Supporting Information for "Assessing Cost-effectiveness of the Conservation Reserve Program (CRP) and Interactions between CRP and Crop Insurance"

(The Supporting Information is only to be available online.)

Item A

In this item we show that the two matching approaches described in the "Simulation Approach and Data" section yield very similar crop insurance subsidy and final simulation result predictions. We first describe the insurance subsidy data at the insured-unit level. Then we describe the alternative matching approach, named quantile matching, which utilizes these data. An insured unit can be a single field or several fields on a farm. At the end we compare the results from quantile matching with those from the matching approach utilized in the main text, which is labeled as regression matching hereafter.

The two matching approaches utilize the same CRP data. The difference in data between the two approaches lies in the crop insurance subsidy data used. Unit-level crop insurance subsidy data for corn, soybean, and wheat in 2003 and 2011 and in 12 Midwestern states are obtained from Risk Management Agency (RMA) at USDA. These states are: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. This dataset includes rate yield (yield expected for a crop unit), insurance type, coverage level, premium, and premium subsidy for each insured unit. Table S2 shows corn, soybean and wheat insurance data summary statistics for each of the 12 states. In 2011, in total 2.4 million insured units covered 186 million acres of corn, soybean, and wheat within the 12 states. Crop insurance premiums and subsidies more than tripled between 2003 and 2011, largely due to increases in crop prices over that period. Moreover, like CRP rental rates, premiums and premium subsidies varied significantly across states. On average, premium subsidies accounted for about 50-65% of premiums across the states for the two years.

Even though both CRP offer data and the RMA datasets for corn, soybean, and wheat were contract unit level data, the location of each contract unit within a county is not released for either type of dataset. Thus, we cannot directly link these datasets by land parcels and have to seek an alternative approach. The rate yield variable in the RMA data indicates an insured unit's yield potential. Similarly, the weighted average soil rental rate (WASRR) in the CRP data represents the parcel's productivity potential. To identify crop insurance subsidy for each parcel offered to CRP, we also develop a quantile-matching approach to establish a link between land parcels in CRP and RMA datasets using rate yield and WASRR as linkage variables. More specifically, for each county we estimate cumulative distribution functions (CDF) for corn rate yield, soybean rate yield, wheat rate yield, and WASRR, respectively. To match a CRP parcel with units in RMA corn, soybean, and wheat datasets, we first identify the CDF value of this parcel's WASRR. The matched RMA units will be the corn, soybean, and wheat units that have the same CDF values based on the estimated rate yield distributions. Since we expect that land offered to CRP is usually less fertile, in the matching we only consider RMA units that have rate yield less than a certain percentile (the 30th percentile in this study) within a county. Below is the specific matching procedure.

Procedure A

Step 1. For each crop (corn, soybean, and wheat) in each county, we identify RMA units that have rate yields less than the 30th percentile. Note that in this step we view all the rate yield observations for one crop within one county as the population.

Step 2. Based on the RMA units obtained from Step 1, for each crop in each county, we estimate an empirical yield distribution. The empirical distributions are estimated using kernel density estimation which is implemented by MATLAB function "ksdensity." Specifically, let e_{jk}^{i} denote the unit-level yield for crop *i*'s observation *j* in county *k*, where $i \in \{c, s, w\}$ with *c* standing for corn, *s* for soybean, and *w* for wheat. The crop *i* kernel yield density estimate in county *k*, $g_k^i(x),$ can be written as

$$g_k^i(x) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{\lambda_i}K\left(\frac{x-e_{jk}^i}{\lambda_i}\right), \qquad \text{[SI1]}$$

where n is the number of yield observations for crop *i* in county *k*; λ_i is the bandwidth for crop i, and $K(\cdot)$ is the kernel function. In this study we set $K(\cdot)$ to be the Normal Kernel because it is one of the most commonly used kernel functions and the choice of kernel function is not critical (Greene 2003, p. 455). Then crop *i*'s cumulative yield distribution function in county *k* can be written as

$$G_k^i(x) = \frac{1}{n\lambda_i}\sum_{j=1}^{n}\int_{-\infty}^{x}K\left(\frac{z-e_{jk}^i}{\lambda_i}\right)dz. \qquad \text{[SI2]}$$

Step 3. Based on CRP offer data, for each county, we estimate an empirical distribution of WASRR. Let $R_k(\cdot)$ denote the estimated CDF of WASRR in county *k*.

Step 4. Suppose the parcel *j* WASRR in county *k* is x_{jk} . Based on the estimation result in Step 3 we can obtain $R_k(x_{jk})$. Then an RMA corn unit that matches with this parcel *j* will be the RMA corn unit that minimizes $|G_k(y_{ck}) - R_k(x_{jk})|$, where y_{ck} is the rate yield of a corn unit in county *k*. Following the same method we can match parcel *j* with a soybean unit and a wheat unit.

Step 5. Based on matching results in Step 4, parcel *j*'s estimated crop insurance subsidy will be the weighted average subsidy of the matched corn, soybean, and wheat units. The weights are reported acres for the matched units. This completes our description of the quantile matching procedure. This finishes Procedure A.

Table S3 summarizes the mean and standard deviation of the matched insurance subsidies for each state based upon the two matching approaches. We can see that on average the two matching approaches yield very close insurance subsidy mean values. For Signup 26 the mean of predicted insurance subsidies from the two approaches are almost the same (differ only after the hundredths decimal place). For Signup 41, the subsidy means from the regression matching and quantile matching approaches are $30.81/acre and $30.52/acre, respectively. Since aggregate insurance subsidy data (i.e., county-level average) are used in regression matching, it is not surprising that the standard deviation of insurance subsidies obtained from the regression-matching approach is smaller than that from the quantile-matching approach.

Table S4 presents simulation results such as total CRP acres enrolled, total annual CRP real payment, etc., within the 12 Midwestern States under the four scenarios based on data obtained from the two matching approaches. Results show that these two matching approaches yield negligible differences. For example, the total acres enrolled under Scenarios 2 and 3 simulated by using the data from regression matching are almost the same as those simulated by using the data from quantile matching (may differ after the hundredths decimal place). The payments (including real, nominal, and saved insurance subsidy payments) differ slightly between the simulation results based on the alternative matching approaches. The difference arises because the predicted insurance subsidies from the two approaches differ slightly.

Item B

In this item we describe the simulation procedure and results examining the robustness of OP1 and OP2 when EEBI measurement errors are randomly drawn from probability distributions. Since we have no data or other information for measurement errors, we will base our simulation on assumed probability distribution for the EEBI measurement errors. Here we assume that the measurement errors have generalized Pareto distributions (GPD) because GPDs are widely used in describing socio-economic, physical, or biological phenomena (Singh and Guo 1995). Pareto distribution (PD), a special case of GPD, has been shown to be appropriate for modeling a wide variety of economic variables, including distribution of income and city size (Gabaix 2009). Another reason we choose GPD is that, unlike normal distributions, the support for a GPD can be set as non-negative. The probability density function for a GPD with shape parameter $k > 0$, scale parameter σ, and location parameter θ can be written as,

$$f(x) = \frac{1}{\sigma}\left(1 + k\frac{x-\theta}{\sigma}\right)^{-1-\frac{1}{k}}, \qquad \text{[SI3]}$$

where the support is $x \geq \theta$. It is readily checked that when the location parameter $\theta = \sigma / k$ then

$$f(x) = \frac{\frac{1}{k}\left(\frac{\sigma}{k}\right)^{\frac{1}{k}}}{x^{\frac{1}{k}+1}}, \qquad \text{[SI4]}$$

which is the probability distribution function of a Pareto distribution with scale parameter σ / k and shape parameter $1/k$.

In the simulation we construct a GPD based upon county-level population data that we have used in section *On Motivating the Current EBI Design* of this paper. We admit that doing so does not necessarily generate a GPD that is closer to the actual distribution of EEBI measurement errors than an arbitrarily assumed GPD. This is because, as we have discussed in the paper's main text, there are various ways that the measured EEBI can deviate from the actual environmental benefits of a CRP offer and population is only one of numerous factors to be considered in the actual environmental benefits. Once we have obtained a GPD for the measurement errors, we will obtain random draws from this GPD as the measurement error for each CRP offer. Since county-level population can be hundreds of thousands and EEBI values are only in the hundreds (see Table 2), we first normalize the county-level population data through dividing each county's population by the median population across all the U.S. counties. One can check that the product of a constant and a random variable that follows a

GPD also follows a GPD. The procedure below describes how we obtain a GPD based on the county-level population data and how we use random draws from the GPD to examine the robustness of OP1 and OP2 to EEBI measurement errors.

Procedure B

Step 1. Normalize the county-level population by using the median population across all U.S. counties. Do the normalization separately for 2003 population data and 2011 population data. Specifically, let P_{it} denote county *i*'s population in year $t \in \{2003, 2011\}$. Suppose the median of the county-level population in year *t* is M_t. Then the normalized population in county *i* in year *t* is $p_{it} = P_{it} / M_t$.

Step 2. Base on the normalized county-level population data obtained in Step 1, we estimate a GPD by using MATLAB© command "gpfit". Then we obtain one random draw from the estimated GPD by using MATLAB© command "gprnd" for each county. These random draws are used as values for multiplicative measurement errors, ξ, of all CRP offers within one county. For additive errors, ϵ, we simply let $\epsilon = 50\xi$. Notice that since the chance that ξ takes values around 1 is large, letting $\epsilon = \xi$ does not work well for additive errors because a) ϵ would be too small relative to EEBI in the additive format of measurement errors and b) we would see a negligible impact of measurement error correction. In order to obtain a sizable impact for our illustration purpose, we enlarge ϵ by setting $\epsilon = 50\xi$.

Similar to execution in the main text, we let all CRP offers within one county have the same measurement error. The reasons for doing so are twofold. First, CRP offers within the same county may have similar geographical and environmental properties and are valued by similar populations. Therefore, no matter what the missing benefits are in the EEBI, these missing benefits would have much in common. Second, information (e.g., distance to rivers or lakes) of CRP offers within the same county is likely to be gathered by the same local FSA office and ‘local offices can influence the mix of environmental benefits arising from the CRP, as well, since they recommend what mixtures of seed cover should be planted where, for example’ (Hamilton 2010, p. 38).[1] Therefore, the EEBI measurement errors are more likely to be consistent across offers within the same county.

Step 3. Accounting for the measurement errors obtained in Step 2, we perform optimization problems $\mathrm{OP1}^{\mathrm{corr}}$ and $\mathrm{OP2}^{\mathrm{corr}}$. CRP enrollment results of these two optimization problems are recorded.

Step 4. Steps 2 and 3 are repeated 2,000 times for Signups 26 and 41 under each type of measurement error to obtain an average CRP enrollment results of optimization problems $\mathrm{OP1}^{\mathrm{corr}}$ and $\mathrm{OP2}^{\mathrm{corr}}$. This finishes Procedure B.

Table S5 presents simulation results obtained from conducting Procedure B. To facilitate comparison, we also include CRP enrollment results under OP1 and OP2 using the EEBI without considering measurement errors. We find that similar conclusions drawn from Table 5 carry through in Table S5. First, the total $\mathrm{EEBI}^{\mathrm{corr}}$ under OP2 is always greater than that under OP1 across the two signups and the two types of measurement errors, indicating that for the same amount of CRP outlay, OP2 achieves higher environmental benefits than does OP1. Second, OP2 is more robust than OP1 across all the two signups and the two types of measurement error. For instance, under multiplicative measurement error, total $\mathrm{EEBI}^{\mathrm{corr}}$ achieved by OP1 is about 84% of that achieved by $\mathrm{OP1}^{\mathrm{corr}}$ for Signup 41. However, for the same Signup, total $\mathrm{EEBI}^{\mathrm{corr}}$ achieved by OP2 is about 96% of that achieved by $\mathrm{OP2}^{\mathrm{corr}}$. The explanation discussed in the main text for results in Table 5 also applies here. That is, the correlation coefficient between EBI values before and after measurement error correction under OP2 is greater than that under OP1 (see Table S6) indicating that, when compared with OP1, the CRP offer ranking under OP2 is less likely to be changed by accounting for EEBI

[1] We are indebted to an anonymous referee for comments that pointed to this second reason.

measurement errors.

Maps in Figure S3 depict changes in acres enrolled into CRP after EEBI measurement errors drawn from Generalized Pareto Distributions are accounted for additively. Under OP1, we find that once measurement errors are additively corrected, then counties on the Northern Great Plains would gain some extra CRP acreage whereas counties in the Midwest would lose CRP acreage (see the two maps in the left panel of Figure S3). However, under OP2, the opposite is true (see the two maps in the right panel of Figure S3). Patterns of acreage changes under the multiplicative error type (maps in Figure S4) are almost exactly the same as those under the additive error type.

The patterns of CRP acreage change in Figures S3 and S4 are by no means surprising. Recall that Figures S3 and S4 present the difference between the *average* CRP acreage under $OP1^{corr}$ (respectively, $OP2^{corr}$) and CRP acreage under OP1 (respectively, OP2). The average CRP acreage under $OP1^{corr}$ and $OP2^{corr}$ is obtained by first repeatedly shocking EEBI with an error term randomly drawn from an estimated GPD and then taking an average of the resulting CRP enrollment acreage obtained from each round of shocks. Suppose, for example, without accounting for measurement errors (i.e., based on the current EEBI values), the EEBI for CRP offer A is greater than the EEBI for offer B: $EEBI_A > EEBI_B$. We further assume that offer A is accepted while offer B is not. However, once we include an error term in the EEBI values then there will be a chance that offer B is accepted while offer A is not because $EEBI_B$ may be matched with a large error whereas $EEBI_A$ is matched with a small one. Therefore, on average, we would expect that areas with larger CRP acreage under OP1 (respectively, OP2) tend to lose some acreage under $OP1^{corr}$ (respectively, $OP2^{corr}$) whereas areas with smaller CRP acreage under OP1 (respectively, OP2) tend to gain some acreage under $OP1^{corr}$ (respectively, $OP2^{corr}$).

Figure S5 includes maps regarding county-level enrolled acreage under Signups 26 and

41 without accounting for EEBI measurement errors. Take Signup 26 in Figure S5 as an example. Under OP1, North Dakota has small CRP acreage while southern Iowa area has larger CRP acreage (see the upper left map in Figure S5). Based upon our analysis above, we should expect that under $OP1^{corr}$ North Dakota would gain CRP acreage while the southern Iowa would lose some acreage. The upper left maps in Figures S3 and S4 confirm this conjecture. Under OP2, North Dakota has larger CRP acreage whereas Iowa has little (see the upper right map in Figure S5), which indicates that under $OP2^{corr}$ North Dakota would lose some acreage whereas Iowa would experience the opposite (see the upper right maps in Figures S3 and S4).

Figure S6 presents four maps that depict changes in county-level enrolled acreage under the two Signups were the enrollment mechanism to be switched from OP1 to $OP2^{corr}$. We find that patterns of acreage changes across the four maps are quite similar. Specifically, the Midwestern area would lose CRP acreage whereas the North Great Plains would see an increase in CRP acreage. This indicates that across the two Signups and the two types of measurement errors, the effect of switching from OP1 to OP2 (which causes the Midwest to lose some CRP acreage) dominates the effect of switching from OP2 to $OP2^{corr}$ (which causes the Midwest to gain CRP acreage).

References

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Hamilton, J.T. 2010. Conserving Data in the Conservation Reserve: How a Regulatory Program Runs on Imperfect Information. Resource for the Future (RFF) Press, Washington, DC.

Singh, V.P. and H. Guo. 1995. “Parameter estimation for 3-parameter generalized pareto distribution by the principle of maximum entropy (POME).” *Hydrological Science Journal* 40(2):165-181.

Table S1. Correlation Coefficient between EBI before and after correction under OP1 and OP2

		Additive Errors	Multiplicative Errors
Signup 26	OP1	0.85	0.40
	OP2	0.97	0.66
Signup 41	OP1	0.91	0.42
	OP2	0.96	0.50

Table S2. Summary Statistics for RMA Insurance Data of the 12 Midwestern States in 2003 and 2011

		Corn				Soybean				Wheat			
	States	Number of Units	Reported Acres	Premium ($/acre)	Subsidy ($/acre)	Number of Units	Reported Acres	Premium ($/acre)	Subsidy ($/acre)	Number of Units	Reported Acres	Premium ($/acre)	Subsidy ($/acre)
2003	Illinois	148,562	10,833,809	12	6	141,909	9,210,779	6	3	11,275	472,270	8	5
	Indiana	62,740	4,088,162	15	8	60,025	3,677,722	9	5	4,066	170,899	7	4
	Iowa	167,339	13,526,638	12	7	154,663	11,989,988	7	4	131	8,814	12	7
	Kansas	45,458	3,761,712	12	6	54,671	3,089,506	8	5	176,867	15,234,345	7	4
	Michigan	19,316	1,266,461	14	8	17,726	1,086,768	10	6	7,178	338,192	9	5
	Minnesota	85,188	7,443,395	15	9	91,101	8,215,170	9	5	18,121	2,045,047	12	7
	Missouri	42,348	3,305,906	13	8	65,532	5,448,817	8	5	10,467	626,953	6	4
	Nebraska	132,763	10,214,861	14	7	93,401	5,845,373	9	5	34,643	2,507,902	8	5
	North Dakota	18,584	1,678,414	18	11	35,358	3,934,778	10	5	108,686	11,475,508	9	5
	Ohio	42,692	2,470,580	15	8	48,006	2,971,164	10	5	10,771	422,095	6	4
	South Dakota	63,143	5,395,230	15	9	60,952	5,457,440	10	5	33,595	3,865,914	10	6
	Wisconsin	36,780	2,049,808	19	11	21,064	1,092,798	10	6	2,045	71,018	12	7
	12 States	864,913	66,034,975	14	7	844,408	62,020,302	8	4	417,845	37,238,957	8	5
2011	Illinois	165,720	13,437,896	38	22	151,798	9,753,491	23	13	14,341	633,482	31	20
	Indiana	70,306	4,936,483	48	28	70,276	4,358,936	33	19	6,081	281,279	32	19
	Iowa	176,911	15,875,033	43	25	140,707	11,085,629	26	15	244	8,705	40	24
	Kansas	74,988	6,578,764	40	25	71,810	4,650,846	30	19	144,258	12,870,889	21	13
	Michigan	30,019	1,787,419	51	35	25,250	1,380,584	39	25	9,692	479,259	31	20
	Minnesota	107,444	8,927,060	49	31	95,452	7,922,207	33	20	17,209	1,746,336	44	30
	Missouri	52,575	4,063,231	49	32	77,997	6,059,521	28	18	10,806	680,467	23	15
	Nebraska	146,215	12,052,479	42	25	92,018	6,194,190	30	18	25,911	2,049,950	21	12
	North Dakota	39,143	3,276,239	69	46	56,882	5,265,896	38	24	117,137	11,553,909	35	23
	Ohio	52,388	3,045,180	52	32	64,379	3,867,055	39	23	14,790	566,906	27	16
	South Dakota	86,722	6,851,722	55	37	78,141	5,497,352	32	21	34,034	3,586,358	35	23
	Wisconsin	54,207	2,806,803	67	44	27,950	1,225,292	44	28	6,037	213,181	37	24
	12 States	1,056,638	83,638,309	46	28	952,660	67,260,999	30	19	400,540	34,670,720	29	18

Table S3. Mean and Standard Deviation of Matched Insurance Subsidies per Acre from Regression Matching and Quantile Matching

	Signup 26				Signup 41			
	mean ($/acre)		standard deviation		mean ($/acre)		standard deviation	
State	regression	quantile	regression	quantile	regression	quantile	regression	quantile
Illinois	8.00	8.08	1.09	3.20	32.13	31.41	4.30	14.57
Indiana	9.32	7.92	2.04	2.87	34.44	30.58	4.19	12.07
Iowa	7.43	7.19	1.44	2.74	29.07	29.05	2.52	9.87
Kansas	7.15	8.50	0.76	2.72	27.90	26.50	2.46	8.90
Michigan	8.54	7.93	0.55	3.54	30.11	27.89	1.79	9.83
Minnesota	8.96	8.58	0.86	3.40	33.14	35.94	3.12	13.37
Missouri	8.24	8.82	1.33	3.11	35.06	35.05	7.62	12.14
Nebraska	9.26	9.76	1.03	2.88	27.15	26.28	4.59	7.35
North Dakota	7.73	7.43	1.96	2.91	29.53	29.49	5.71	11.11
Ohio	8.04	7.40	0.72	2.59	34.08	28.54	2.19	8.02
South Dakota	8.30	8.23	1.15	2.53	30.51	32.06	6.08	10.24
Wisconsin	9.56	9.33	0.95	3.99	36.73	37.54	2.62	15.59
average	8.21	8.21	1.42	3.15	30.81	30.52	5.46	11.85

Table S4. Comparing Simulation Results based on Regression Matching and Quantile Matching

	Regression matching				Quantile matching			
	Baseline	Scen. 1	Scen. 2	Scen. 3	Baseline	Scen. 1	Scen. 2	Scen. 3
Signup 26								
Total acres enrolled (million acres)	1.1	1.1	1.5	1.6	1.1	1.1	1.5	1.6
Total annual CRP real payment (million $)	62.5	62.3	62.5	62.5	62.2	61.6	62.2	62.2
Total annual CRP nominal payment (million $)	71.5	71.3	75.0	75.2	71.5	71.1	75.2	75.7
Crop insurance subsidy saved per year (million $)	9.0	9.0	12.4	12.7	9.3	9.5	13.0	13.4
Total EEBI of enrolled acres (million)	237	237	278	278	237	237	279	279
Average EEBI per enrolled acre	213	213	181	179	213	213	181	179
Average EEBI per CRP real payment dollar	3.8	3.8	4.4	4.5	3.8	3.8	4.5	4.5
Acres that change status when compared with Baseline (million acres)	-	0.04	0.85	0.92	-	0.05	0.85	0.92
Signup 41								
Total acres enrolled (million acres)	0.9	0.9	1.1	1.1	0.9	0.9	1.1	1.1
Total annual CRP real payment (million $)	31.9	32.1	31.9	31.9	31.9	31.4	31.9	31.9
Total annual CRP nominal payment (million $)	57.0	57.3	63.5	64.4	57.0	57.1	63.6	64.7
Crop insurance subsidy saved per year (million $)	25.1	25.2	31.6	32.5	25.1	25.7	31.8	32.8
Total EEBI of enrolled acres (million)	156	156	173	174	156	156	173	174
Average EEBI per enrolled acre	181	181	160	157	181	181	160	157
Average EEBI per CRP real payment dollar	4.9	4.9	5.4	5.4	4.9	5.0	5.4	5.5
Acres that change status when compared with Baseline (million acres)	-	0.02	0.27	0.32	-	0.04	0.27	0.31

Note: Baseline scenario and Scenario 1 are under acreage constraints, which are 1,111,714 acres and 860,445 acres in the 12 states, respectively, for Signups 26 and 41. Scenarios 2 and 3 are under real-payment constraints. Regarding data from regression matching, the real payment constraints are $62,517,849 and $31,865,548, respectively, for Signups 26 and 41. Regarding data from quantile matching, the real payment constraints are $62,218,752 and $31,870,389, respectively, for Signups 26 and 41. The real payment constraints from the two matching approaches differ slightly because the predicted crop insurance subsidies under these two approaches differ slightly.

Table S5. Simulation Results Based on Additive Error and Multiplicative Error Drawn from Generalized Pareto Distribution

	Additive Correction				Multiplicative Correction			
	OP1	OP1^{corr}	OP2	OP2^{corr}	OP1	OP1^{corr}	OP2	OP2^{corr}
Signup 26								
Total acres enrolled (million acres)	2.0	2.0	2.8	2.7	2.0	2.0	2.8	2.3
Total annual CRP real payment (million $)	95.6	91.2	95.6	95.6	95.6	90.1	95.6	95.6
Total annual CRP nominal payment (million $)	112.5	108.1	119.5	118.3	112.5	106.8	119.5	115.0
Crop insurance subsidy saved per year (million $)	16.9	16.9	23.9	22.7	16.9	16.8	23.9	19.4
Total EEBI^{corr} of enrolled acres (million)	838.3	1178.3	1097.2	1282.4	1779.9	2902.4	2145.9	2941.7
Average EEBI^{corr} per enrolled acre	252.5	261.0	212.5	216.9	180.1	234.5	128.7	220.6
Average EEBI^{corr} per CRP real payment dollar	8.8	12.9	11.5	13.4	18.6	32.2	22.5	30.8
Acres that change status when compared with Baseline (million acres)	-	1.5	1.8	1.9	-	1.9	1.8	1.9
Signup 41								
Total acres enrolled (million acres)	2.8	2.8	3.5	3.5	2.8	2.8	3.5	3.3
Total annual CRP real payment (million $)	50.2	45.9	50.2	50.2	50.2	44.4	50.2	50.2
Total annual CRP nominal payment (million $)	134.3	131.6	156.1	156.2	134.3	128.8	156.1	149.2
Crop insurance subsidy saved per year (million $)	84.1	85.7	105.9	106.0	84.1	84.4	105.9	99.0
Total EEBI^{corr} of enrolled acres (million)	1109.0	1282.5	1345.7	1377.9	2189.0	2596.0	2517.9	2612.7
Average EEBI^{corr} per enrolled acre	207.8	215.8	191.2	191.0	106.6	122.5	96.7	113.5
Average EEBI^{corr} per CRP real payment dollar	22.1	27.9	26.8	27.5	43.6	58.5	50.2	52.1
Acres that change status when compared with OP1 (million acres)	-	0.9	0.8	0.9	-	1.2	0.8	1.1

Note: Although OP1 and OP2 optimize on EEBI without accounting for measurement errors, we record EEBI^{corr} achieved under OP1 and OP2 for comparison purpose.

Table S6. Average Correlation Coefficient between EBI before and after Correction under OP1 and OP2 across 2,000 Iterations in Procedure B

		Additive Errors	Multiplicative Errors
Signup 26	OP1	0.06	0.05
	OP2	0.22	0.12
Signup 41	OP1	0.06	0.06
	OP2	0.19	0.12

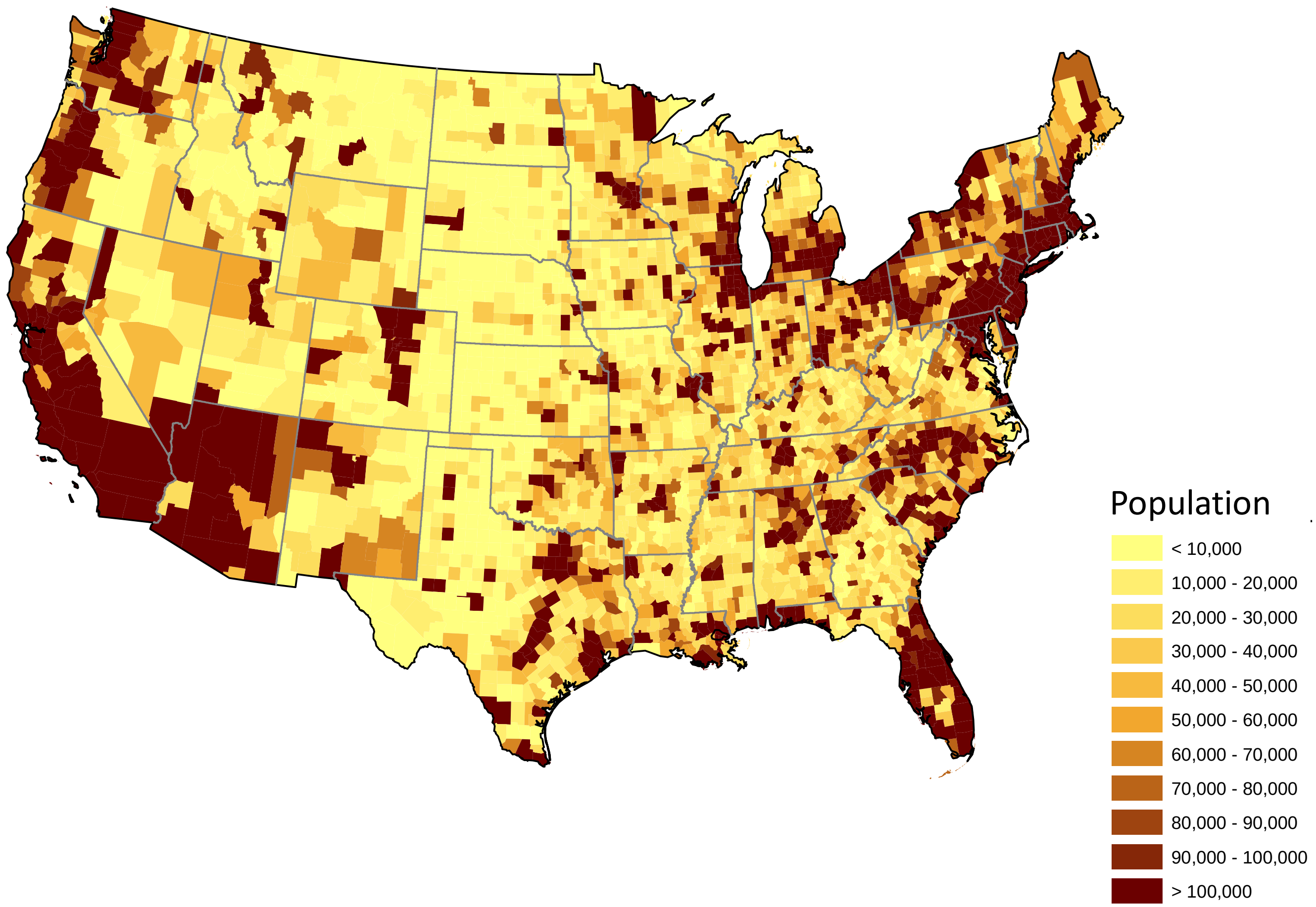

Figure S1. County-level Population of the Contiguous United States in 2011. Data source: the U.S. Census Population Estimates (link: https://www.census.gov/popest/data/historical/index.html, accessed on September 9, 2015).

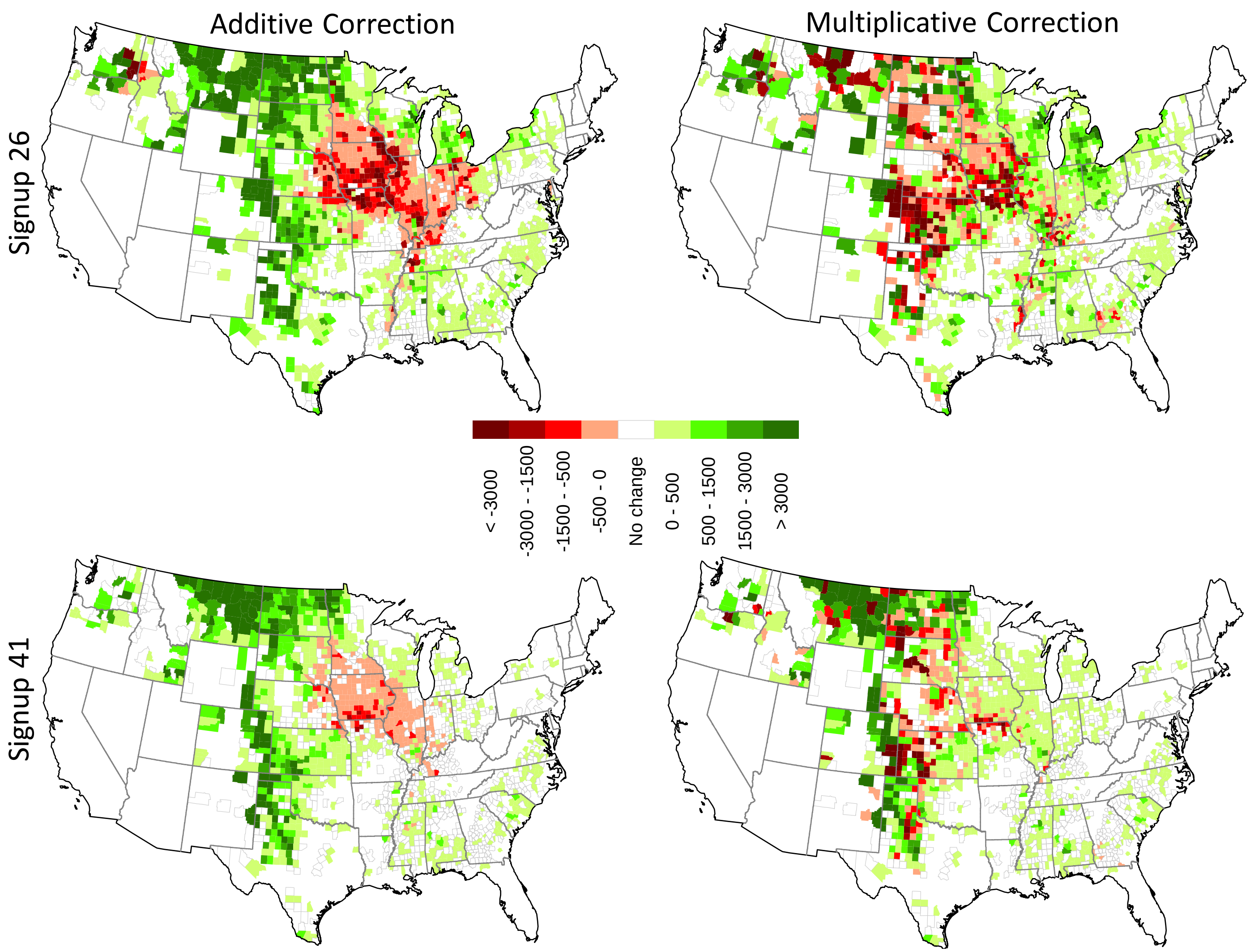

Figure S2. Changes of Acres Enrolled into CRP when Comparing OP2^{corr} with OP1 with Measurement Errors Constructed by Using County-level Population Data. Notes: in the maps, positive numbers indicate an increase in CRP acres after switching from OP1 to OP2^{corr}. Counties with gray border but without color had no enrollment acreage changes whereas counties with neither border nor color had no CRP offers.

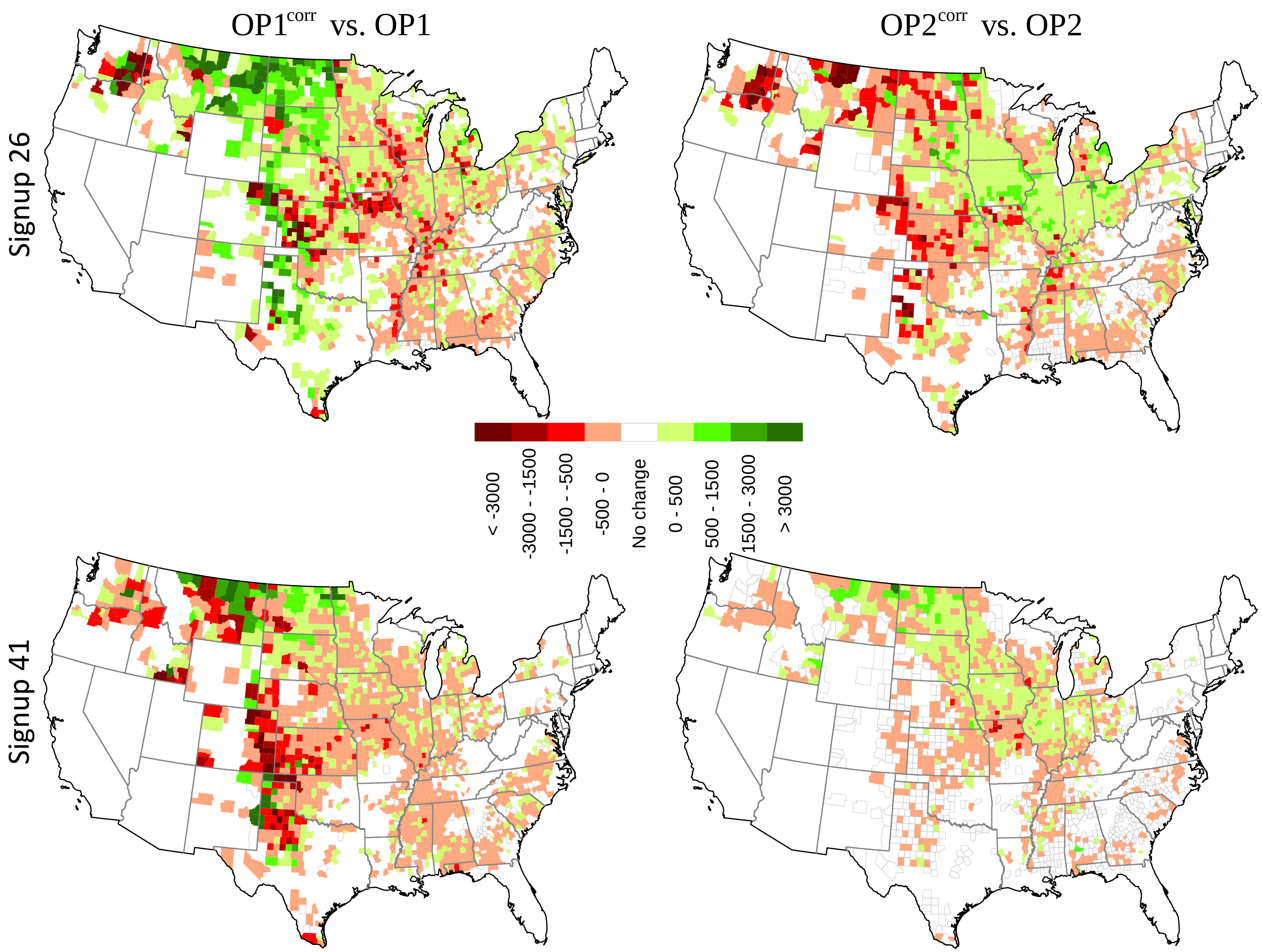

Figure S3. Changes of Acres Enrolled into CRP after Measurement Errors Drawn from a Generalized Pareto Distribution are Added to EEBI. Notes: in the maps, positive numbers indicate an increase in CRP acres after accounting for the measurement errors. Counties with gray border but without color had no enrollment acreage changes whereas counties with neither border nor color had no CRP offers.

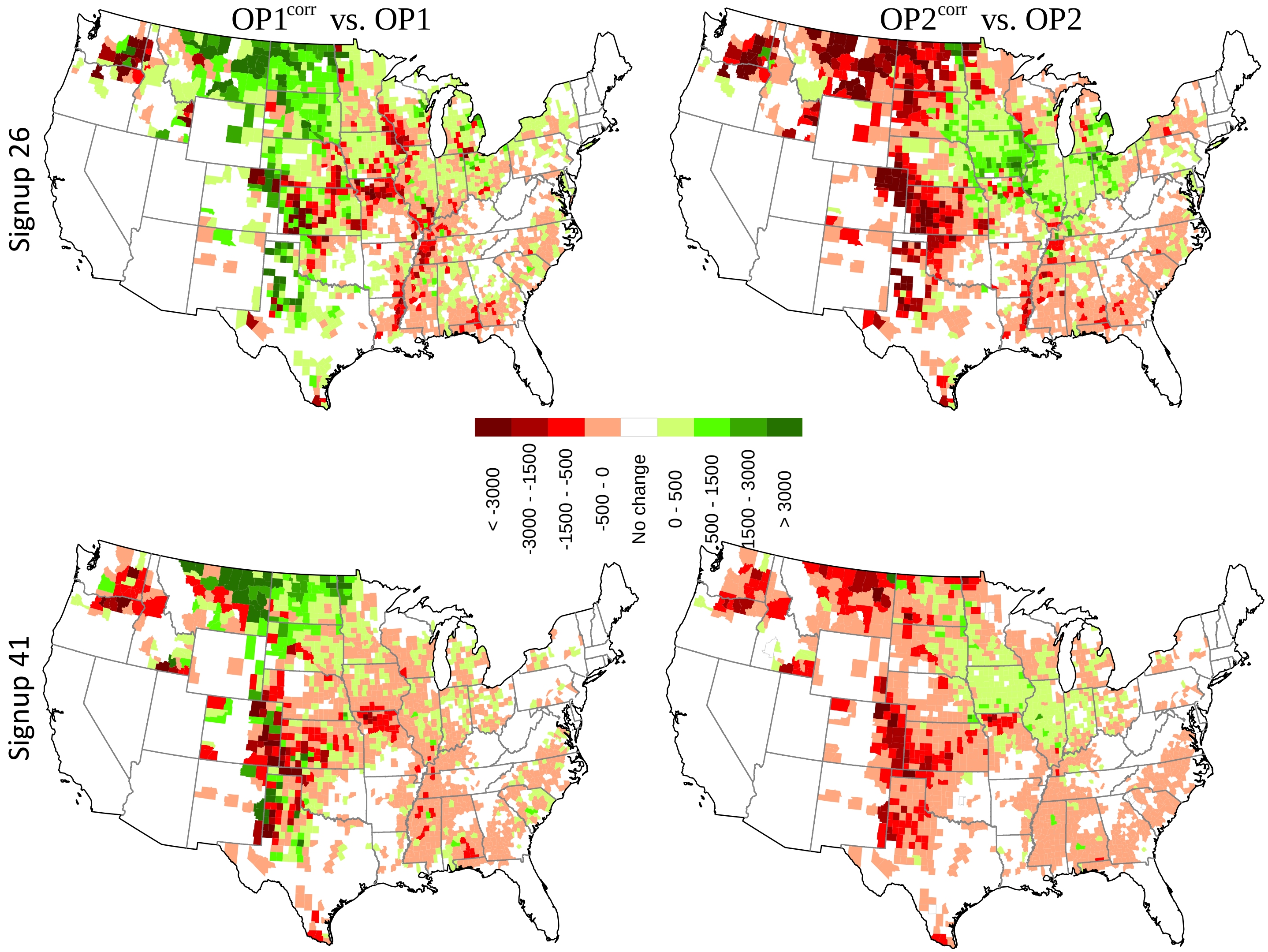

Figure S4. Changes of Acres Enrolled into CRP after Measurement Errors Drawn from a Generalized Pareto Distribution are Multiplied to EEBI. Notes: in the maps, positive numbers indicate an increase in CRP acres after accounting for the measurement errors. Counties with gray border but without color had no enrollment acreage changes whereas counties with neither border nor color had no CRP offers.

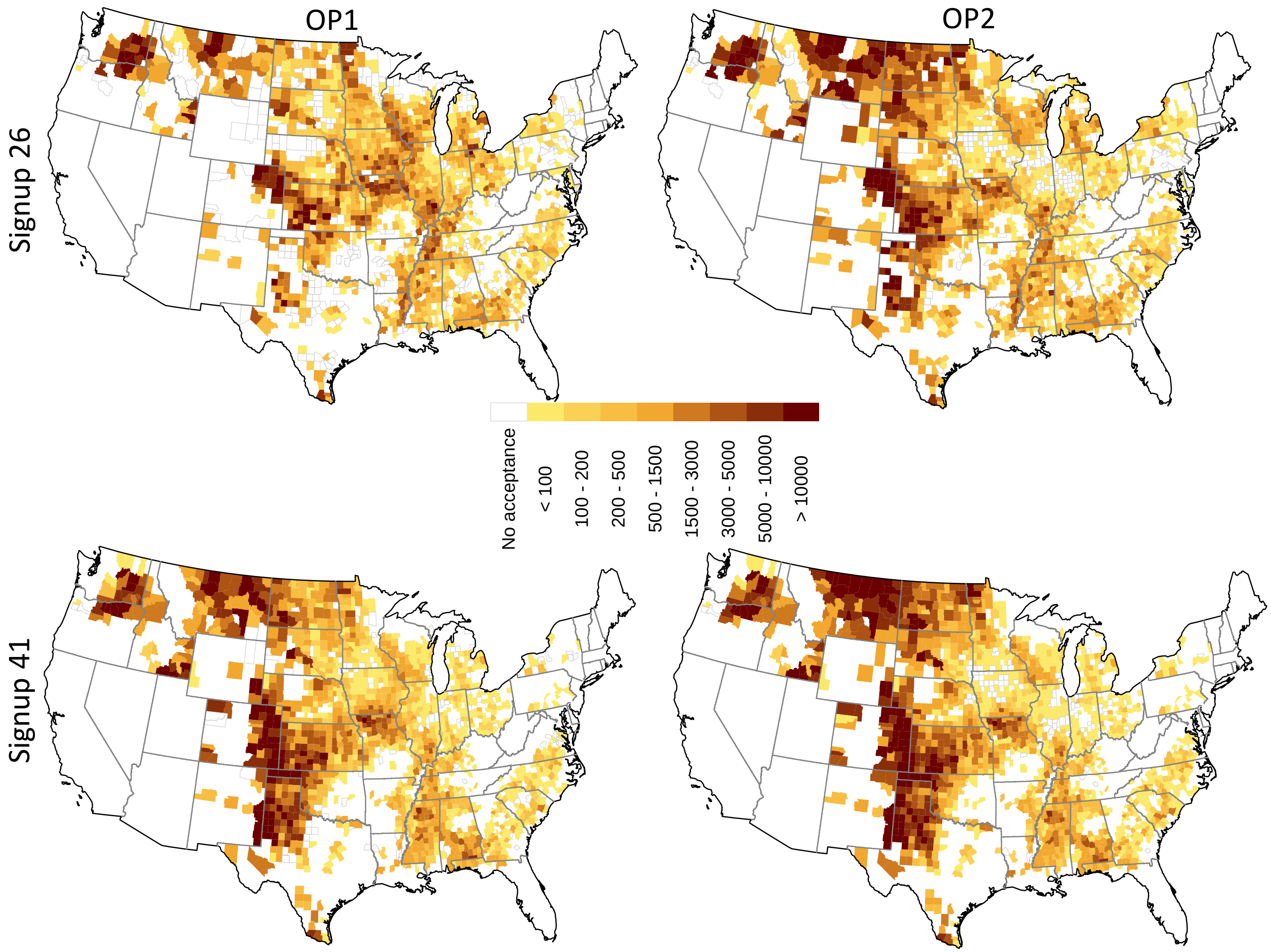

Figure S5. Acres enrolled into CRP under OP1 and OP2 when Measurement Errors are not Accounted For. Notes: in the maps, counties with gray border but without color had CRP offers but none were accepted. Counties with neither border nor color had no CRP offers.

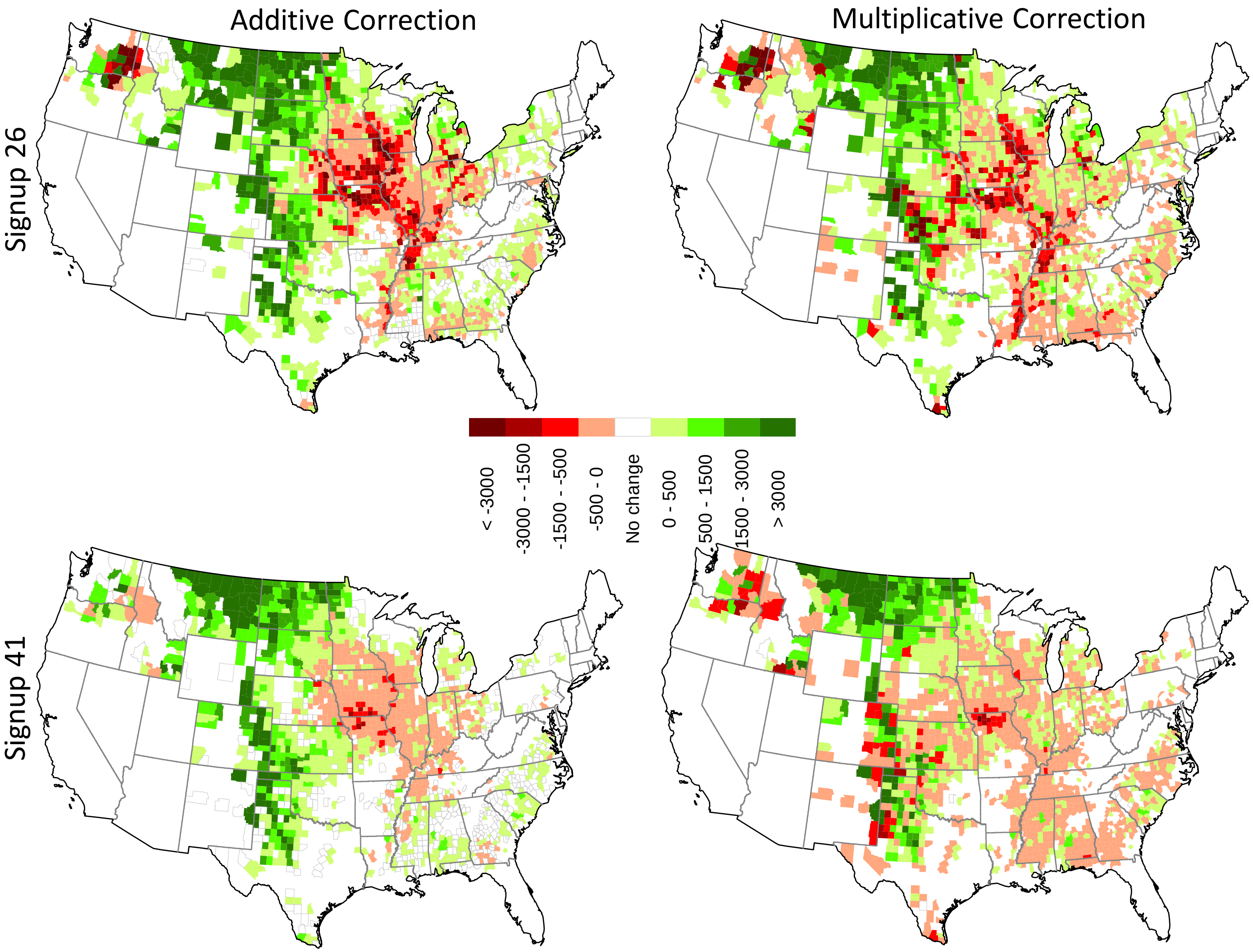

Figure S6. Changes of Acres Enrolled into CRP when Comparing OP2^{corr} with OP1 under Measurement Errors Drawn from General Pareto Distributions. Notes: in the maps, positive numbers indicate an increase in CRP acres after switching from OP1 to OP2^{corr}. Counties with gray border but without color had no enrollment acreage changes whereas counties with neither border nor color had no CRP offers.