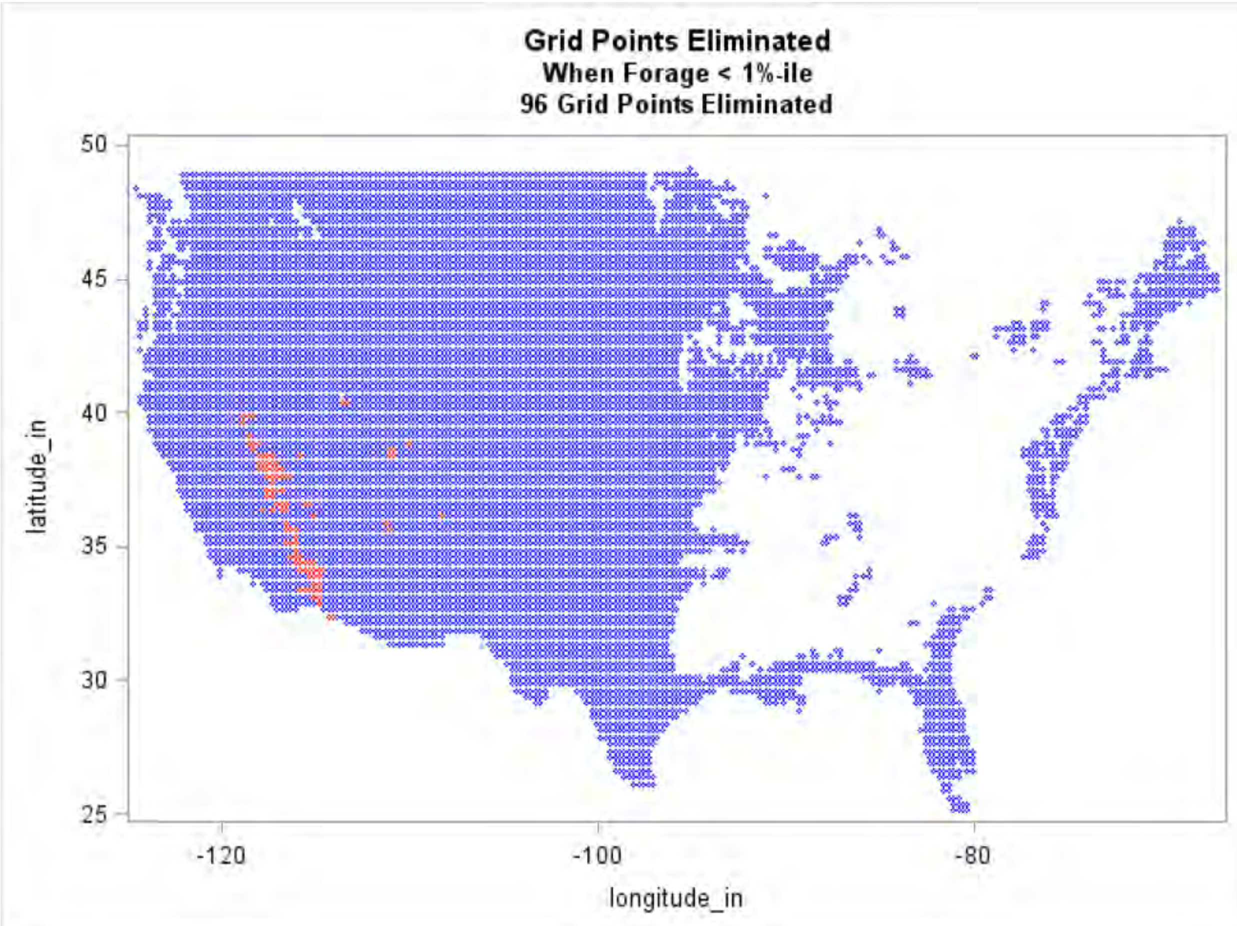


Figure 6-14: Grid Points Dropped from PRF

Based on the 1st Percentile



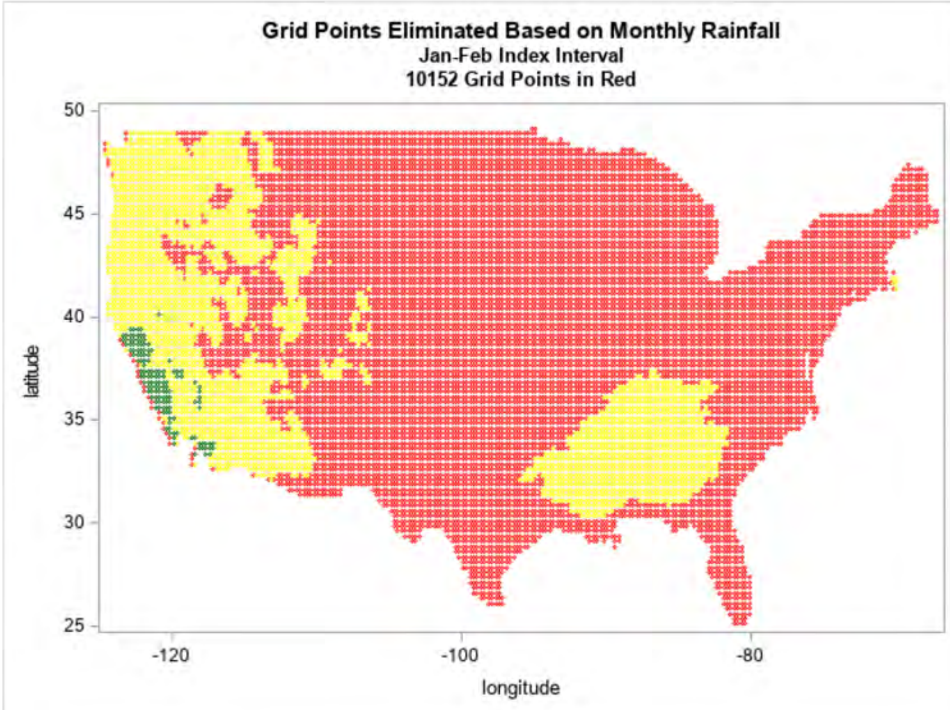
An alternative approach based on the percent of annual rainfall

One possible approach to reducing irrelevant intervals is to simply eliminate grid intervals that contribute a small percentage of the annual rainfall. The premise being that intervals that contribute a small percentage of annual rainfall have less to do with producer risk than periods of more significant rainfall. We evaluated this approach and the maps in Figures 6-15 – 6-26 below reflect the analysis of the following two conditions:

1. if the month's expected rainfall is less than 1/12 of the average total annual rainfall then the month and any associated interval is removed
2. if the interval's expected rainfall is less than 1/12 of the average total annual rainfall then the interval is removed.

Two maps, one for each of the above conditions, are generated for each two-month interval. Grids in red are grids that would be removed if the respective condition is imposed as they fail the condition. Each map indicates the number of grids that would be removed. For grids in yellow, the month's (interval's) expected rainfall is greater than 1/12 but less than 1/6 of the average total annual rainfall. For grids in green, the month's (interval's) expected rainfall is greater than 1/6 of the average total annual rainfall.

The first condition would result in a large number of grids being removed for almost all intervals and therefore is not recommended. We also examined some other variants but reached the conclusion this approach is highly sensitive to the specific parameters chosen.


Grid Points Eliminated Based on Monthly Rainfall
Jan-Feb Index Interval
10152 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

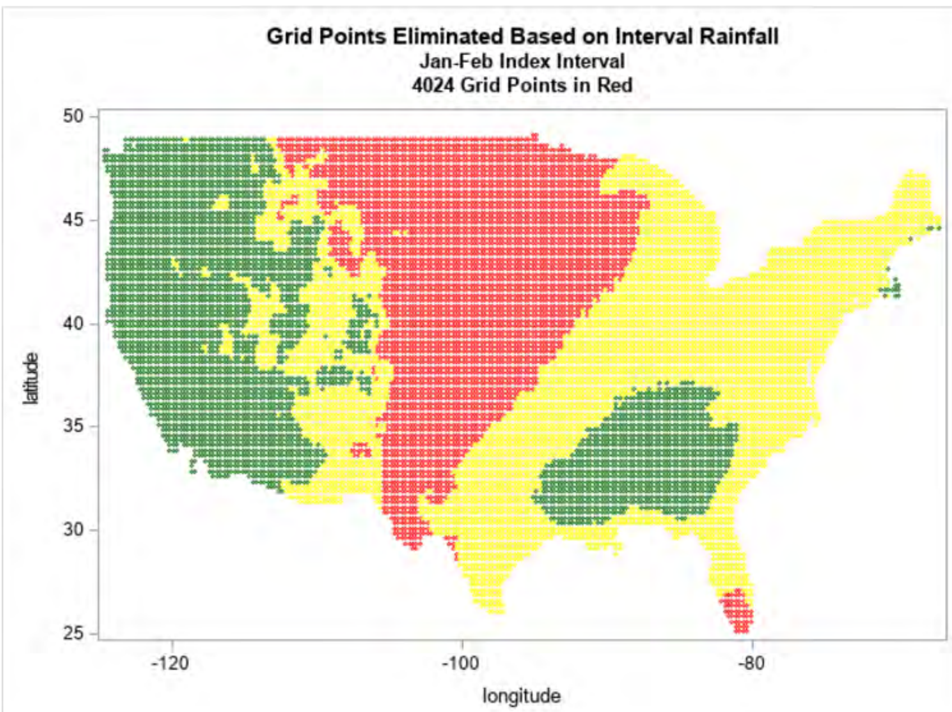
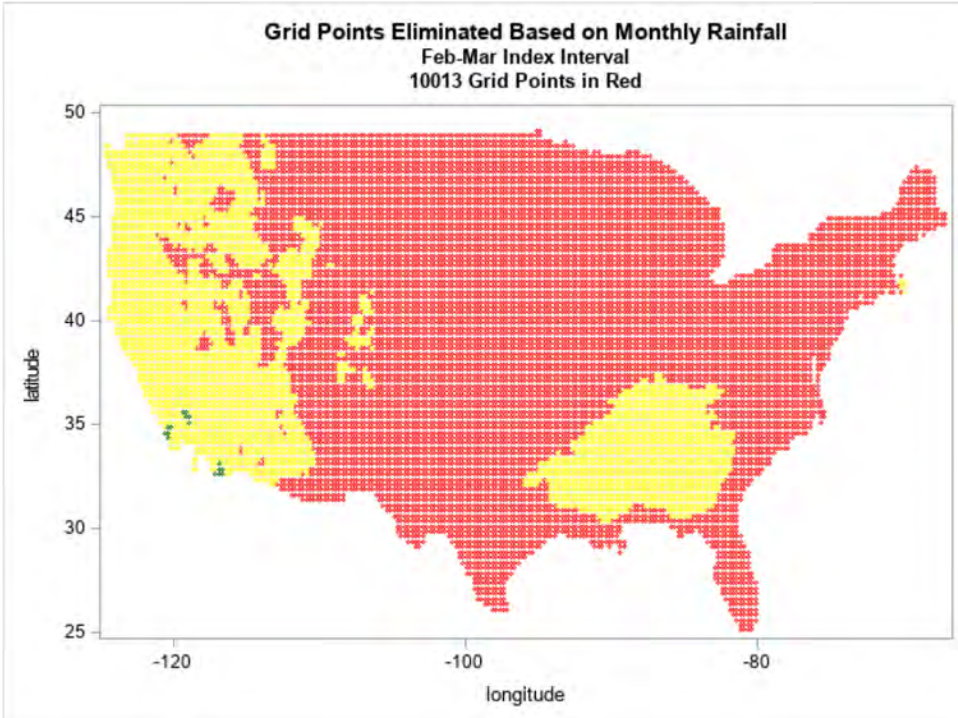

Grid Points Eliminated Based on Interval Rainfall
Jan-Feb Index Interval
4024 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

Figure 6-15


Grid Points Eliminated Based on Monthly Rainfall
Feb-Mar Index Interval
10013 Grid Points in Red
latitude
50
45
40
35
30
25
-120
-100
-80
longitude

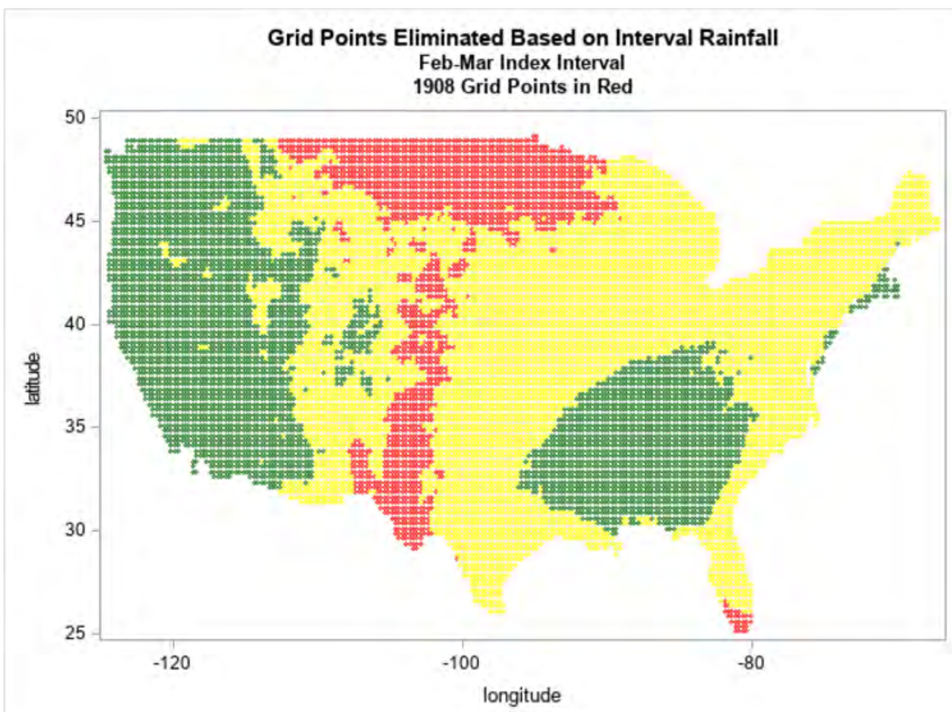

Grid Points Eliminated Based on Interval Rainfall
Feb-Mar Index Interval
1908 Grid Points in Red
latitude
50
45
40
35
30
25
-120
-100
-80
longitude

Figure 6-16

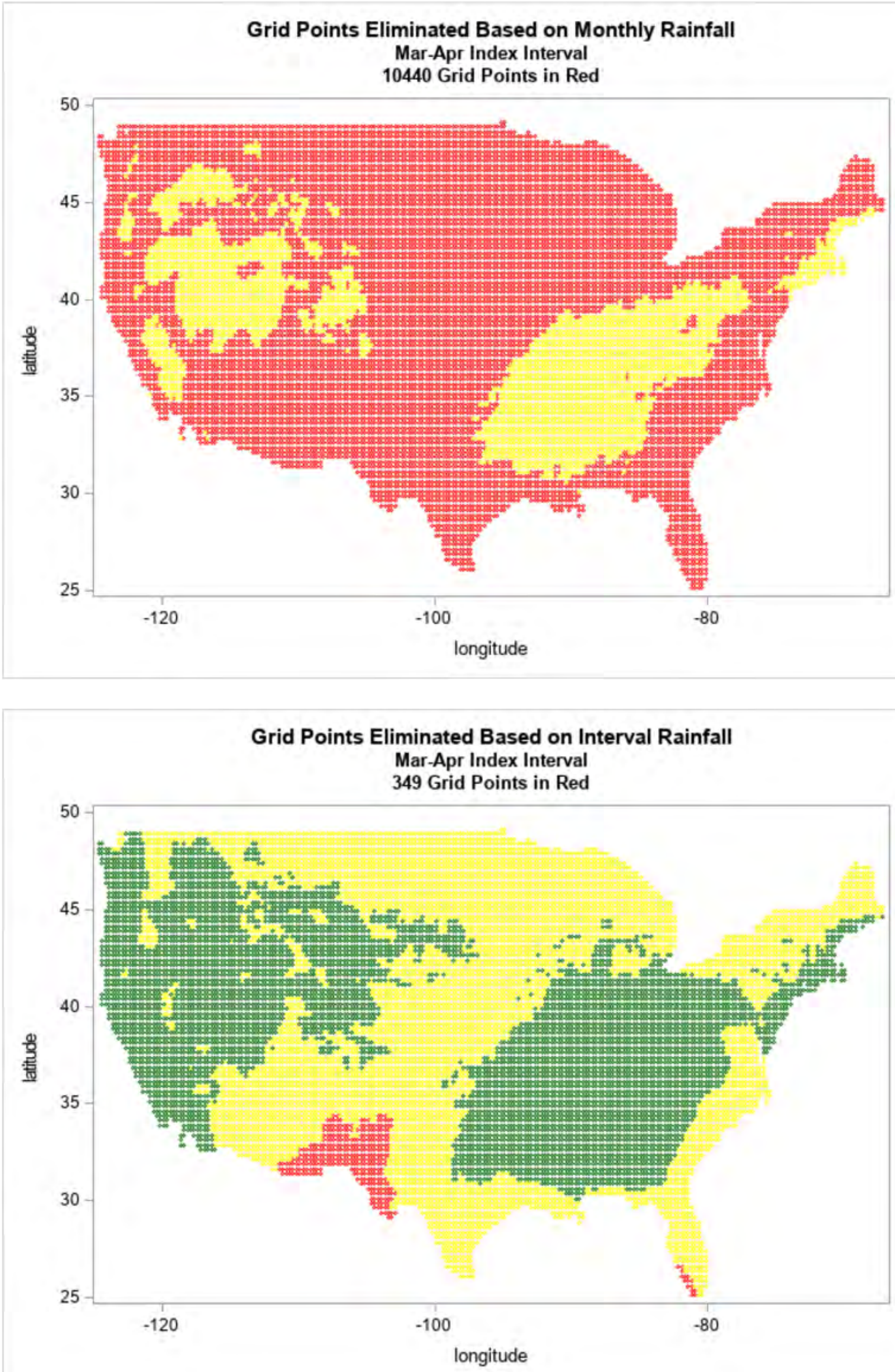
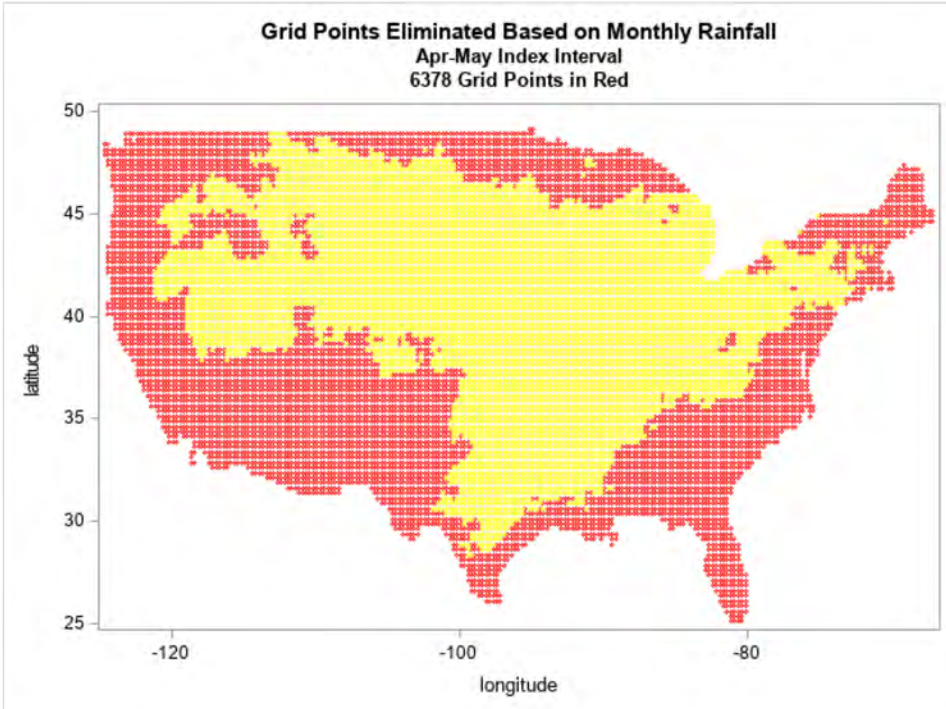

Grid Points Eliminated Based on Monthly Rainfall
Mar-Apr Index Interval
10440 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80
Grid Points Eliminated Based on Interval Rainfall
Mar-Apr Index Interval
349 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

Figure 6-17


Grid Points Eliminated Based on Monthly Rainfall
Apr-May Index Interval
6378 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

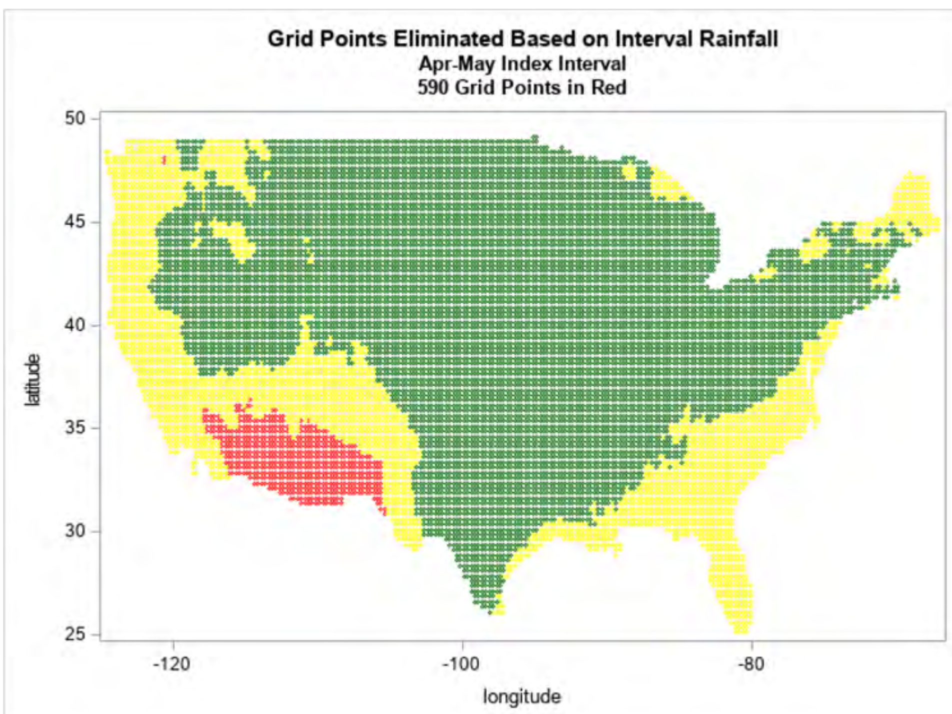
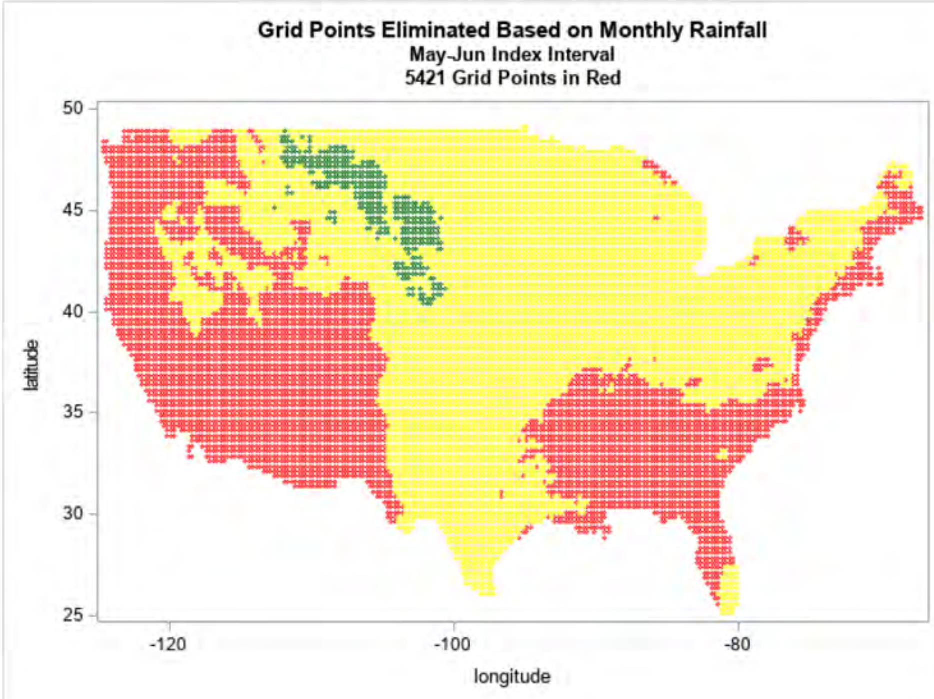

Grid Points Eliminated Based on Interval Rainfall
Apr-May Index Interval
590 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

Figure 6-19


Grid Points Eliminated Based on Monthly Rainfall
May-Jun Index Interval
5421 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

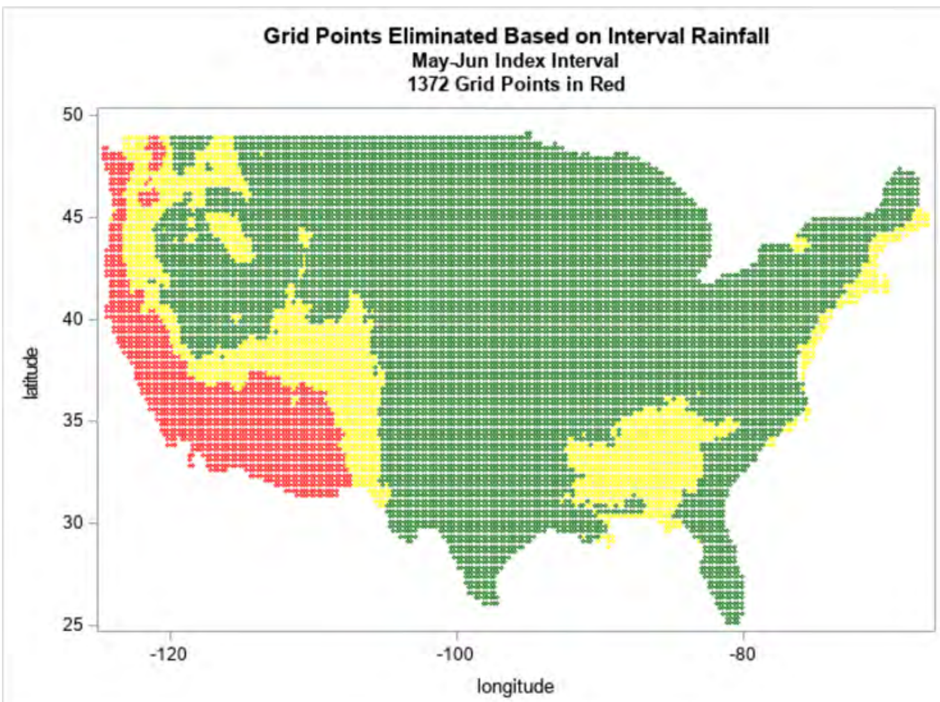
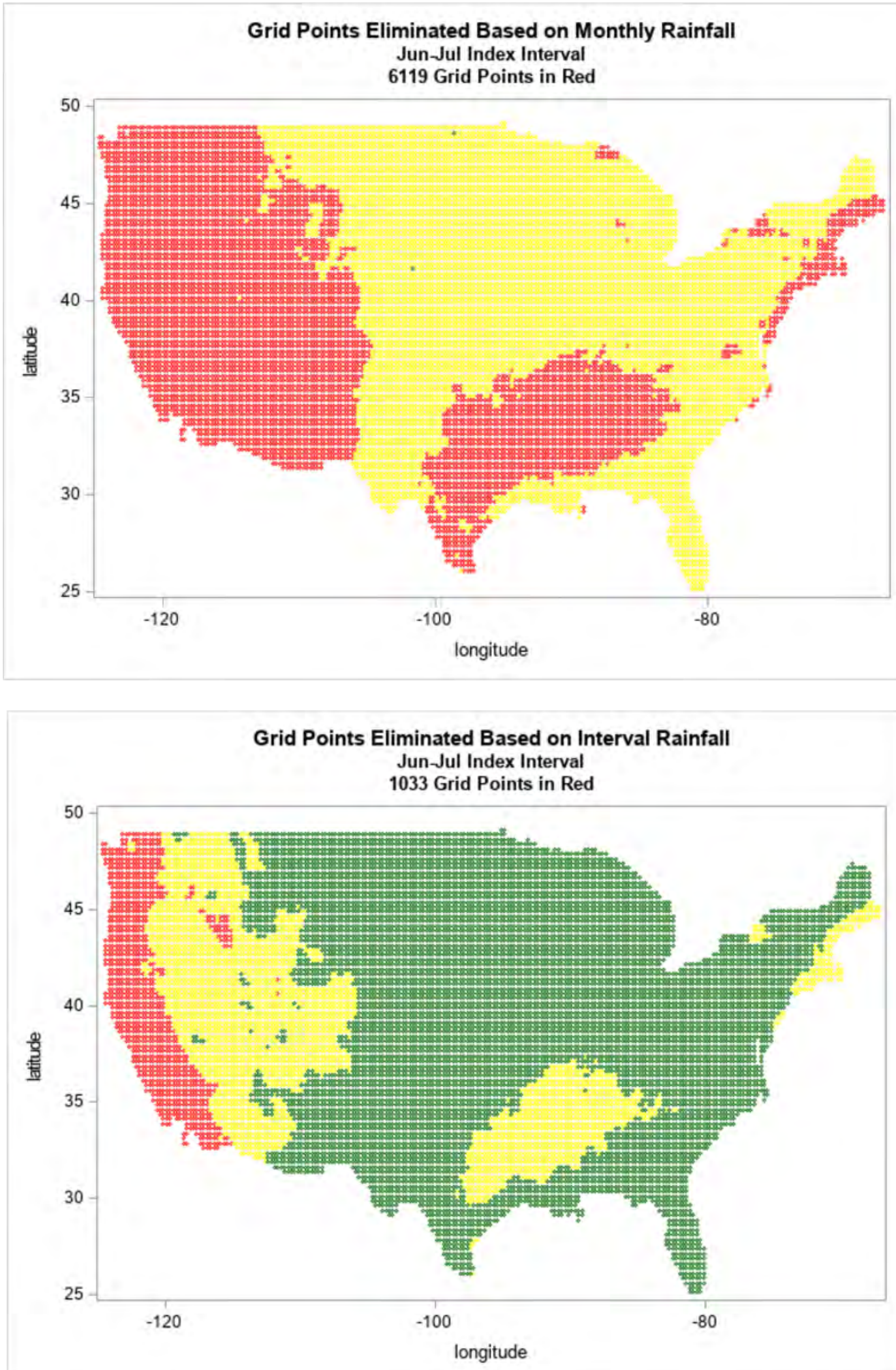
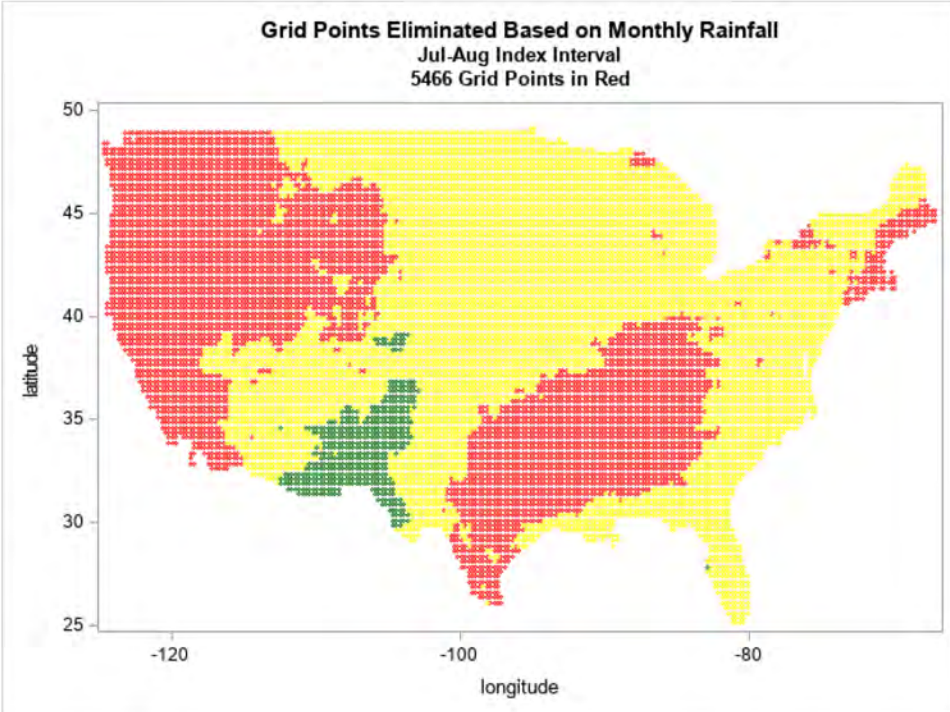

Grid Points Eliminated Based on Interval Rainfall
May-Jun Index Interval
1372 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

Figure 6-20



Grid Points Eliminated Based on Monthly Rainfall
Jun-Jul Index Interval
6119 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80
Grid Points Eliminated Based on Interval Rainfall
Jun-Jul Index Interval
1033 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

Figure 6-21


Grid Points Eliminated Based on Monthly Rainfall
Jul-Aug Index Interval
5466 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

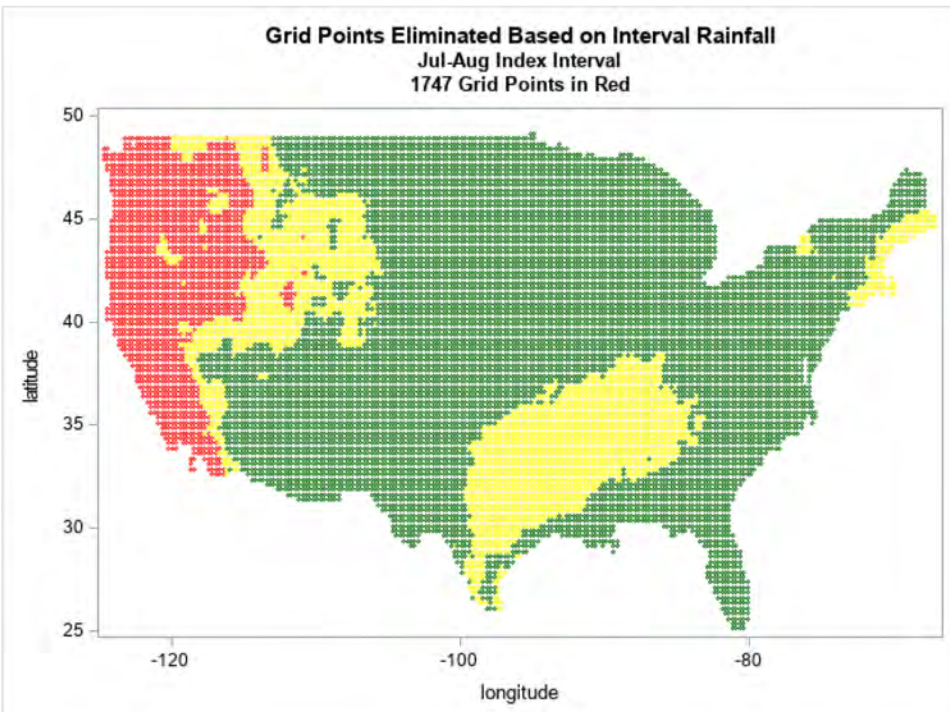
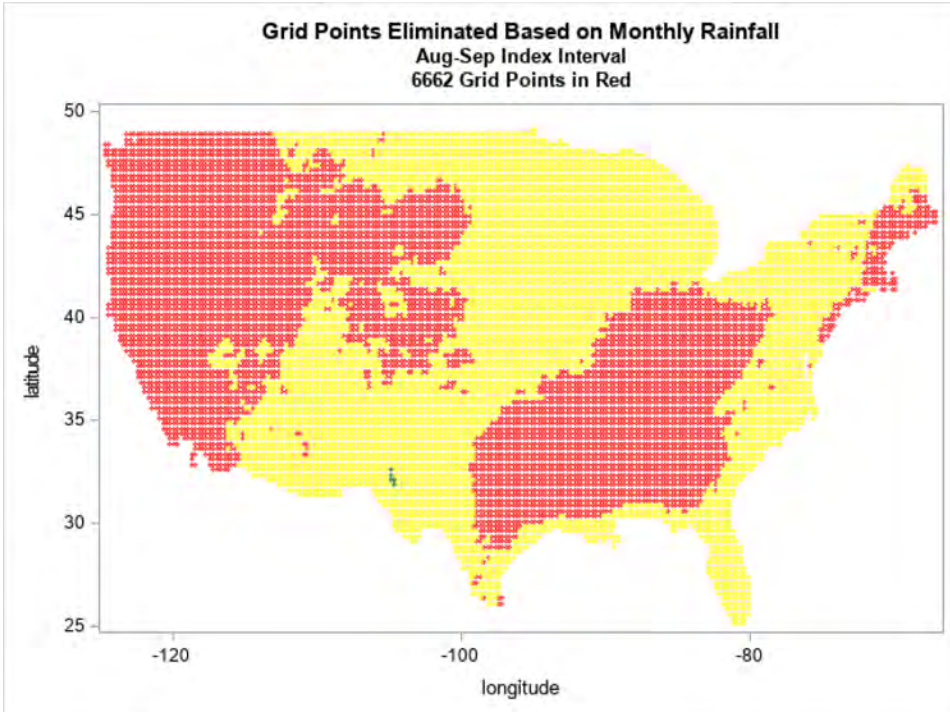

Grid Points Eliminated Based on Interval Rainfall
Jul-Aug Index Interval
1747 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

Figure 6-22


Grid Points Eliminated Based on Monthly Rainfall
Aug-Sep Index Interval
6662 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

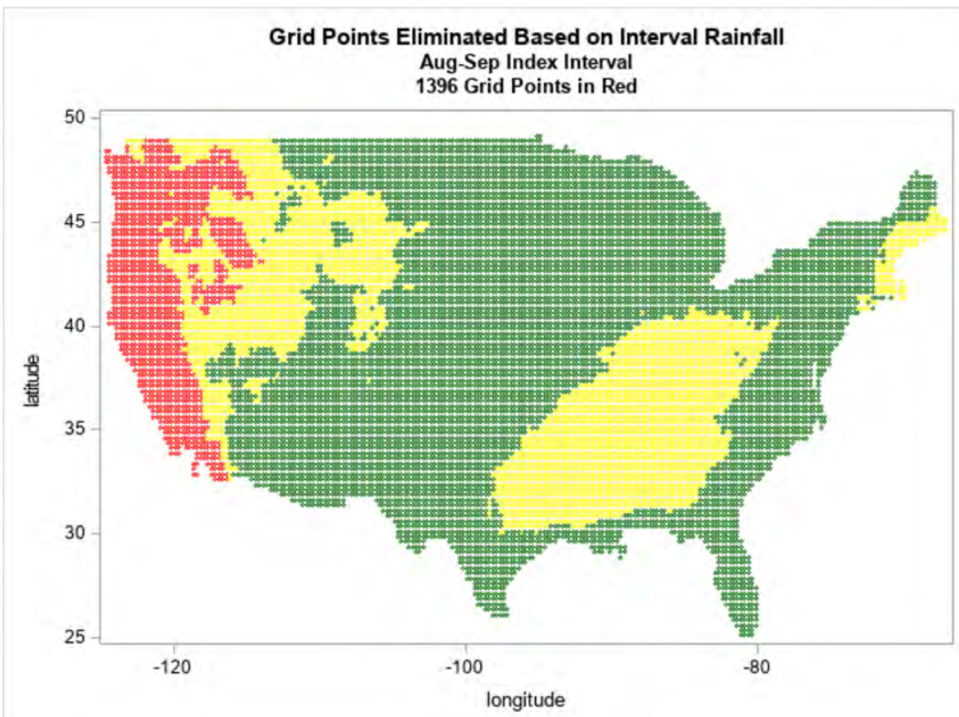
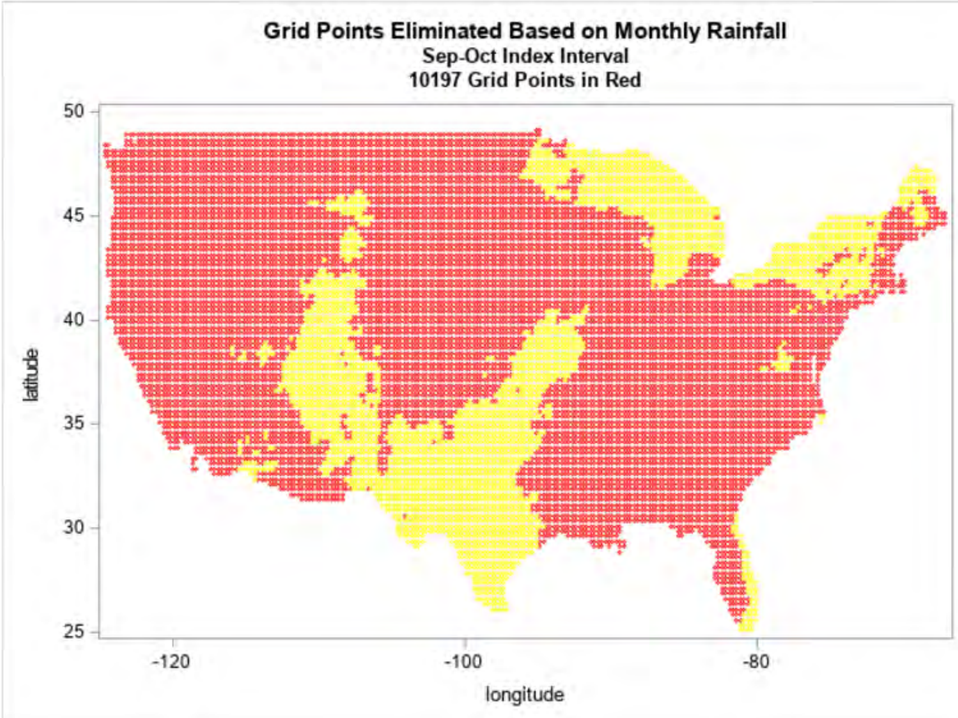

Grid Points Eliminated Based on Interval Rainfall
Aug-Sep Index Interval
1396 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

Figure 6-23


Grid Points Eliminated Based on Monthly Rainfall
Sep-Oct Index Interval
10197 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

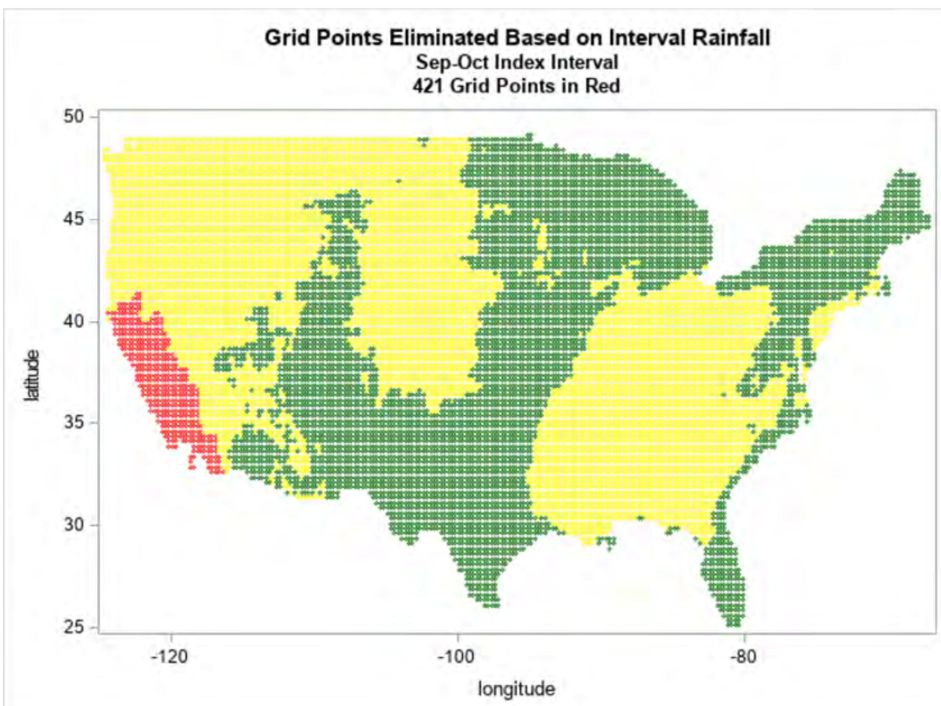
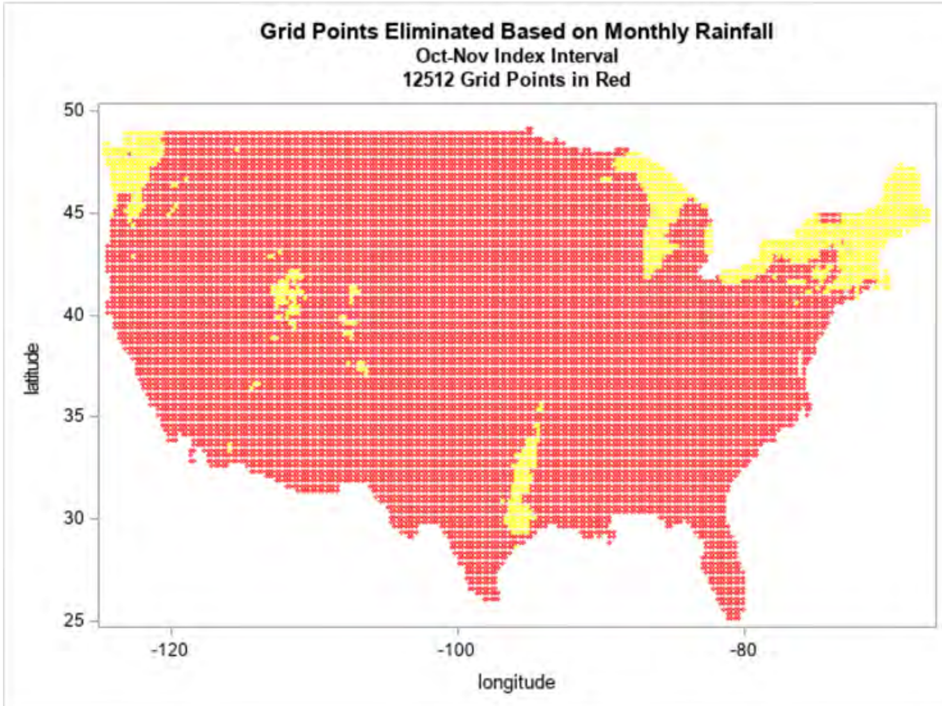

Grid Points Eliminated Based on Interval Rainfall
Sep-Oct Index Interval
421 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

Figure 6-24


Grid Points Eliminated Based on Monthly Rainfall
Oct-Nov Index Interval
12512 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

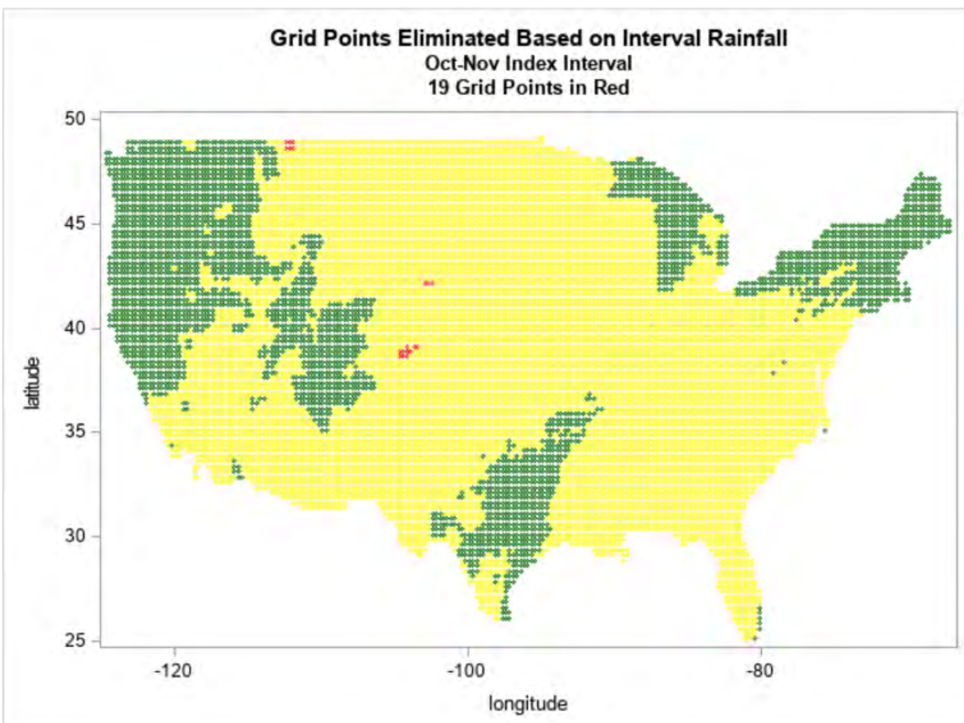
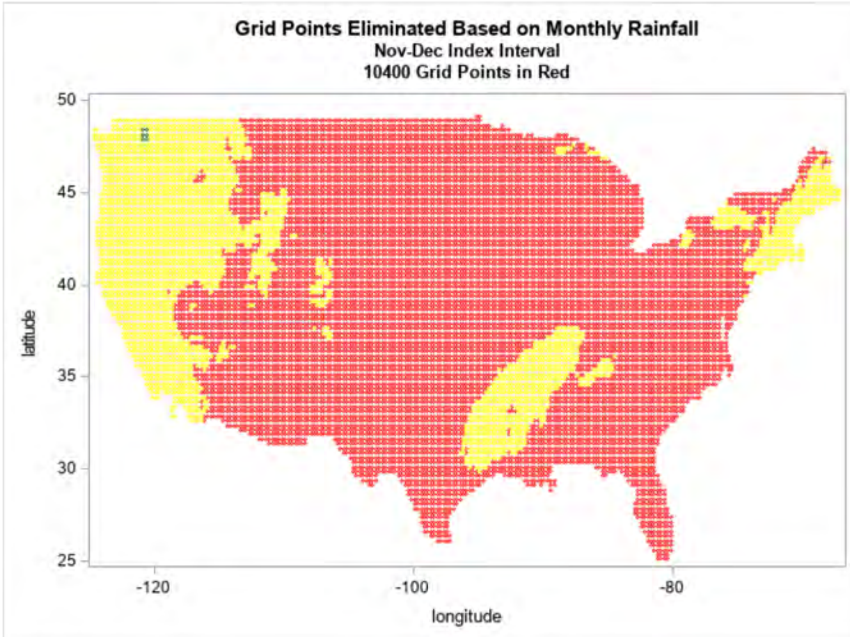

Grid Points Eliminated Based on Interval Rainfall
Oct-Nov Index Interval
19 Grid Points in Red
latitude
longitude
50
45
40
35
30
25
-120
-100
-80

Figure 6-25


Grid Points Eliminated Based on Monthly Rainfall
Nov-Dec Index Interval
10400 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

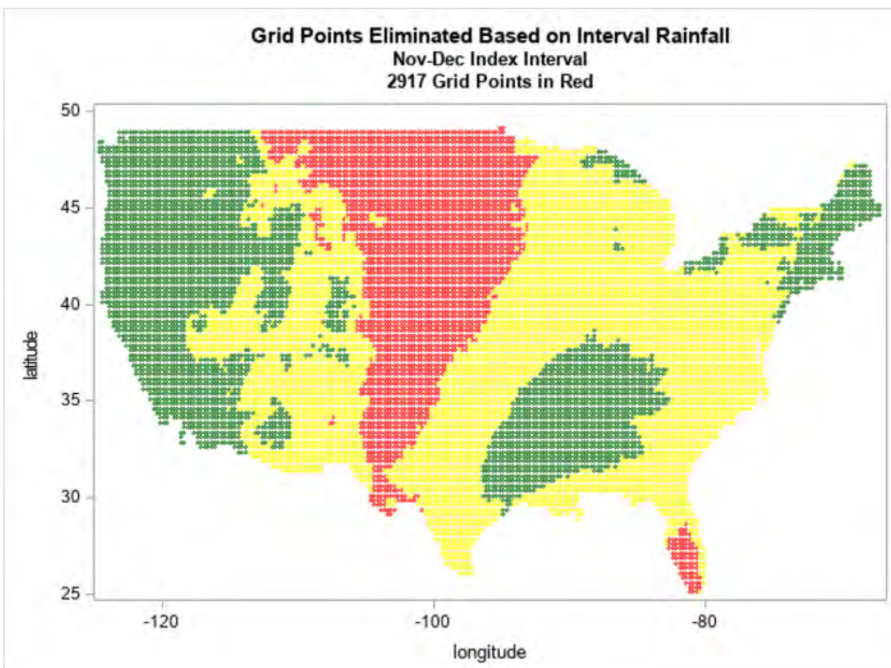

Grid Points Eliminated Based on Interval Rainfall
Nov-Dec Index Interval
2917 Grid Points in Red
50
45
40
35
30
25
latitude
-120
-100
-80
longitude

Figure 6-26

Chapter 7 Improving the PRF loss function and weather variables

PRF is an index product that inherently has basis risk. That is the loss function is imperfectly correlated with actual on-farm losses when forage is reduced. Basis risk exists because rainfall does not explain all causes of forage and hay losses. Another form of basis risk arises due to the grid measure not matching the rainfall at the farm. However, using the grid appears the smallest feasible area. So we make no recommendations in this area.

Data for this part of the analysis consists of alfalfa hay prices ($/ton) from NASS, precipitation (mm), temperature (degree C), and Palmer Drought Severity Index (PDSI) (generally between -2 and 2) data. Data are observed monthly at the state level.

The relationship of forage losses with replacement value

Data for this part of the analysis consists of alfalfa hay prices ($/ton) from NASS, precipitation (mm), temperature (degree C), and Palmer Drought Severity Index (PDSI) (generally between -2 and 2) data. Data are observed monthly at the state level.

The dependent variable for this analysis consists of alfalfa hay price and other (excluding alfalfa) hay prices. The discussion here is for the case of other (excluding alfalfa) hay price. Findings are similar for the case of the alfalfa hay price. The independent variables are divided into two sets. The first set includes precipitation and temperature while the second set consists of PDSI. A trend variable is also included in both sets. Real hay prices were derived by deflating the nominal hay prices by the farm level implicit price deflator obtained from the U.S. Bureau of Economic Analysis (FRED (a), 2019). The GDP implicit price deflator obtained from the U.S. Bureau of Economic Analysis (FRED (b), 2019) was also investigated. The results were similar to the case when the farm level implicit price deflator was used.

Several issues were investigated:

1. What is the lag length of the monthly precipitation, temperature, and PDSI variables on hay prices?
2. What is the effect of the neighboring states' aggregate precipitation, temperature, and PDSI variables on the hay prices of a target state?
3. Is there a nonlinear (quadratic) relationship between precipitation, temperature, and PDSI and hay prices?

The results for each of these issues are discussed below.

1. What is the lag length of the monthly precipitation, temperature, and PDSI variables on hay prices?

Table 7-1 presents the results of the stepwise regression of the hay price on current and eleven lagged values of precipitation and temperature variables. Table 7-2 presents the results of the stepwise regression of the hay price on current and eleven lagged values of PDSI variables.

Some general notation description for all the tables is provided here again. P indicates precipitation, T indicates temperature, and PDSI indicates the Palmer Drought Severity Index. The numbers in parenthesis following P, T, and PDSI indicate lags, for example, P(3) indicates the value of precipitation lagged by three months. The numbers without parenthesis following P, T, and PDSI indicate the calendar month, for example, P3 indicates the value of precipitation for March. X^2 indicates the square term of the variable X while NB_X indicates the aggregate value from the neighboring states for the variable X.

Results of Table 7-1 show that the maximum number of significant lags for precipitation varies from state to state from a low of zero to a high of eleven lags. For temperature, the number of significant lags varies from zero to eight. Additionally, all eleven lags for both precipitation and temperature have a significant effect on hay prices for at least one state. Note that current precipitation has a significant effect on hay price only for NM out of the 29 states while current temperature has a significant effect in four states.

Results of Table 7-2 show that the maximum number of significant lags for PDSI varies from zero to three months. Additionally, all twelve lags have a significant effect on hay prices for at least one state. Results of Table 7-1 show that precipitation, temperature, and a trend variable explain from a low of 2% for the state of AR to a high of 65% for OR of the variation in hay prices. Results of Table 7-2 show PDSI explains from a low of 1% for the state of KS to a high of 65% for OR of the variation in hay prices. Comparing the R-squares from Table 7-1 and 7-2 indicates that PDSI explains the variation in hay prices better than precipitation and temperature in 15 of 29 states.

2. What is the effect of the neighboring states' aggregate precipitation, temperature, and PDSI variables on the hay prices of a target state?
3. Is there a nonlinear (quadratic) relationship between precipitation, temperature, and PDSI and hay prices?

Results of the investigation for the two remaining issues are reported in Table 7-3 for temperature and precipitation and Table 7-4 for PDSI, respectively.

Results of Table 7-3 highlight several findings. First, for 16 of the 29 states that show a significant relationship between hay prices and precipitation exists, the relationship is nonlinear (quadratic). Further, the nonlinear relationship between hay prices and precipitation is of the form that hay prices are high for low levels of precipitation, prices decrease as precipitation increases, reaches a minimum for a certain precipitation level, and start rising again as precipitation level continues to increase. In other words, hay prices are lower within a certain optimal range of precipitation. Too little or too much precipitation would cause hay prices to increase. The exceptions to this form of relationship are the states of NV, NY, OH, and OR. *This nonlinear relationship between hay prices and precipitation justifies the adjustment of CBVs for low levels of precipitation in such a way to allow for accelerated higher levels of indemnity for low levels of precipitation.*

Second, a significant relationship between hay prices and temperature exists for all states, and for sixteen of the 29 states the relationship is nonlinear (quadratic). The direction of the relationship between hay prices and the temperature is not consistent across the 29 states.

Third, for 13 states in the case of precipitation and 13 states in the case of temperature, the aggregate precipitation and temperature of the neighboring states affect the hay prices of the target state.

Results of Table 7-4 show that for 22 of the 29 states a significant relationship exists between hay prices and PDSI, and for seventeen of these states, the relationship is nonlinear (quadratic). Further, similar to precipitation, for the majority of the states (ten out of seventeen), the nonlinear relationship between hay prices and PDSI is of the form that hay prices are high for low levels of PDSI, prices decrease as PDSI increases, reach a minimum for a certain PDSI level, and start rising again as PDSI level continues to increase.

Assessment of the relationship between alfalfa hay prices and yields and weather variables

The dependent variable for this part of the analysis consists of alfalfa hay prices and alfalfa hay yields. Results are presented in Tables 7.5 through 7.8. Findings are similar to the previously discussed findings for the case of the other (excluding alfalfa) hay price and other (excluding alfalfa) hay yield.

Chapter 7 References

FRED (a), 2019. https://fred.stlouisfed.org/series/A372RD3Q086SBEA. Accessed February 2020.

FRED (b), 2019. https://fred.stlouisfed.org/series/GDPDEF. Accessed February 2020.

Table 7-1. Results of the stepwise regression of the hay (excluding alfalfa) price on current and eleven lagged values of precipitation and temperature

State	Constant	Trend	P	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)	P(8)	P(9)	P(10)	P(11)	T	T(1)	T(2)	T(3)	T(4)	T(5)	T(6)	T(7)	T(8)	T(9)	T(10)	T(11)	P_max	T_max	Rsq
AZ	1.211***	0.002***										0.001**								-0.003**							1	1	0.57
AR	1.016***																				0.002*						0	1	0.02
CA	1.495***	0.001***			-0.000*													-0.010***									1	1	0.2
CO	2.090***	0.002***					-0.002**	-0.002***	-0.002***	-0.002**	-0.002***	-0.002***	-0.003***	-0.003***			-0.005**										8	1	0.45
ID	1.125***	0.002***															-0.005*						-0.007**				0	2	0.45
IL	1.177***	0.000***									-0.000*										0.003***						1	1	0.06
IN	1.734***	0.001***								-0.001**	-0.001***	-0.001**	-0.001*			-0.012***											4	1	0.24
IA	1.533***	0.000***									-0.000*	-0.000*	-0.001**	-0.001**	-0.010***		-0.009***		-0.007**		-0.006**		-0.008***				4	5	0.16
KS	1.105***											-0.000**															1	0	0.01
KY	1.410***	-0.001***																									0	0	0.15
MI	1.428***	0.001***			-0.001*		-0.001**	-0.001*			-0.001**	-0.001***			-0.010***												5	1	0.3
MN	1.890***					-0.001**	-0.001*	-0.001**	-0.001**	-0.001***	-0.001***	-0.001**	-0.001**	-0.001**	-0.013***	-0.008**	-0.007**		-0.008**	-0.007*	-0.008**			-0.008**	-0.007*		9	8	0.23
MO	1.292***	-0.001***																									0	0	0.29
MT	1.564***	0.000***							-0.001*	-0.001**	-0.001**	-0.002***	-0.002***	-0.001**			-0.006***										6	1	0.17
NE	1.846***	0.000***		-0.001**	-0.001**	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***				-0.008***								-0.010***	11	2	0.33
NV	1.405***	0.001***														0.003*											0	1	0.29
NM	1.387***	0.001***	-0.001**						-0.001**			-0.001**							0.011**						0.016***		3	2	0.26
NY	1.523***	0.001***				-0.001**					-0.001*																2	0	0.1
ND	0.732***	-0.000***						0.001**		0.000*										0.006***						0.008***	2	2	0.15
OH	1.415***			-0.001*							-0.001**										0.006***						2	1	0.05
OK	1.109***	-0.001***				-0.000**	-0.000**	-0.001***		-0.001***	-0.001***	-0.001***	-0.000**		0.009***						0.016***						7	2	0.22
OR	1.473***	0.003***															-0.014***			-0.010***		-0.012***			-0.014***		0	4	0.65
PA	1.780***	0.001***			-0.001**																						1	0	0.12
SD	0.793***	0.001***																						0.002***			0	1	0.14
TX	0.898***								-0.001*	-0.001*			-0.001**				0.012**						0.015***				3	2	0.05
UT	1.044***	0.001***																									0	0	0.24
WA	2.372***	0.002***															-0.014**		-0.016**			-0.030***				-0.024***	0	4	0.29
WI	1.542***	-0.000*						-0.001*	-0.001*			-0.001**	-0.001**	-0.001**		-0.010***				-0.006**							5	2	0.11
WY	1.660***	0.000***			-0.001*				-0.001*	-0.002**			-0.002**	-0.001**													6	0	0.11
Total			1	2	5	5	5	7	8	9	11	12	10	7	4	4	8	2	4	5	6	2	3	2	3	3			

Table 7-2. Results of the stepwise regression of the hay (excluding alfalfa) price on current and eleven lagged values of PDSI

State	Constant	Trend	PDSI	PDSI(1)	PDSI(2)	PDSI(3)	PDSI(4)	PDSI(5)	PDSI(6)	PDSI(7)	PDSI(8)	PDSI(9)	PDSI(10)	PDSI(11)	PDSI_max	Rsq
AZ	1.160***	0.003***								0.018**					1	0.57
AR	1.024***	0.001***	-0.026***												1	0.12
CA	1.316***	0.001***	-0.022***											0.028***	2	0.2
CO	1.399***	0.001***		-0.046***											1	0.4
ID	1.050***	0.002***													0	0.44
IL	1.155***	0.000***						-0.026***							1	0.1
IN	1.175***	0.002***	0.026**						-0.054***						2	0.16
IA	1.011***	0.000***				-0.020***									1	0.09
KS	1.080***								-0.007*						1	0.01
KY	1.390***	-0.001***			-0.019***										1	0.18
MI	0.987***	0.001***													0	0.21
MN	1.053***							-0.032***							1	0.07
MO	1.281***	-0.001***									-0.013***				1	0.31
MT	1.160***	0.001***				-0.038***									1	0.13
NE	0.923***	0.000***			-0.037***			-0.035***						0.036***	3	0.2
NV	1.472***	0.001***					-0.022**							-0.017*	2	0.32
NM	1.708***	0.001***	-0.031***						-0.028***						2	0.34
NY	1.303***	0.001***	-0.013*						-0.027***					-0.018**	3	0.21
ND	0.811***	-0.000***	-0.034***											0.010**	2	0.17
OH	1.350***			-0.058***										0.070***	2	0.15
OK	1.200***	-0.000***					-0.029***							0.025***	2	0.15
OR	1.035***	0.003***											0.022***		1	0.64
PA	1.658***	0.001***		-0.034***								-0.024**			2	0.17
SD	0.807***	0.001***					-0.022***								1	0.17
TX	1.267***			-0.020*				-0.021*						0.040***	3	0.06
UT	1.034***	0.001***						0.010*							1	0.24
WA	1.665***	0.002***										0.031***			1	0.27
WI	1.103***	-0.000**						-0.034***						0.026**	2	0.04
WY	1.374***	0.000***		-0.024***						-0.048***				0.026***	3	0.18
Total			6	5	2	2	3	6	4	2	1	2	1	10		

Table 7-3. Results of the nonlinear regression of the hay (excluding alfalfa) price on precipitation and temperature and neighboring states

State	Constant	Trend	P	P^2	NB_P	NB_P^2	T	T^2	NB_T	NB_T^2	Rsq
AZ	2.667**	0.002***	0.01	0	-0.025**	0.000*	-0.197***	0.004	0.16	-0.004	0.59
AR	16.796*	0	0.013	0	-0.013	0	-1.640***	0.051	-0.349	0.012	0.05
CA	-4.567	0.001***	-0.016***	0.000***	-0.016***	0	1.060***	-0.032	-0.206	0.004	0.29
CO	6.145***	0.001***	-0.262***	0.003***	0.035**	-0.000**	0.214***	-0.013**	-0.189	0.009	0.54
ID	1.559*	0.001***	0.009	0	-0.026**	0.000**	-0.000***	-0.014	-0.025	0.011	0.5
IL	-0.153	0	0.003	0	-0.058***	0.000***	1.156***	-0.047***	-0.517***	0.020***	0.28
IN	3.245	0.002***	-0.051	0	0.021	0	-3.120***	0.136***	3.120***	-0.141***	0.3
IA	3.210***	0.000***	-0.021**	0.000**	0.012	0	0.369***	-0.021	-0.694***	0.036***	0.25
KS	3.882**	0.000*	-0.029***	0.000***	0.001	0	-0.748***	0.028**	0.532***	-0.023***	0.14
KY	3.078	-0.001***	-0.008	0	-0.051***	0.000***	0.240***	-0.006	-0.163	0.005	0.28
MI	5.213***	0.002***	-0.015	0	-0.033	0	1.298***	-0.090***	-1.491***	0.083***	0.37
MN	0.963	-0.000**	-0.01	0	0.024*	-0.000*	-0.325***	0.007	0.207	0	0.26
MO	-1.025	-0.001***	-0.008	0	-0.036***	0.000***	1.216***	-0.045***	-0.612**	0.024**	0.37
MT	3.580***	0.001***	-0.057***	0.000*	0.006	0	-0.830***	0.053***	0.545**	-0.034*	0.3
NE	1.733**	0.000***	-0.109***	0.001***	0.028**	-0.000**	0.230***	-0.017*	0.125	-0.004	0.43
NV	11.572***	0.001***	0.022***	-0.000**	-0.061***	0.000***	-1.596***	0.091***	-0.119	-0.004	0.5
NM	-8.312*	0.000***	-0.018***	0.000***	0.012	-0.000*	0.671***	-0.024	0.784***	-0.027***	0.36
NY	0.442	0.001***	0.057***	-0.000***	0.01	0	0.699***	-0.054	-1.035	0.064	0.2
ND	0.783***	-0.000***	-0.022***	0.000*	0.008	0	-0.379***	0.028***	0.392***	-0.023**	0.37
OH	5.210***	-0.001***	0.053***	-0.000***	-0.132***	0.001***	0.343***	-0.002	-0.403	0.008	0.16
OK	8.269***	-0.001***	-0.007	0	0	0	-0.877***	0.029**	-0.05	0.004	0.29
OR	4.824***	0.002***	0.039***	-0.000***	-0.038***	0.000***	-0.131***	0.006	-0.530*	0.02	0.72
PA	0.673	0.001***	0.001	0	0.02	0	0.005***	-0.001	0.067	-0.003	0.15
SD	0.774***	0.001***	-0.069***	0.001***	0.042***	-0.000***	0.220***	-0.022**	-0.068	0.015*	0.31
TX	8.027	0	-0.025***	0.000***	0.009*	0	-0.731***	0.024	-0.072	0.001	0.12
UT	3.060***	0.001***	-0.054***	0.001***	-0.004	0	0.264***	-0.016*	-0.446***	0.023***	0.34
WA	4.891***	0.002***	-0.073***	0.000***	-0.032**	0	2.482***	-0.144***	-2.190***	0.124***	0.53
WI	2.803***	0	-0.023	0	-0.008	0	0.439***	-0.028**	-0.396**	0.016	0.13
WY	1.597*	0.001***	-0.02	0	-0.086**	0.001**	-0.902***	0.088***	1.380***	-0.100***	0.38

Table 7-4. Results of the nonlinear regression of the hay (excluding alfalfa) price on PDSI and neighboring states

State	Constant	Trend	PDSI	PDSI^2	NB_PDSI	NB_PDSI^	Rsq
AZ	1.173***	0.003***	0.024**	-0.008*	-0.011	0.008*	0.57
AR	1.014***	0.001***	-0.023***	0.006*	0.022***	0.001	0.15
CA	1.344***	0.001***	0.031**	-0.009**	-0.032*	0.003	0.21
CO	1.204***	0.002***	0.002	0.008**	-0.008	0.047***	0.48
ID	0.988***	0.002***	-0.003	0.013***	0.016	-0.009	0.46
IL	1.148***	0.001***	-0.004	-0.004*	-0.049***	-0.014***	0.15
IN	1.192***	0.001	-0.099***	0.042***	0.025	0.001	0.3
IA	1.028***	0.000***	-0.032***	0.003	0.011	-0.007	0.1
KS	1.085***	0	0.015*	-0.006**	-0.030***	0.011***	0.06
KY	1.416***	-0.000***	-0.041***	0.006**	0.022***	-0.017***	0.24
MI	0.925***	0.002***	0.032***	-0.006	-0.096***	0	0.28
MN	1.064***	0	-0.060***	0.022***	0.013	-0.031***	0.16
MO	1.312***	-0.001***	-0.023***	0.012***	-0.008	0.016***	0.37
MT	1.235***	0.000***	-0.038***	0.011***	-0.01	-0.027***	0.17
NE	0.929***	0.000**	0.004	-0.008***	-0.056***	0.023***	0.24
NV	1.395***	0.001***	-0.037**	0.006	0	0.015**	0.37
NM	1.765***	0.000***	-0.099***	0.003	0.038***	-0.024***	0.38
NY	1.335***	0.001***	-0.044***	0.007*	-0.017	0.006	0.22
ND	0.826***	-0.000***	0.002	-0.004*	-0.039***	0.015***	0.2
OH	1.447***	0	0.024***	-0.008***	-0.044***	-0.001	0.05
OK	1.199***	-0.001***	-0.008	0.008***	-0.016*	-0.006	0.13
OR	1.043***	0.003***	0.099***	-0.011*	-0.102***	0.019**	0.67
PA	1.798***	0.000***	-0.089***	0.026***	0.057***	-0.013**	0.23
SD	0.786***	0.001***	-0.015	-0.008**	-0.014	0.024***	0.19
TX	1.253***	0.000***	-0.040***	-0.005	0.030**	-0.030***	0.16
UT	1.063***	0.001***	0.106***	0.018***	-0.131***	-0.016***	0.4
WA	1.580***	0.002***	0.052***	0.019***	-0.021	-0.004	0.29
WI	1.117***	-0.000***	-0.082***	0.023***	0.081***	-0.021***	0.07
WY	1.292***	0.000***	-0.071***	0.035***	0.014	-0.034***	0.33

Table 7-5. Results of the stepwise regression of the alfalfa hay price on current and eleven lagged values of precipitation and temperature

State	Constant	Trend	P	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)	P(8)	P(9)	P(10)	P(11)	T	T(1)	T(2)	T(3)	T(4)	T(5)	T(6)	T(7)	T(8)	T(9)	T(10)	T(11)	P_max	T_max	Rsq
AZ	1.438***	0.001***							-0.001**														0.010***	0.006**			1	2	0.3
AR	1.076***	0.000**																		0.002**							0	1	0.05
CA	1.892***	0.001***															-0.008***										0	1	0.16
CO	2.021***	0.002***				-0.001*	-0.001**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**		-0.005***											9	1	0.54
ID	1.506***	0.001***															-0.008**						-0.012***				0	2	0.32
IL	1.459***	0.001***																				0.004***					0	1	0.12
IN	1.681***	0.002***								-0.001**	-0.002**	-0.001**	-0.001**									0.013***					4	1	0.27
IA	2.499***	0.001***				-0.001*			-0.001**	-0.001*		-0.001**	-0.001**	-0.001*	-0.011**	-0.010*	-0.012**		-0.017***		-0.013***		-0.013***		-0.013***		6	7	0.2
KS	2.331***	0.001***		-0.001**	-0.001*	-0.001**	-0.001*	-0.001**	-0.001**	-0.001**	-0.001**	-0.001*	-0.001*	-0.001**	-0.011**					-0.009*	-0.008*					-0.012**	11	4	0.23
KY	1.629***	-0.000**							-0.000*	-0.001**																	2	0	0.06
MI	1.830***	0.001***			-0.001*		-0.001*	-0.001*	-0.001*	-0.001*	-0.001**	-0.001***			-0.012***												7	1	0.29
MN	2.533***	-0.000**				-0.001**	-0.001**	-0.001*	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.014**	-0.014***		-0.009**	-0.012**	-0.011**			-0.008*	-0.008*?	-0.010**		9	8	0.26
MO	1.261***	-0.001***														0.005**						0.008***					0	2	0.21
MT	1.780***	0.000**							-0.001	-0.002**	-0.002**	-0.002**	-0.002**	-0.002***			-0.007***										6	1	0.14
NE	2.302***	0.001***		-0.001**	-0.001**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002***		-0.011***		-0.009**						-0.013***			11	3	0.38
NV	1.711***	0.001***																									0	0	0.15
NM	1.843***	0.001***								-0.001**	-0.001**			-0.001**						0.010***					0.016***		3	2	0.26
NY	1.775***	0.000***				-0.001*					-0.001*																2	0	0.04
ND	1.015***	-0.000***													-0.005***				0.004***							0.010***	0	3	0.08
OH	1.551***	-0.001***																	0.020***			0.003			0.016***		0	3	0.07
OK	1.745***	-0.001***				-0.001**	-0.000*	-0.001***		-0.001**	-0.001**	-0.001**	-0.000*								0.010***	.					7	1	0.24
OR	1.722***	0.002***														-0.007*						-0.013***					0	2	0.42
PA	2.061***	0.000***			-0.001**																						1	0	0.04
SD	1.044***	0.001***																						0.002*			0	1	0.08
TX	1.423***	-0.000**						-0.001*	-0.001**	-0.001**	.	-0.001**	-0.001**	-0.001**	0.014***							0.009**					6	2	0.16
UT	1.376***	0.001***																				-0.003**					0	1	0.27
WA	2.633***	0.002***															-0.022**	-0.019***			-0.022**	-0.022***			-0.017**	-0.020**	0	6	0.35
WI	2.038***						-0.001**	-0.001***			-0.001*	-0.002**	-0.002**	-0.001**			-0.014***										6	1	0.14
WY	1.713***	0.001***			-0.002***			-0.001**		-0.001*	-0.002**		-0.001*	-0.002**													6	0	0.16
Total			0	2	5	7	7	9	10	13	12	11	11	10	6	6	6	3	4	4	4	8	4	4	5	3			

Table 7-6. Results of the stepwise regression of the alfalfa hay price on current and eleven lagged values of PDSI

State	Constant	Trend	PDSI	PDSI(1)	PDSI(2)	PDSI(3)	PDSI(4)	PDSI(5)	PDSI(6)	PDSI(7)	PDSI(8)	PDSI(9)	PDSI(10)	PDSI(11)	PDSI_max	Rsq
AZ	1.620***	0.001***	-0.028***								0.034***				2	0.2
AR	1.100***	0.001***	-0.021***												1	0.11
CA	1.748***	0.001***												0.035***	1	0.15
CO	1.377***	0.002***		-0.026***					-0.026**					0.037***	3	0.5
ID	1.383***	0.001***													0	0.3
IL	1.489***	0.001***						-0.016***							1	0.11
IN	1.352***	0.002***	0.029**						-0.057***						2	0.18
IA	1.324***	0.001***				-0.041***									1	0.12
KS	1.297***	0.001***		-0.021***						-0.025**				0.026***	3	0.13
KY	1.495***					-0.029***									1	0.07
MI	1.273***	0.001***													0	0.18
MN	1.476***	-0.000**	0.030**			-0.031*		-0.031**							3	0.09
MO	1.412***	-0.001***						-0.009*						-0.013**	2	0.24
MT	1.328***	0.000***				-0.037***						-0.034*		0.042**	3	0.08
NE	1.005***	0.001***		-0.049***			-0.046***							0.053***	3	0.27
NV	1.717***	0.001***	-0.025***							0.015*					2	0.17
NM	2.193***	0.000***	-0.038***					-0.033***			-0.027***				3	0.39
NY	1.546***	0.001***	-0.012*						-0.024**			-0.025**			3	0.17
ND	1.006***			-0.036***											1	0.13
OH	1.945***	-0.000**	-0.045***											0.041***	2	0.07
OK	1.513***	-0.001***					-0.029***							0.036***	2	0.18
OR	1.535***	0.002***										0.033***			1	0.44
PA	1.926***	0.001***	-0.045***									-0.023**			2	0.1
SD	1.049***	0.001***					-0.030***				-0.025*			0.027**	3	0.14
TX	1.501***				-0.044***									0.031***	2	0.08
UT	1.334***	0.001***	-0.012*											0.025***	2	0.29
WA	1.609***	0.001***										0.025***			1	0.27
WI	1.410***						-0.047***							0.022*	2	0.04
WY	1.394***	0.001***			-0.024**				-0.028*		-0.030*			0.041***	4	0.21
Total			10	4	2	4	4	4	4	2	4	5	0	13		

Table 7-7. Results of the nonlinear regression of the alfalfa hay price on precipitation and temperature and neighboring states

State	Constant	Trend	P	P^2	NB_P	NB_P^2	T	T^2	NB_T	NB_T^2	Rsq
AZ	-6.669	0	-0.005	0	-0.024**	0.000**	1.544***	-0.044	-0.566	0.018	0.29
AR	5.768	0	-0.003	0	-0.002	0	-0.381***	0.01	-0.16	0.007	0.06
CA	-4.22	0.001***	-0.019***	0.000**	0.018	0	0.790***	-0.031	0.179	-0.008	0.18
CO	8.904***	0.002***	-0.166***	0.002***	0.02	0	0.199***	-0.011*	-0.764	0.027	0.61
ID	3.419**	0.002***	-0.039*	0	0.009	0	0.016***	-0.017	-0.272	0.022	0.37
IL	-0.428	0.001***	-0.073***	0.000***	0.044*	-0.000**	1.368***	-0.060***	-0.878***	0.043***	0.18
IN	10.776	0.001*	-0.135***	0.001**	0.073*	0	5.516***	-0.260***	-6.836***	0.331***	0.3
IA	7.742***	0	-0.033***	0.000***	0.003	0	-0.811***	0.024	-0.127	0.022	0.3
KS	4.556*	0.000***	-0.003	0	-0.107***	0.001***	0.698***	-0.017	-0.506	0.003	0.43
KY	-0.551	-0.000***	0.003	0	-0.032**	0.000***	0.700***	-0.029	-0.247	0.015	0.15
MI	2.581**	0.001***	-0.004	0	-0.031	0	0.922***	-0.063**	-0.656*	0.038	0.3
MN	2.305*	-0.000*	0.065***	-0.001***	-0.085***	0.001***	-0.527***	0.022	0.398	-0.011	0.28
MO	-1.752	-0.001***	-0.012	0	-0.031***	0.000***	1.193***	-0.043***	-0.453	0.016	0.29
MT	5.962***	0.001***	-0.051**	0	0	0	0.199***	-0.022	-1.049**	0.076**	0.3
NE	2.35	0.001***	-0.133***	0.001***	0.001	0	0.071***	-0.007	0.509	-0.027	0.49
NV	2.872	0.000*	-0.029***	0.000***	-0.043***	0.000***	-0.214***	0.011	0.336	-0.018	0.25
NM	-10.95*	0.000**	-0.015**	0	-0.034*	0.000*	2.146***	-0.083**	0.144	-0.007	0.36
NY	-2.939	0.001***	0.04	-0.000*	0.001	0	-0.840***	0.037	1.241	-0.049	0.17
ND	0.258	0	-0.051***	0.000***	0.068***	-0.001***	-0.433***	0.040***	0.425*	-0.033*	0.27
OH	-1.337	-0.000**	-0.025	0	0.059	0	0.657***	-0.028	-0.359	0.016	0.08
OK	-1.857	-0.001***	0.024***	-0.000***	-0.041***	0.000***	-0.272***	0.012	0.930***	-0.039***	0.32
OR	-0.911	0.002***	-0.038***	0.000***	0.040***	-0.000***	-0.512***	0.021***	1.047***	-0.050***	0.51
PA	-0.055	0.001***	-0.072***	0.000***	0.120***	-0.001***	-1.122***	0.054	1.182**	-0.057**	0.1
SD	4.037***	0.001***	0.052**	-0.001***	-0.117***	0.001***	-2.147***	0.112***	2.211***	-0.126***	0.38
TX	9.39	-0.000**	-0.026***	0.000***	-0.004	0	0.006***	0.005	-1.033*	0.030*	0.18
UT	1.424	0.001***	-0.041***	0.001***	-0.022	0	-0.153***	0.006	0.414**	-0.020**	0.37
WA	8.069***	0.002***	-0.008	0	-0.018	0	-1.883***	0.093**	0.908*	-0.056*	0.41
WI	1.96	0	0.012	0	-0.060*	0.000*	-0.328***	0.045	0.787	-0.073	0.15
WY	3.258*	0.001***	-0.080***	0.001***	0.032	-0.001	-0.225***	0.024	0.135	-0.019	0.36

Table 7-8. Results of the nonlinear regression of the alfalfa hay price on PDSI and neighboring states

State	Constant	Trend	PDSI	PDSI^2	NB_PDSI	NB_PDSI^	Rsq
AZ	1.573***	0.001***	-0.001	0.004	0.034***	0.001	0.2
AR	1.103***	0.001***	-0.018**	-0.003	0.016**	-0.01	0.12
CA	1.756***	0.001***	0.011	-0.011***	0.038**	0.005	0.16
CO	1.290***	0.002***	0.013	0.002	-0.030**	0.014**	0.49
ID	1.282***	0.002***	0.001	-0.005	0.008	0.034***	0.35
IL	1.490***	0.001***	-0.006	-0.004	-0.018	0.003	0.11
IN	1.352***	0.001*	-0.088***	0.037***	0.023	0.016	0.32
IA	1.370***	0.001***	-0.076***	0.007	0.031*	-0.016**	0.14
KS	1.295***	0.001***	-0.012	-0.005	-0.014	0.012	0.11
KY	1.553***	0	-0.046***	0.009***	0.008	-0.019***	0.14
MI	1.248***	0.001***	0.028**	-0.008**	-0.081***	-0.007	0.23
MN	1.471***	0	-0.081***	0.026***	0.029**	-0.045***	0.16
MO	1.430***	-0.001***	-0.044***	-0.012***	0.015	0.023***	0.29
MT	1.396***	0	-0.047***	0.015***	0.012	-0.024***	0.12
NE	1.012***	0.000***	0.009	-0.018***	-0.069***	0.040***	0.24
NV	1.660***	0.001***	-0.059***	0.004	0.066***	0.005	0.2
NM	2.222***	0.000***	-0.117***	0.003	0.024	-0.017**	0.4
NY	1.556***	0.001***	-0.045***	-0.006	-0.003	0.025***	0.21
ND	1.026***	-0.000**	-0.001	-0.005*	-0.041***	0.017***	0.17
OH	1.956***	-0.000**	0.030***	0.005	-0.081***	-0.005	0.08
OK	1.504***	-0.001***	0.011	0.006*	-0.029**	0.001	0.14
OR	1.491***	0.002***	0.101***	-0.007	-0.100***	0.026***	0.5
PA	2.071***	0	-0.102***	0.032***	0.070***	-0.012**	0.18
SD	1.037***	0.001***	-0.005	-0.008	-0.039*	0.020**	0.14
TX	1.511***	0.000***	-0.046***	-0.008	0.023*	-0.024***	0.13
UT	1.368***	0.001***	0.092***	-0.006*	-0.118***	0.021***	0.41
WA	1.540***	0.002***	0.026**	0.015***	0.007	-0.005	0.29
WI	1.416***	0	-0.074***	0.016**	0.044**	-0.023**	0.04
WY	1.355***	0.000***	-0.078***	0.037***	0.026*	-0.042***	0.37

Mitigating forage replacement cost with a disappearing deductible

Given the relationship of forage yield to replacement forage prices, we investigated the potential to increase payments when a deep loss occurred. In other words, replacement cost is likely to be higher in a severe loss situation than in a less severe shortfall. Our team looked at mechanisms such as triggering higher payments when the grid is in drought region. Also, we considered some defined spatial region having a shortfall to trigger larger indemnities. All of these options have some merit. However, for the sake of simplicity, we opted for modifying the indemnity function by recommending a disappearing deductible.

Disappearing deductibles were once a common option in property insurance in the United States, particularly for commercial policies. Although disappearing and franchise deductibles are still found in Europe, this method of risk sharing is now relatively rare in the United States, where the elimination of the deductible in the event of a large loss is generally not viewed as worth the additional premium required.

The International Risk Management Institute, Inc. provides the following definition:

> "Disappearing Deductible — a formula deductible that decreases as the amount of loss increases and disappears entirely to provide full coverage when the loss reaches a specified amount. Disappearing deductibles were once commonly used in property insurance policies."

Theory and Practice of Insurance describes the concept of a disappearing deductible:

"Besides the usual deductibles, the concept of disappearing deductible is often used for large business risks. Under a disappearing deductible, the size of the deductible decreases as the size of the loss increases. At a given level of loss (L*) the deductible is equal to zero (disappears). The formula to apply the reduction in the deductible (D) is the following:

Compensation by the insurer = (Amount of loss – Deductible) x (1+k)

Where k is the adjusting factor:

$$k = D / (L^* - D)$$

and $$L^* = D/k + D$$

If the adjusting factor is fixed at 5% and the deductible is $1,000, then the deductible will disappear when the loss equals or exceeds $21,000. All losses under $1,000 are absorbed by the insured. On a loss of $15,000 the insurer would pay $14,700 (a $300 deductible).

Similarly, Cízek, Härdle, and Weron (2005) describe various types of deductibles, including franchise and disappearing deductibles:

Franchise Deductible

One of the deductibles that can be incorporated in the contract is the so-called franchise deductible. In this case, the insurer pays the whole claim, if the agreed deductible amount is exceeded. More precisely, under the franchise deductible of a, if the loss is less than a the insurer pays nothing, but if the loss equals or exceeds a claim is paid in full. This means that the payment function can be described as:

$$h_{FD(a)}(x) = \begin{cases} 0, & x < a, \\ x, & \text{otherwise.} \end{cases}$$

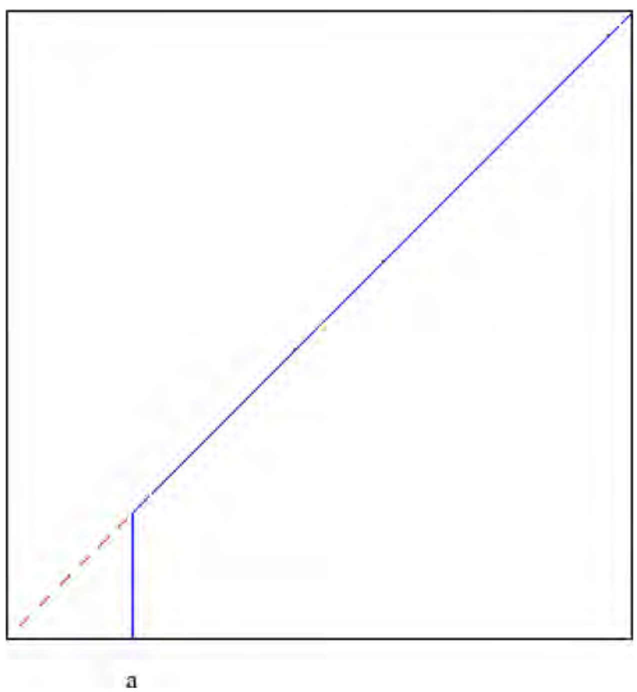


Figure 7-1

STFded01.xpl

The payment function under the franchise deductible (solid blue line) and no deductible (dashed red line).

The pure risk premium under the franchise deductible can be expressed in terms of the premium in the case of no deductible and the corresponding limited expected value function:

$$P_{FD(a)} = P - L(a) + a\{1 - F(a)\}.$$

It can be easily noticed that this premium is a decreasing function of a. When $a = 0$ the premium is equal to the no deductible case and if a tends to infinity the premium tends to zero.

Disappearing Deductible

There is another type of deductible that is a compromise between the franchise and the fixed amount deductible. In the case of a disappearing deductible, the payment depends on the loss in the following way: if the loss is less than an amount of $d_1 > 0$, the insurer pays nothing; if the loss exceeds

d_2 $(d_2 > d_1)$ amount, the insurer pays the loss in full; if the loss is between d_1 and d_2 , then the deductible is reduced linearly between d_1 and d_2. Therefore, the larger the claim, the less of the deductible becomes the responsibility of the policyholder. The payment function is given by Figure 7.2

$$h_{DD(d_1,d_2)}(x) = \begin{cases} 0, & x \leq d_1, \\ \frac{d_2(x-d_1)}{d_2-d_1}, & d_1 < x \leq d_2, \\ x, & \text{otherwise.} \end{cases}$$

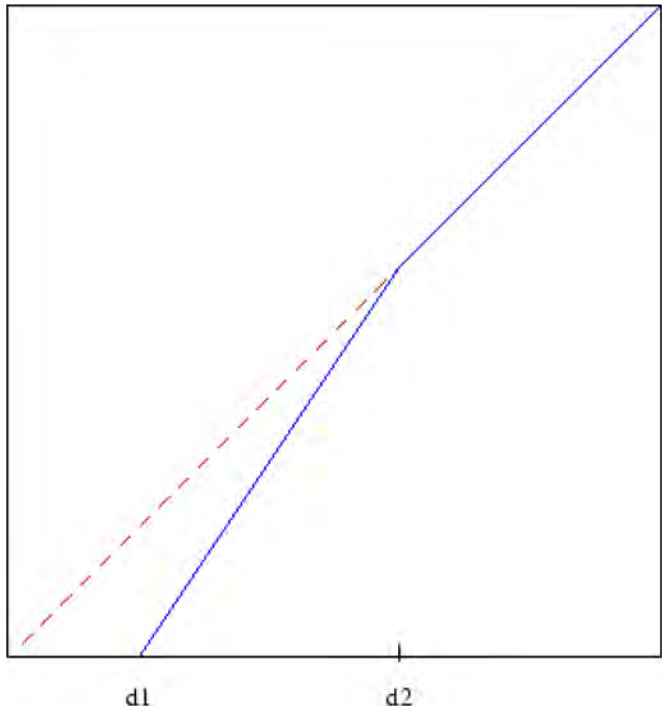


Figure 7-2

The payment function under the disappearing deductible (solid blue line) and no deductible (dashed red line).

The following formula shows the premium under the disappearing deductible in terms of the premium in the case of no deductible and the corresponding limited expected value function

$$P_{DD(d_1,d_2)} = P + \frac{d_1}{d_2 - d_1} L(d_2) - \frac{d_2}{d_2 - d_1} L(d_1).$$

If $d_1 = 0$,, the premium does not depend on d_2 and it becomes the premium in the case of no deductible. If $d_2$tends to infinity, then the disappearing deductible reduces to the fixed amount deductible of d_1.

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Recommendation: Targeting Indemnities to make PRF a better risk management tool

Our review leads us to conclude that the current program frequently pays for shallow losses that are likely not significant financial threats while at times not sufficiently compensating for deep losses that are often a part of widespread droughts driving up replacement forage costs. We believe the program can become a better risk management tool. Based on the evidence we find a relationship between the replacement cost of forage and deep losses. We recommend dropping the maximum coverage level to 80 percent while also adding a disappearing deductible and adjustment to enhance indemnities when in an extreme loss situation. One could develop more elaborate drought triggers, but they add significant complexity. For the sake of operational simplicity, we believe the indemnity function should be in the form of a disappearing deductible and perhaps reflect an accelerated disappearing deductible.

In the Pasture, Rangeland, Forage (PRF) Crop Provisions, section 5. (a) states:

5. Amounts of Protection and Coverage Levels

In lieu of section 7(a)(1) of the Basic Provisions, catastrophic risk protection is not available under these Crop Provisions.

(a) In lieu of section 7(a)(2) of the Basic Provisions, for additional coverage policies, when available in the actuarial documents:

(i) You may select only one coverage level from 70 percent through 90 percent for the county, crop, intended use, irrigated practice, and organic practice; and Merely reducing the maximum coverage level without making further adjustments disadvantages the grower who previously elected higher coverage. The following graph illustrates indemnity levels for growers with 90 percent and 80 percent coverage:

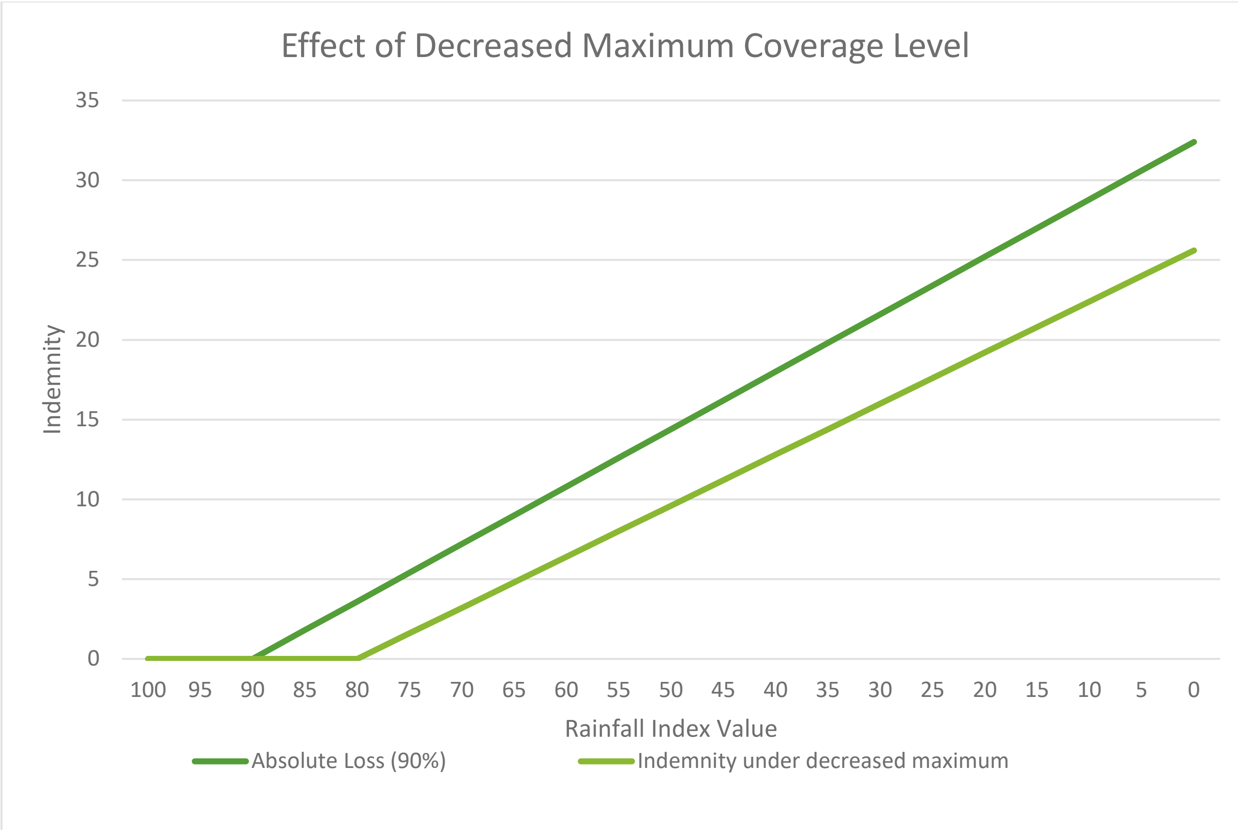

Effect of Decreased Maximum Coverage Level
35
30
25
20
15
10
5
0
Indemnity
100 95 90 85 80 75 70 65 60 55 50 45 40 35 30 25 20 15 10 5 0
Rainfall Index Value
Absolute Loss (90%)
Indemnity under decreased maximum

Figure 7-3

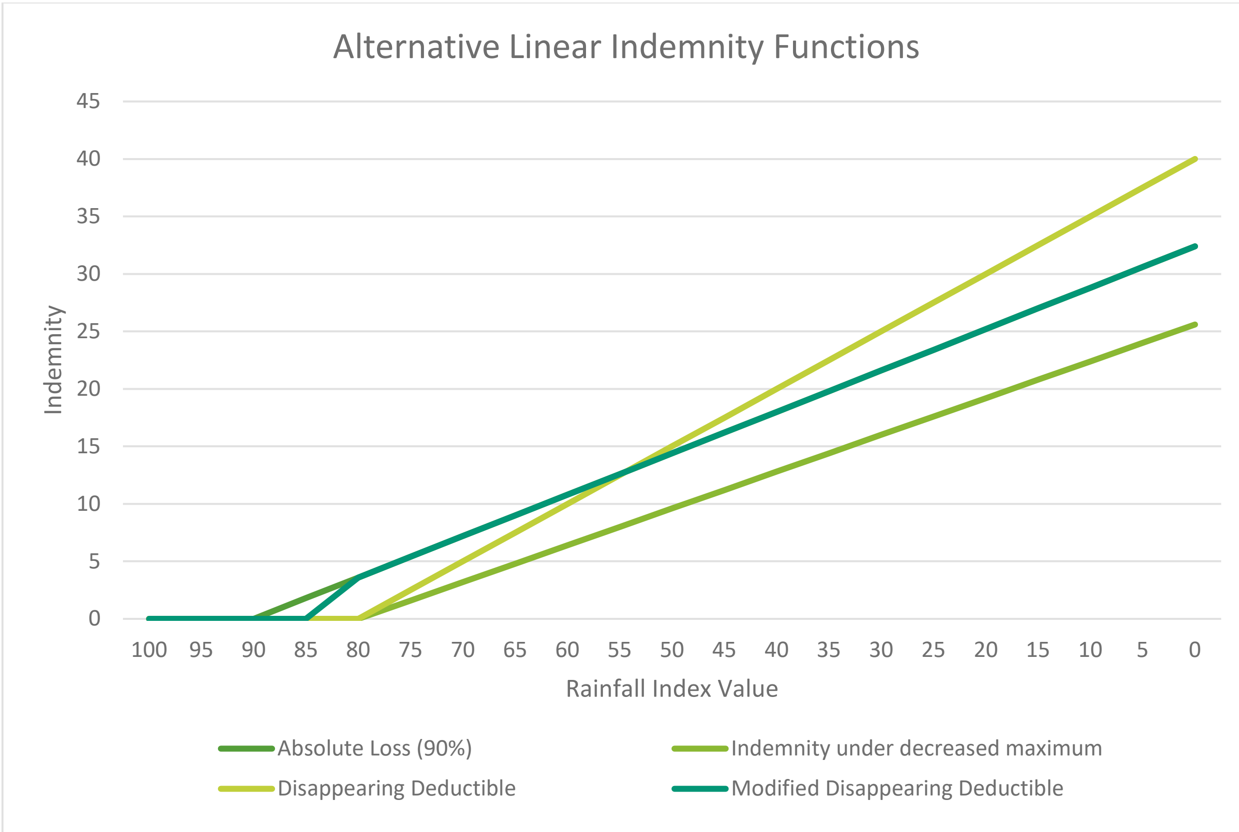


Figure 7-3

To illustrate the combination of decreased maximum coverage with a disappearing deductible consider a standard indemnity function

CBV = $40

Expected Index value = 100.

Previous coverage level = 90%

New maximum coverage level = 80%

Trigger level = Expected Index Value * Coverage level = 0.80

Final Index value = 0.50

Previous coverage level indemnity = Maximum (prior trigger level – final index value) * Trigger level * CBV), 0) = (0.9 – 0.5) * $40 = 0.4 * $36 = $16.00

Absolute Deductible Indemnity with new maximum coverage level = Maximum ((trigger level – final index value) * Trigger level * CBV), 0) = (0.8 – 0.5) * 0.8 * $40 = 0.3 * $32 = $9.60

Conversely a disappearing deductible could be targeted to gradually eliminate the deductible as the loss increases:

Disappearing Deductible Indemnity = Maximum (((trigger level – final index value))/ trigger level * CBV), 0) = 0.375 * $40 = $15

Or, a modified Disappearing Deductible could simply return the producer to the same level of coverage desired (90%) once coverage is triggered (80%):

Modified Disappearing Deductible Indemnity = $0 when final index < new maximum coverage level, otherwise previous coverage level indemnity

In the extreme case of a rainfall index equal to zero

Absolute Deductible Indemnity = Maximum ((trigger level – final index value) * Trigger level * CBV), 0) = 1.0 * $32 = $32.00

Disappearing Deductible Indemnity = Maximum (((trigger level – final index value))/ trigger level * CBV), 0) = 1.0 * $40 = $40

Linear approaches to making up the gap in coverage due to the decreased maximum indemnity may still overcompensate the grower in the event of relatively shallow losses. We note that the disappearing deductible function does not necessarily need to follow a linear function as shown above. It can be scaled to provide more coverage in the event of deeper losses using an exponent. Extending our example:

Non-linear disappearing deductible

Scaling exponent = 1.25

Non-linear Deductible Indemnity = Maximum (((trigger level – final index value)) ^ scaling exponent / trigger level * CBV), 0) = 0.375 ^ 1.25 * $40 = $11.70

Another approach is to speed up the loss function such that maximum indemnity is reach when the total factor loss is reached. This approach is described in Martin, Barnett, and Coble (2001).

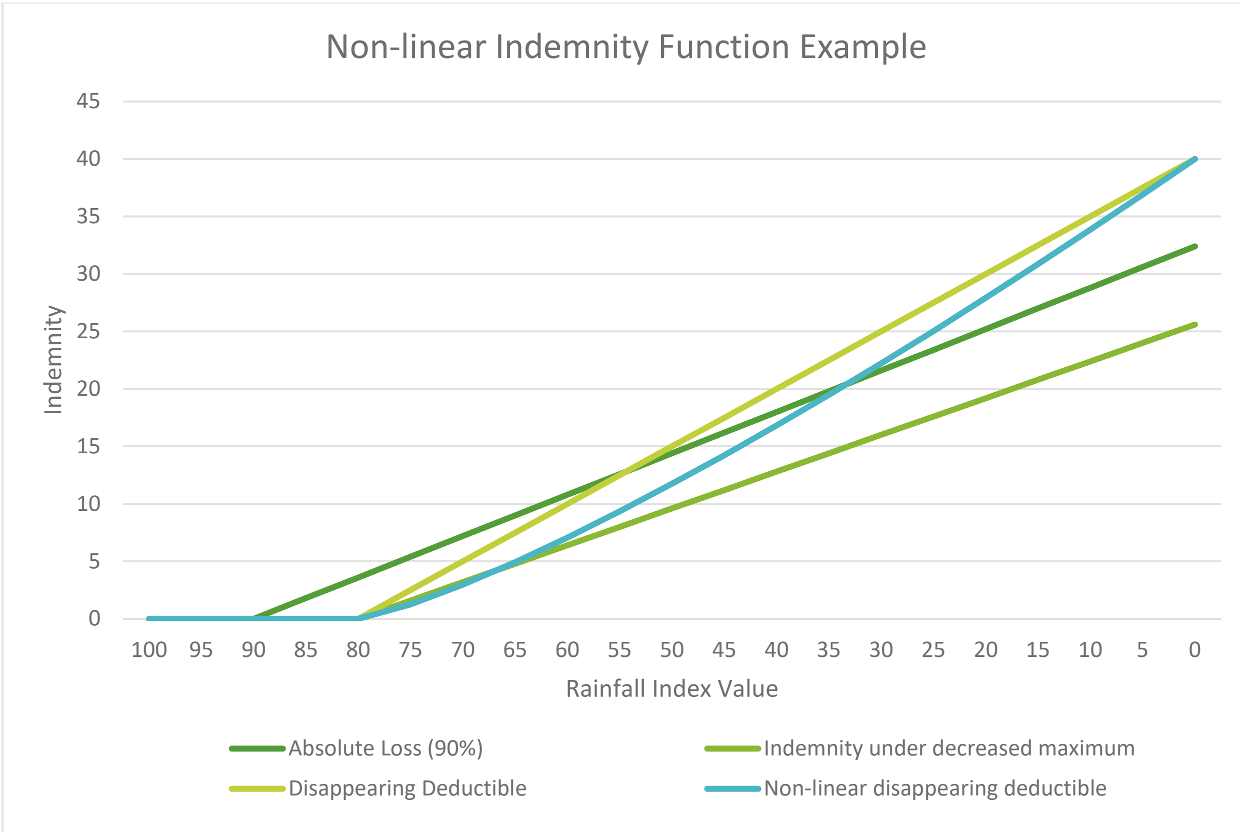


Figure 7-4

Chapter 7 References:

J. François Outreville (1998), *Theory and Practice of Insurance*, Springer Science+Business Media, page 136. https://books.google.com/books?id=YfAHCAAAQBAJ&pg=PA136&lpg=PA136&dq=disappearing+deductible+formula&source=bl&ots=hCq-fKPIuM&sig=ACfU3U03s9VIwNC4Lyfv-fmvZHaObR2iEA&hl=en&sa=X&ved=2ahUKEwib4KPniOToAhUDEqwKHThvBQoQ6AEwE3oECA8QKA#v=onepage&q=disappearing%20deductible%20formula&f=false

Pavel Cízek, Wolfgang Härdle, Rafał Weron, *Statistical Tools for Finance and Insurance*, ebooks, Xplore-Stat.de., http://sfb649.wiwi.hu-berlin.de/fedc_homepage/xplore/ebooks/html/stf/stfhtmlnode120.html

Appendix 1: Summary of CBV Calculation Steps

Non-irrigated Haying CBV Calculation

A. Calculate non-irrigated hay yield (in tons/acre)

1. Take the 10-year average of the most recent state-level NASS non-irrigated "all hay" yield data:

$$AHY_{State}^{10} = \frac{1}{10}\sum_{i=1}^{10} AHY_i \ ,$$

where: AHY_{State}^{10} is the 10-year state-level average non-irrigated yields, and AHY_i is the NASS state-level non-irrigated "all hay" yield in the year *i*.

2. Calculate the non-irrigated haying factor (*NHF*) from the FRIS data on non-irrigated hay yields (NHY^F) and "all hay" yields (AHY^F):

$$NHF = \frac{NHY^F}{AHY^F} \ .$$

3. Multiply *NHF* to the AHY_{State}^{10} to get the state-level non-irrigated hay yield (NHY_{State}^{10}):

$$NHY_{State}^{10} = NHF \times AHY_{State}^{10} \ .$$

4. From the NRCS HPM, derive percent difference between district-level and state-level net primary productivities (NPP), which we call the NPP district-state factor (*NDSF*).

5. Multiply *NDSF* to the NHY_{State}^{10} to get the district-level non-irrigated hay yield value ($NHY_{District}^{10}$) in tons/acre: $NHY_{District}^{10} = NDSF \times NHY_{State}^{10}$.

B. Calculate non-irrigated hay price (in $/ton)

1. Take the 3-year average of the most recent NASS "all hay, excluding alfalfa" price data:

$$HP_{State}^{3} = \frac{1}{3}\sum_{i=1}^{3} HP_i \ .$$

where: HP_{State}^{3} is the 3-year average state-level non-irrigated hay price, and HP_i is the NASS "all hay, excluding alfalfa" price in year *i*.

2. For certain states (with predominantly irrigated hay production), a regional average of HP_{State}^{3} for the Plain states are used.

C. Calculate the non-irrigated hay CBV (in $/acre)

1. Multiply $NHY_{District}^{10}$ with HP_{State}^{3} to get the non-irrigated hay CBV estimate (CBV^{NIH}) at the district-level:

$$CBV^{NIH} = NHY_{District}^{10} \times HP_{State}^{3}.$$

Irrigated Haying CBV Calculation

1. Collect data from FRIS on state-level irrigation cost (per acre inch) (IC_s^{State}) by different irrigation source *s*.
2. Take the weighted average of IC_s^{State} to get an overall estimate of the average state-level irrigation cost (per acre inch) (IC^{State}): $IC^{State} = \frac{1}{s}\sum_{s=1}^{s}\left(\gamma_s \times IC_s^{State}\right)$ where γ_s is the weight by source.
3. Multiply IC^{State} to the inches of rainfall (*R*) at the grid-level to get the irrigated haying CBV $\left(CBV^{IH}\right)$ in \$/acre: $CBV^{IH} = IC^{State} \times R$.

Grazing CBV Calculation

A. Calculate grazing yield (in tons/acre)

1. Collect yearly pasture rental rate (\$/acre) and grazing rate (\$/AUM) data at the state level.

2. Calculate the 10-year average of the most recent NASS state-level pasture rental rate (*PR*) and grazing rate (*GR*) data:

$$PR_{State}^{10} = \frac{1}{10}\sum_{i=1}^{10} PR_i \text{ and } GR_{State}^{10} = \frac{1}{10}\sum_{i=1}^{10} GR_i .$$

3. Estimate the average forage consumption (or the forage "harvested" by livestock) that is an estimate of grazing yield (GY_{State}^{AUM})in AUM/acre by dividing PR_{State}^{10} by GR_{State}^{10}:

$$GY_{State}^{AUM} = \frac{PR_{State}^{10}}{GR_{State}^{10}}.$$

4. Multiply GY_{State}^{AUM} by the AUM-Ton conversion factor (*ATCF*) (where *ATCF* = 0.47 tons/AUM) to get an estimate of the grazing yield in tons/acre (GY_{State}):

$$GY_{State} = GY_{State}^{AUM} \times ATCF .$$

B. Calculate grazing price (in \$/ton)

1. Calculate 3-year averages for the most recent yearly state-level grazing rates (*GR*) in \$/AUM and most recent NASS "all hay, excluding alfalfa" price (HP) data in \$/ton:

$$GR_{State}^{3} = \frac{1}{3}\sum_{i=1}^{3} GR_i \text{ and } HP_{State}^{3} = \frac{1}{3}\sum_{i=1}^{3} HP_i .$$

2. Convert GR^3_{State} to its \$/ton equivalent by dividing GR^3_{State} by the ATCF:

$$GR_{State} = GR^3_{State} \times ATCF \ .$$

3. Calculate the "blended" grazing price (BGP) in \$/ton by taking the ave. of GR_{State} and HP^3_{State}:

$$BGP_{State} = \frac{1}{2}\left(GR_{State} + HP^3_{State}\right).$$

C. Calculate the grazing CBV (in \$/acre)

1. Calculate the state-level grazing CBV (CBV^G_{State}) by multiplying GY_{State} and BGP_{State} :

$$CBV^G_{State} = GY_{State} \times BGP_{State} \, .$$

2. From the NRCS HPM, derive NPP county-state factor (*NCSF*) by taking the ratio of the county-level NPP and the state-level NPP.

3. Compute the county-level grazing CBV (CBV^G_{County}) by multiplying CBV^G_{State} with the *NCSF*:

$$CBV^G_{County} = CBV^G_{State} \times NCSF \ .$$

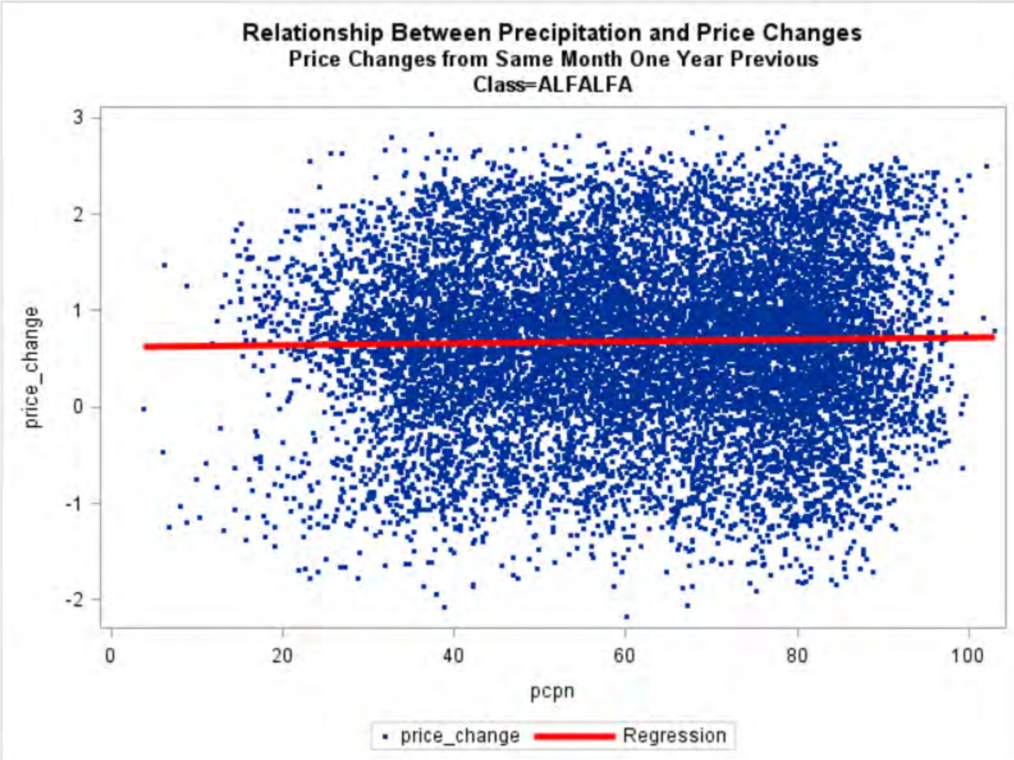
4. For each agricultural district in the state, the district-level grazing CBV (CBV^G) used in the PRF contract is derived by taking the average of the county-level grazing CBVs from the counties that comprise each district:

$$CBV^G = \frac{1}{n}\sum_{i=1}^{n} CBV^G_{County,i} \ .$$

Appendix 2 Price Yield Relationship

To evaluate the extent to which a relationship exists between yield, price, precipitation, and temperature, we collected hay (alfalfa and all classes) prices and yields from NASS. In light of likely changes in the technology associated with pasture and forage production, we limited our analysis to the period spanning 1980-2018. Prices and weather (precipitation and temperature) were observed monthly. Yields were only available on an annual basis and thus the yield data were compared to annual aggregates of precipitation and temperature. Temperature data are reported for the maximum temperature, the minimum temperature, and the average temperature.

Figure A1 to A5 illustrates the relationship between price changes (given as the log of the ratio of price to the previous year's price in the same month). Figure A2 considers the change in precipitation relative to the previous month. Linear regression lines were included in the evaluation to consider whether any simple relationships between yields, prices, and the various weather variables were obvious. None were found. Given the limited data available on pasture, hay, and forage yields and prices, we were unable to discern any significant relationship between prices, yields, and weather. Although the relevant agronomic/rangeland literature has noted the importance of both temperature and precipitation to pasture and range health, our analysis does not reveal any relationships that might prove helpful in establishing a payoff schedule based upon precipitation and temperature.



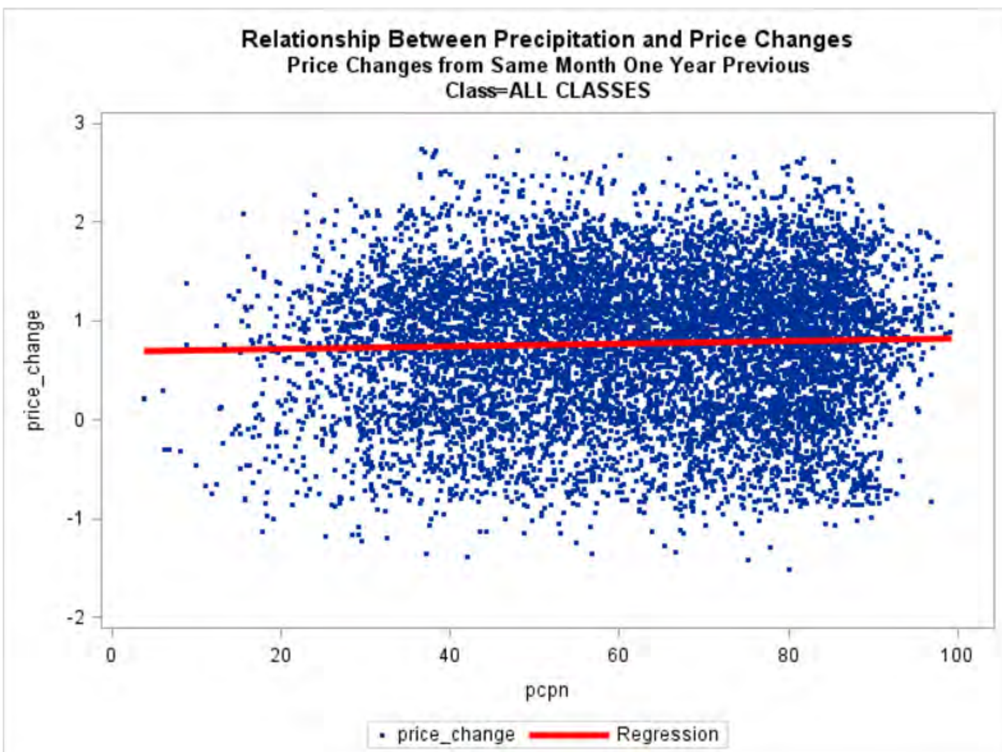
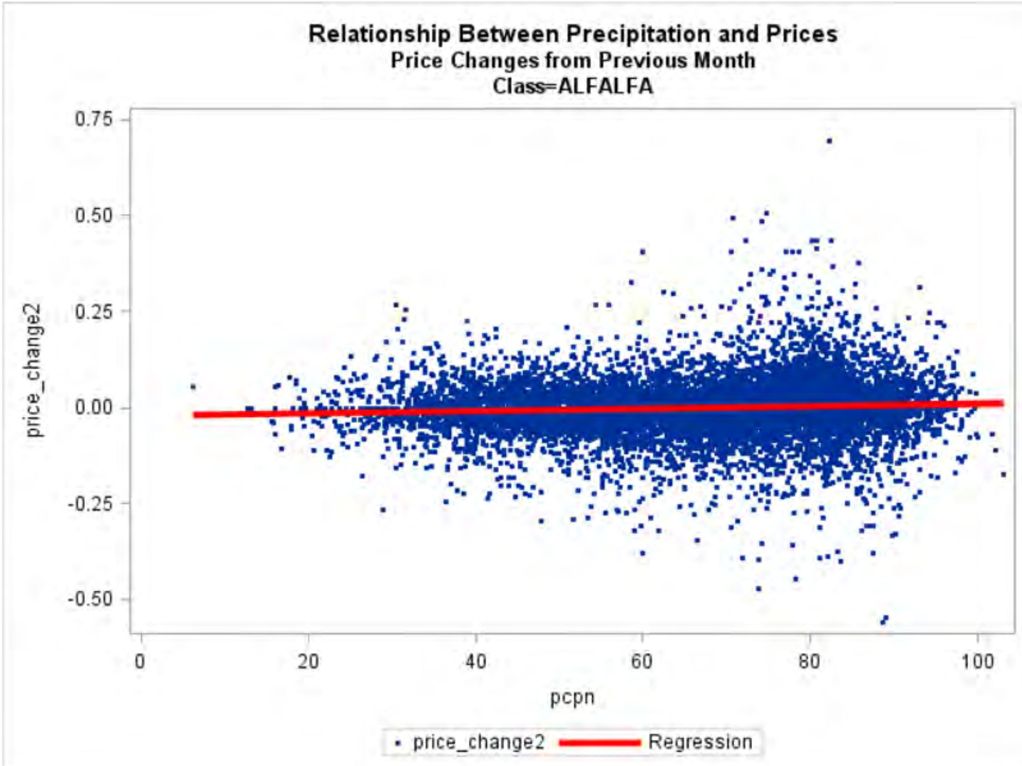


Figure A1. Precipitation and Price Change from Previous Year



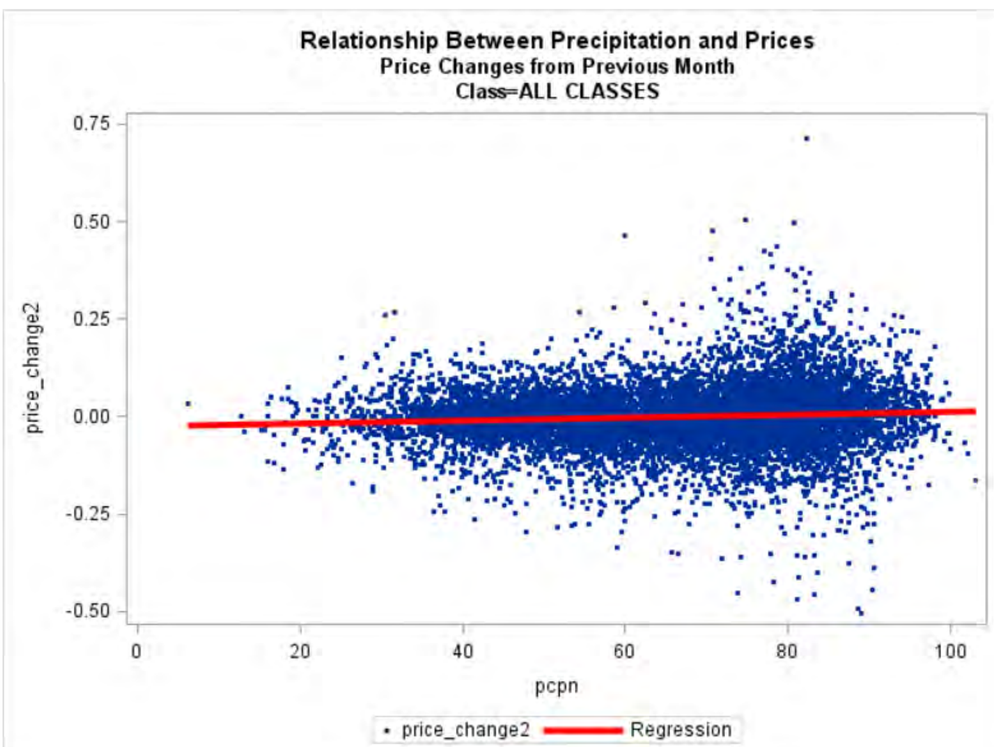
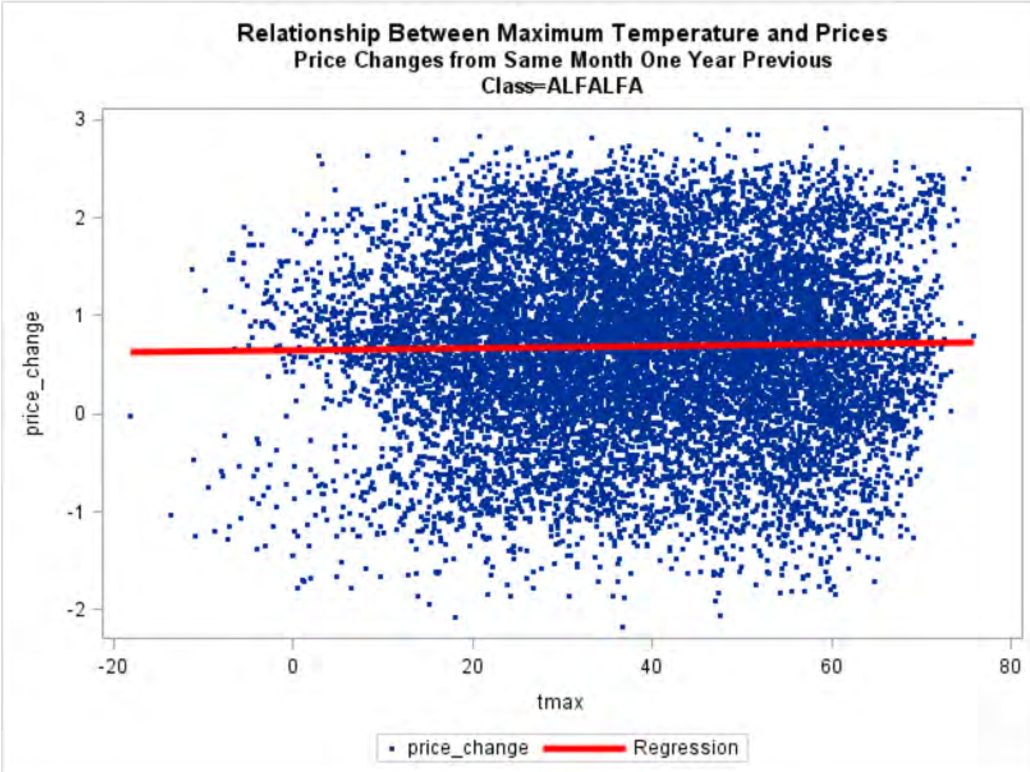


Figure A2. Precipitation and Price Change from Previous Month



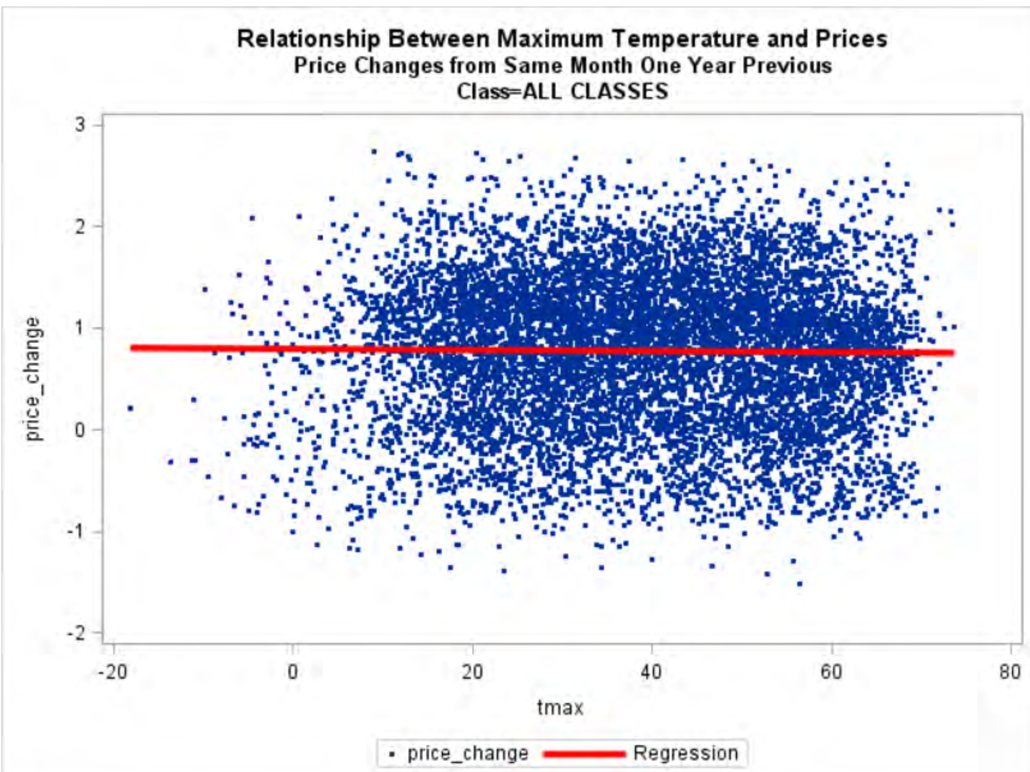
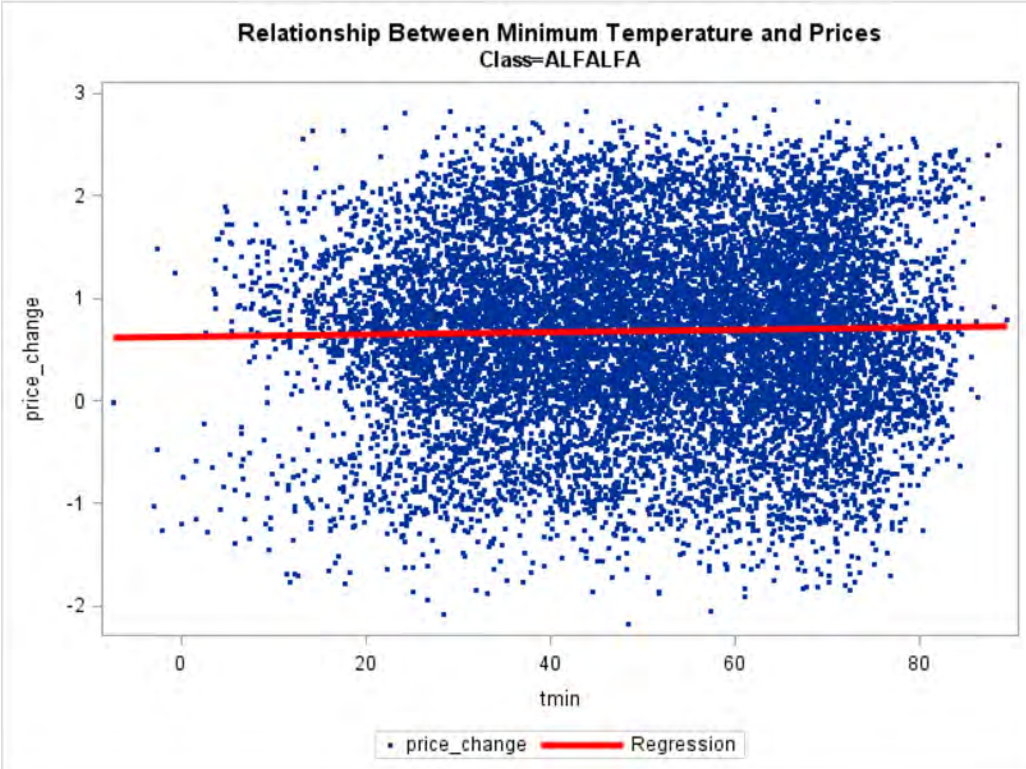


Figure A3. Maximum Temperature and Price Change from Previous Year



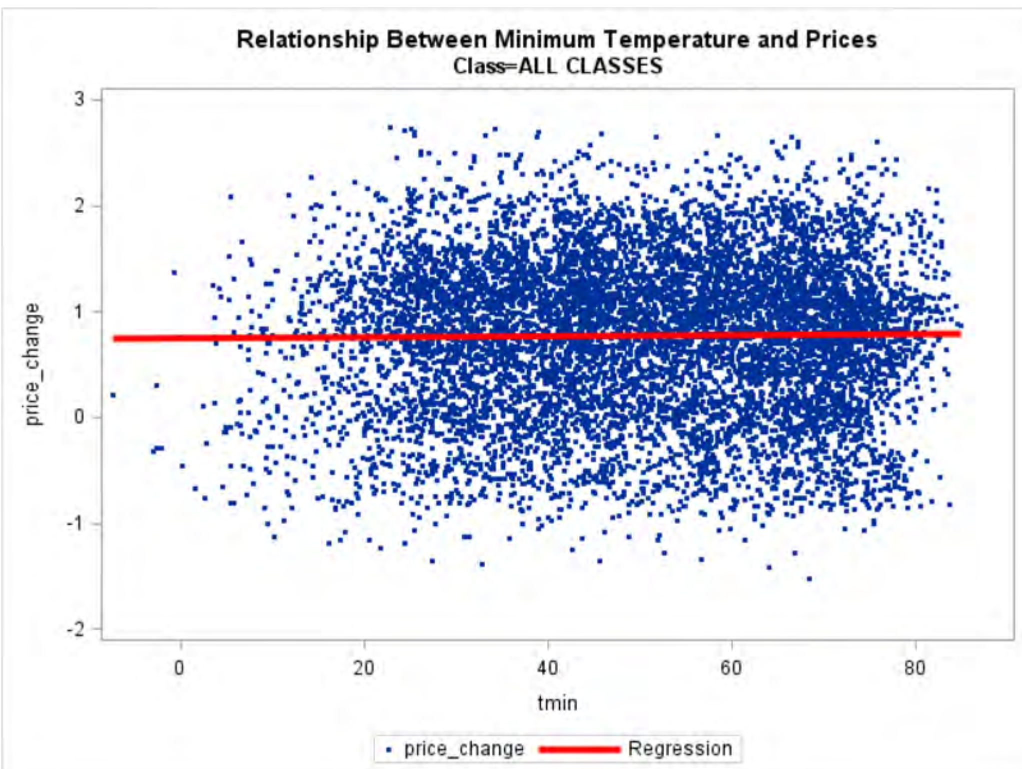
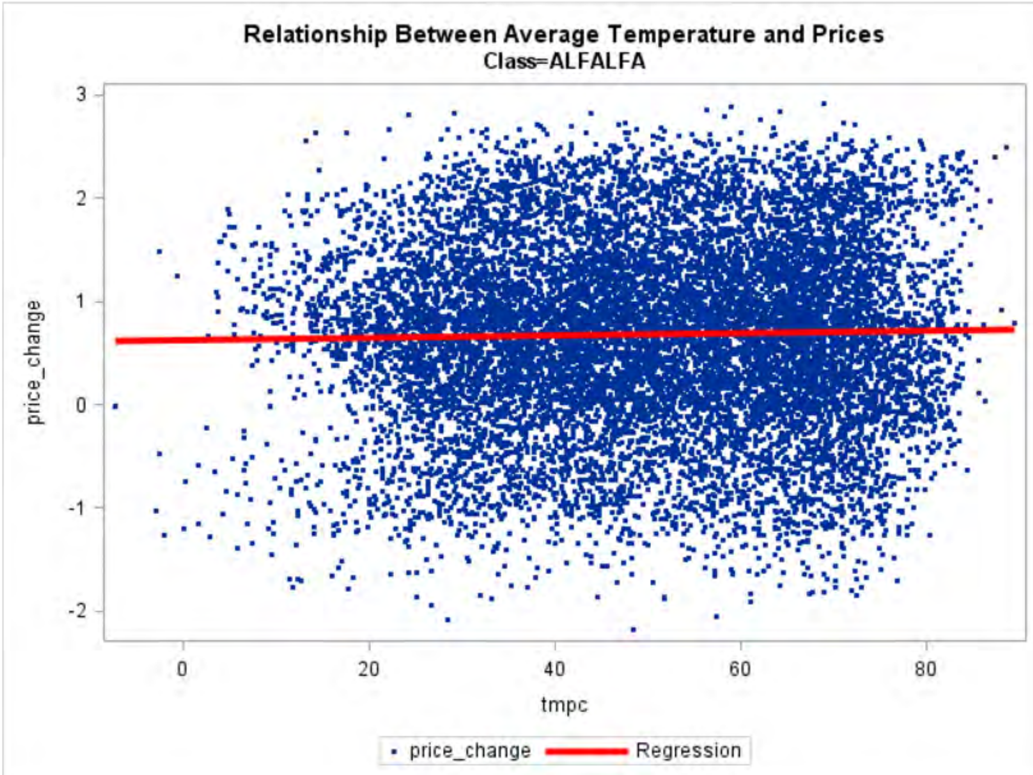


Figure A4. Minimum Temperature and Price Change from Previous Year



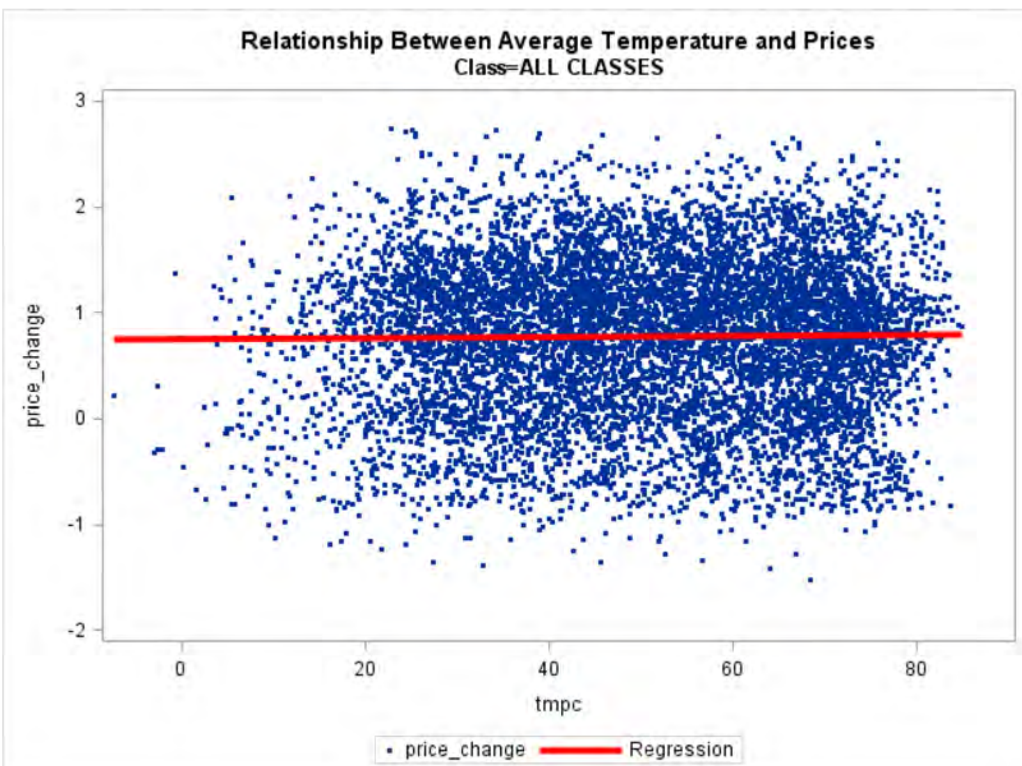


Figure A5. Average Temperature and Price Change from Previous Year

Appendix 2 Station IDs With LCC 8/U > 50% of Land Area

FIPS Codes	FIPS Codes
4001	22051
4003	22057
4007	22075
4009	22087
4012	22089
4015	22095
4021	22101
8009	22109
8079	34017
8099	35028
12087	35031
13051	35049
16037	36085
16081	38075
20071	44001
20075	46035
20171	46061
20187	46119
20203	48383
22023	

Appendix 3 Station IDs With Forage Production < 1st Percentile

Station ID	Latitude	Longitude	Station ID	Latitude	Longitude
14763	32.375	-114.375	19854	36.625	-116.625
14764	32.375	-114.125	19858	36.625	-115.625
15361	32.875	-114.875	19859	36.625	-115.375
15660	33.125	-115.125	20150	36.875	-117.625
15661	33.125	-114.875	20151	36.875	-117.375
15957	33.375	-115.875	20450	37.125	-117.625
15958	33.375	-115.625	20451	37.125	-117.375
15959	33.375	-115.375	20452	37.125	-117.125
15960	33.375	-115.125	20453	37.125	-116.875
15961	33.375	-114.875	20751	37.375	-117.375
16260	33.625	-115.125	21050	37.625	-117.625
16261	33.625	-114.875	21051	37.625	-117.375
16559	33.875	-115.375	21052	37.625	-117.125
16560	33.875	-115.125	21053	37.625	-116.875
16561	33.875	-114.875	21054	37.625	-116.625
16857	34.125	-115.875	21055	37.625	-116.375
16858	34.125	-115.625	21348	37.875	-118.125
16859	34.125	-115.375	21349	37.875	-117.875
16860	34.125	-115.125	21350	37.875	-117.625
16861	34.125	-114.875	21351	37.875	-117.375
16862	34.125	-114.625	21352	37.875	-117.125
17156	34.375	-116.125	21353	37.875	-116.875
17157	34.375	-115.875	21648	38.125	-118.125
17158	34.375	-115.625	21649	38.125	-117.875
17159	34.375	-115.375	21650	38.125	-117.625
17160	34.375	-115.125	21651	38.125	-117.375
17455	34.625	-116.375	21652	38.125	-117.125
17456	34.625	-116.125	21948	38.375	-118.125
17457	34.625	-115.875	21949	38.375	-117.875
17756	34.875	-116.125	21950	38.375	-117.625

18054	35.125	-116.625	21951	38.375	-117.375
18055	35.125	-116.375	21957	38.375	-115.875
18056	35.125	-116.125	21976	38.375	-111.125
18356	35.375	-116.125	21977	38.375	-110.875
18654	35.625	-116.625	22247	38.625	-118.375
18655	35.625	-116.375	22276	38.625	-111.125
18656	35.625	-116.125	22277	38.625	-110.875
18676	35.625	-111.125	22546	38.875	-118.625
18954	35.875	-116.625	22547	38.875	-118.375
18975	35.875	-111.375	22548	38.875	-118.125
19260	36.125	-115.125	22580	38.875	-110.125
19287	36.125	-108.375	22846	39.125	-118.625
19549	36.375	-117.875	23445	39.625	-118.875
19551	36.375	-117.375	23745	39.875	-118.875
19553	36.375	-116.875	23746	39.875	-118.625
19554	36.375	-116.625	23747	39.875	-118.375
19852	36.625	-117.125	24366	40.375	-113.625
19853	36.625	-116.875	24367	40.375	-113.375