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# Understanding the food water nexus: Characterizing the impact of climatological anomalies on agrosystems

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**UNDERSTANDING THE FOOD WATER NEXUS:  
CHARACTERIZING THE IMPACT OF CLIMATOLOGICAL ANOMALIES ON  
AGROSYSTEMS.**

**By**

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Thesis

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### **Abstract**

Climate variability at global and regional scales is escalating with increased atmospheric carbon and is expected to magnify the intensity and duration of meteorological extremes, especially droughts. From the many environmental stresses that diminish crop production (e.g., soil salinity, frost, soil erosion) drought is one of the most prevalent. This study focuses on the sensitivity of three key crops produced in the northwestern United States to climatological anomalies, while controlling for attribution using anomalies in price. The study differs from similar studies in that we focus on variability in production which captures both yield (tonnes/ha) and cropping area (ha), as opposed to only yield. We use multivariate linear regression to determine the timing and time-scale of precipitation and PET anomalies most correlated with annual crop production anomalies, and develop sensitivity coefficients using Markov chain Monte-Carlo. Counties with similar sensitivity to precipitation, PET, and price were then clustered using k-means analysis. Alfalfa was most sensitive to both precipitation and PET anomalies, with as much as 93% and 81% of the precipitation and PET anomalies translating to the production anomaly. Barley was least sensitive. The timing of precipitation and PET anomalies were generally most important in June-August. The time-scale of precipitation and PET anomaly best correlated to production was variable, but generally greater than similar studies focusing on yield. Sensitivity to precipitation anomalies followed gradients in precipitation, temperature, and soil moisture regimes present across the study area. Our research provides simple models of climate effects on production at the county scale using public data which can be implemented by agricultural producers and decision makers to quantify the impacts of climatological and economic fluctuations on annual crop production.

# 1 Introduction

Climate variability at global and regional scales is escalating with increased atmospheric carbon (IPCC, 2014) and is expected to magnify the intensity and duration of meteorological extremes, especially droughts (Easterling et al., 2000; Trenberth, 2011). In agricultural regions, climate variability affects soil moisture availability and the reliability of water sources used for irrigation, presenting challenges to agricultural water managers and increasing the risk farmers assume when they allocate resources. Farmer’s perception of risk affect how they make decisions, with potential consequences for regional agricultural production and food security.

Concerns about rural well-being, economic development and food security have led to an increasing number of studies investigating the sensitivity of crop yield and production to climate variability and drought. From the many environmental stresses that diminish crop production (e.g., soil salinity, frost, soil erosion) drought is one of the most prevalent (Shao et al., 2009). Designating a single definition of drought is impractical due to large variations in environmental, ecologic, sociologic, and agricultural responses to the timing, time-scale, and severity of drought conditions (Van Loon, 2015). In terms of agriculture, crops response to the different constituents of drought varies by cultivation and over the phenology of a given crop. Cereal crops, for example, may experience reduced productivity due to unusually high temperatures during the grain filling period, even though precipitation deficits are not present (Guendouz and Maamari, 2012). Alternatively, unusually high temperatures at the beginning of the growing season may increase cereal crop productivity by allowing for earlier sowing dates (Lanning et al., 2010). Therefore, several drought indices have been developed specifically for agriculture.

The most widely used climate index is the Palmer Drought Severity Index (PDSI), based upon precipitation, temperature, available soil water capacity, runoff, and atmospheric water demand (Palmer, 1965). McKee et al. (1993) developed the Standardized Precipitation Index (SPI), which provides a definition of drought severity accumulated over different time-scales using precipitation alone. Hobbins et al. (2016) developed the Evaporative Demand Drought Index (EDDI) which provides a definition of drought severity accumulated over different time-scales based on potential evapotranspiration (PET). Vicente-Serrano et al. (2010) developed the Standardized Precipitation Evapotranspiration Index (SPEI) to describe drought conditions accumulated over different time-scales based on precipitation and temperature. Drought indices with the ability to capture drought conditions accumulated over different time-scales have been shown to perform better for modeling crop production or yields than traditional ‘static’ indices such as the PDSI (Vicente-Serrano et al., 2012).

These indices and metrics to characterize agricultural drought focus on the impact of climate factors

33 on agricultural yields. However, producers may be able to compensate for yield reductions and maintain  
34 crop production by increasing the planted area. Therefore, total crop production (yield \* planted area)  
35 is an important metric because it captures both the efficacy of agricultural practices through crop yield  
36 (i.e., annual crop production per unit area), as well as the response of producers in terms of land allocated  
37 to particular crops based on their perception of risk, experience of climate variability, and the impact of  
38 other external factors such as agricultural markets and policy incentives (Iizumi and Ramankutty, 2015).  
39 Therefore, while crop yield alone is certainly an important component of annual crop production, focusing on  
40 yields alone fails to capture farmer response and the compensatory effects that the reallocation of land may  
41 have on total food production and may also overemphasize the role of climate variability on food security.

42 Producers not only react to climate, but are sensitive to other factors such as agricultural markets  
43 and may be able to allocate resources to maintain agricultural production even under adverse climate if  
44 market conditions are favorable. Therefore, crop price should also be considered in annual crop production  
45 models (Lobell et al., 2011). We refer to the prices the farmer receives for their produce as crop price.  
46 Crop price can impact both crop yield and crop production in complex ways, and the two are not always  
47 directly related (Miao et al., 2016). Higher crop prices could reasonably be associated with decreased crop  
48 rotation in preference of the better returning crop, which would temporarily increase production but has  
49 been associated with decreased yields over the long term (Hennessy, 2006). Alternatively, higher crop price  
50 for a given crop may encourage different crop rotations to improve soil quality, which would be associated  
51 with lower productivity but greater yields in the long term (Hennessy, 2006). The expectation of higher  
52 crop price may also result in a greater allocation of treatment systems (i.e., fertilizer, higher quality seed,  
53 pest treatment, etc.) accompanied by an increase in cropping area, resulting in increases in both yield and  
54 production. Therefore, crop prices likely play an important role in inter-annual variability in crop production.

55 This study investigates annual crop production anomalies in relation to three factors: precipitation  
56 anomalies, PET anomalies, and anomalies in the price that producers receive for their crops the year prior  
57 to production. We focus on the United States (US) states of Idaho, Montana, North Dakota, South Dakota,  
58 and Wyoming. The objectives of this study were 3 fold: 1) Quantify the sensitivity of alfalfa, barley, and  
59 winter wheat production to precipitation, PET, and price at the county scale; 2) Compare sensitivities of  
60 these factors between crops; 3) Determine and classify spatial patterns of similar sensitivities of annual crop  
61 production to precipitation, PET, and price.

## 2 Methods

### 2.1 Study Area

The study focused on crop production anomalies in Idaho, Montana, North Dakota, South Dakota, and Wyoming, all located in the inland northwest of the US. The study area covers approximately 1.2 million square kilometers, which is roughly 16% of the contiguous United States. The study region encompasses the portions of the intermountain west and the northern great plains region of the US, and includes significant longitudinal physiographic and climatic gradients associated with proximity to the Pacific Ocean and Gulf of Mexico (Salley et al., 2016). Climate gradients are further enhanced by topography and orographic effects. Idaho, western Montana, and western Wyoming are mountainous areas of the Northern Rockies region, while eastern Montana, South Dakota, North Dakota, and eastern Wyoming are flat prairies of northern Great Plains. Generally, a precipitation gradient exists moving west to east, with some areas in ID receiving an average of 1000 mm/yr of precipitation, and some areas in WY and SD receiving 200 mm/yr. Temperature generally follows a similar gradient, with cooler temperatures in the Rocky Mountains and warmer temperatures in the Northern Great Plains. Precipitation and temperature gradients are reflected in soil moisture regimes, where wetter cooler areas are associated with udic and aquic (wetter) soils in the northwest and eastern portions of the region, and dryer warmer areas are associated with xeric and ustic (drier) soils in the southwest and central portions.

Agriculture is a key industry within the study area, but is traditionally dominated by five or six major crops. We focus on three of these major crops: alfalfa, barley, and winter wheat. States in the study area are important contributors to the national production of the three crops under study. Idaho, Montana, and South Dakota ranked second, third, and fourth in US alfalfa production respectively between 2015 and 2017 (USDA NASS). Idaho, North Dakota, Montana, and Wyoming ranked first, second, third, and fifth in the US for barley production. Montana and Idaho ranked sixth and seventh in the US for winter wheat production between 2015 to 2017 (USDA NASS). Crop producers in Idaho, western? Montana, and western Wyoming benefit from widespread irrigation infrastructure, while crop production in eastern Montana, North Dakota, South Dakota, and eastern Wyoming is primarily rain-fed (USDA NASS).

### 2.2 Data

Here we investigate the response of anomalies in the annual crop production of alfalfa, barley, and winter wheat during the period of 1979 - 2016 to anomalies in precipitation, potential evapotranspiration (PET), and crop price. Precipitation and PET anomalies accumulated over 1-15 months were considered for each

92 month from March through September. Price anomalies reflected the price received by farmers the year  
93 prior to the crop production anomaly.

94 Crop production and price data were retrieved through the US Department of Agriculture National  
95 Agricultural Statistics Service (USDA NASS). Production data was retrieved at the county scale for all  
96 available counties with at least 20 years of record across the study period. Prices received were available for  
97 each crop at the state scale. Annual irrigated production of each crop was retrieved for available counties  
98 using USDA NASS. The amount of irrigation was measured by taking the ratio of total irrigated production  
99 of a given crop to the total production of that crop over the study period in each county. Counties with  
100 50% irrigated total crop production was considered as heavily irrigated, and compared to counties with 50%  
101 total irrigated crop production.

102 Precipitation and potential evapotranspiration of alfalfa (PET) data were retrieved from the University  
103 of Idaho Gridded Surface Meteorological Dataset (UofI METDATA). UofI METDATA combines the PRISM  
104 (Parameter elevation Relationships on Independent Slopes Model) and the NLDAS-2 (NASA Land Data  
105 Assimilation System version-2) models to provide a 4 km gridded daily data set for the continental US.  
106 UofI METDATA has been validated against a comprehensive network of weather stations across the US  
107 (Abatzoglou, 2013).

108 Prior to the calculation of anomalies, we detrended productivity, prices, and climatologic data over  
109 the study period using linear regression. Precipitation anomalies were determined using the Standardized  
110 Precipitation Index (SPI) (McKee et al., 1993), which characterizes drought accumulating over different  
111 time-scales, relying only on historic precipitation data. The SPI was calculated by taking the difference  
112 of precipitation, accumulated over monthly time-scales (we used 1 to 15 months), from the the detrended  
113 historic mean of that time-scale, divided by the standard deviation of that time-scale over the period of  
114 record (McKee et al., 1993). We follow the methodology of SPI calculations (McKee et al., 1993) to develop  
115 the Standardized Crop Production Index (SCPI) and the Standardized Crop Value Index (SCVI) to identify  
116 crop production anomalies and prices received anomalies occurring over the period of study at the annual  
117 time-scale. Existing studies have shown that 1 year lagged prices received and crop price futures are highly  
118 correlated, and can be used interchangeably (Miao et al., 2016). Therefore, we used prices lagged by one  
119 year.

120 Anomalies in potential evapotranspiration were determined using the Evaporative Demand Drought Index  
121 (EDDI) (Hobbins et al., 2016). EDDI provides a definition of drought that accumulates over monthly time-  
122 scales (we use 1 to 15 months), relying only on historic PET data. Hobbins et al. (2016) describes in-depth  
123 EDDI calculations over different time-scales, but is briefly described here as first calculating the empirical  
124 probability of ranked PET values summed across the time-scales of interest, and then calculating EDDI

125 values using inverse normal approximation described by Vicente-Serrano et al. (2010).

## 126 2.3 Models

127 Alfalfa yield has been shown to have a significant linear relationship with available water supply (Retta and  
128 Hanks, 1980). Changes in wheat yield in response to changes in temperature were described using linear  
129 regression by Lobell and Asner (2003) and Klink et al. (2014). Vicente-Serrano et al. (2006) predicted the  
130 ratio of sown to harvested barley and wheat using multiple linear regression based on Normalized Difference  
131 Vegetation Index and SPI. We recognized that crop production may have a non-linear relationship with  
132 climatological factors (Porter and Semenov, 2005; Schlenker and Roberts, 2009), many counties showed a  
133 linear relationship between annual crop production anomalies and climatological anomalies. Therefore, our  
134 study operates on the assumption that anomalies in annual crop production respond linearly to combined  
135 fluctuations in climatological and price anomalies. Climate fluctuations are analyzed as anomalies in precip-  
136 itation (atmospheric water supply) and potential evapotranspiration (atmospheric water demand). While  
137 climatological indices that combine precipitation and PET (i.e., SPEI) exist, our objective is to analyze the  
138 impacts of precipitation anomalies and PET anomalies on annual crop production anomalies separately. To  
139 avoid problematic issues with combining correlated independent variables into one model, and to reduce the  
140 dimensionality (e.g., degrees of freedom), we developed two separate linear models, one based on precipita-  
141 tion anomalies and price anomalies and the other based on PET anomalies and price anomalies, to describe  
142 annual crop production anomalies:

$$Prod_A = \alpha P_A + \beta_p PR_A + \gamma_p \tag{1}$$

143 where  $Prod_A$  is the annual production anomaly,  $\alpha$  is the precipitation factor,  $P_A$  is the precipitation anomaly,  
144  $\beta_p$  is the price factor produced by Equation 1,  $PR_A$  is the price anomaly, and  $\gamma_p$  is the fixed factor produced  
145 by Equation 1, and:

$$Prod_A = \delta PET_A + \beta_e PR_A + \gamma_e \tag{2}$$

146 where  $\delta$  is the PET factor,  $PET_A$  is the PET anomaly, and  $\gamma_e$  is the fixed factor produced by 2. Precipitation  
147 and PET factors will be referred to simultaneously as climatological factors. The variables were standardized  
148 so the coefficients (e.g., factors) could be directly compared, and so that coefficients could be interpreted as  
149 the proportion of independent anomaly that translated to crop production anomaly.

150 To decrease the potential of production data errors and outliers to bias the inference of the model factors,



151 we used a robust linear regression approach in which we assume that errors are t-distributed. Furthermore, to  
152 increase the robustness of the model calibration, we employ a hierarchical regression method that reflects that  
153 controls on annual crop production likely operate at different spatial scales (e.g., state wide vs. county wide  
154 irrigation infrastructure, state vs. county regulations, intra-state climate variation). Hierarchical regression  
155 also accommodated the fact that available data also was only available at a certain spatial scale, for example  
156 price data at the state scale and production and climatological data at the county scale.

157 We ran maximum likelihood simulations to identify the timing and time-scale of precipitation anomalies  
158 and PET anomalies which produced models with the lowest root mean square error (RMSE). We then  
159 expand our models to include a full distribution of possible factors using Markov chain Monte Carlo (MCMC)  
160 hierarchical robust linear regression (Figure 1) based on the timing and time-scale of climatological anomalies  
161 that produced the lowest RMSE. We established a significance level of 95% to identify counties with significant  
162 factors determined by the MCMC model.

## 163 2.4 Clustering Analysis

164 Clustering analysis was used to aggregate counties where annual crop production anomalies exhibited similar  
165 sensitivity to precipitation anomalies, PET anomalies, or price anomalies, presumably revealing spatial  
166 patterns due to climatological or economic similarities. For example, the clustering of counties most sensitive  
167 to climatological variability and least sensitive to crop price variability, or vice versa.

168 Cluster analysis is a technique used to group analogous objects (i.e., crop production in a given county)  
169 based on similar characteristics (i.e., sensitivity of crop production to precipitation, PET, and price at the  
170 county scale). Common implementations of cluster analysis include hierarchical clustering, fuzzy partition  
171 clustering, and k-means clustering. We used k-means cluster analysis to group counties with similar crop  
172 production sensitivities to precipitation, PET, and price for each crop under study. K-means cluster analysis  
173 was conducted using the mean precipitation, PET, and price factors taken from the distribution of MCMC  
174 simulations. To maximize available data, all mean factors for each county were used in the clustering analysis,  
175 regardless of the significance of these factors in respect to zero.

## 176 3 Results

177 The independent factors  $(\alpha, \beta, \delta, \gamma)$  determined by Equations 1 and 2 determined at the optimal month  
178 and time-scale represent the proportion of independent anomaly that translated to the crop production  
179 anomaly. Examples of errors produced for months during the growing season over time-scales 1-15 are  
180 provided in Figure 2, and provided for all counties and crops for Equations 1 and 2 in Appendix A and B

181 respectively. The relationship between crop production anomalies and independent anomalies were either  
182 direct or inverse, which was particularly observed for PET anomalies and price anomalies, but also observed  
183 for precipitation anomalies in some counties. Above average PET, for example, was associated with above  
184 normal crop production in some counties, yet was associated with below normal crop production in others.  
185 Similarly, below average price that producers received the year prior was associated with above average crop  
186 production in some counties, but not in others. The spatial distribution of precipitation factors and PET  
187 factors are presented in Figure 5, with counties having non-significant factors also shown. Price factors  
188 determined using both Equations 1 and 2 were similar both spatially and in magnitude, and are presented  
189 for barley and winter wheat in Figure 6 for comparison. However, only price factors determined by Equation  
190 1 are presented in the results for simplicity. Fixed factors were largely non-significant across counties for  
191 each study crop, and were situated around zero, indicating that fixed factors were not important in driving  
192 annual crop production anomalies and so are not further discussed.

### 193 **3.0.1 Alfalfa**

194 Irrigated annual alfalfa production occurred in counties across Idaho, Montana, and Wyoming. The variance  
195 in annual alfalfa production anomalies explained by Equations 1 and 2 in respect to sensitivity to climato-  
196 logical anomalies is shown in Figure 3a. The mean precipitation factor for counties with greater than 50%  
197 total irrigated annual alfalfa production was 41% and the mean PET factor was -33%, compared to a mean  
198 precipitation factor of 60% and a mean PET factor of -51% in counties with less than 50% total irrigated  
199 alfalfa production. The mean  $R^2$  value was near 0.26 for both models in counties with greater than 50%  
200 total irrigated alfalfa production, compared to 0.46 and 0.31 for Equation 1 and Equation 2 respectively for  
201 counties with less than 50% irrigation. There were, however, counties with relatively high irrigated total  
202 alfalfa production which displayed relatively high sensitivity to drought conditions, with precipitation factors  
203 as high as 83% corresponding with a  $R^2$  values as high as 0.63.

204 194 counties had sufficient alfalfa production over the study period to be considered in this study, with  
205 annual alfalfa production anomalies in 138 of these counties having significant sensitivity to precipitation  
206 anomalies. Precipitation factors for alfalfa were significant across much of Montana, North Dakota, South  
207 Dakota, and north-eastern Wyoming, but were non-significant for much of Idaho and western Wyoming.  
208 The timing and time-scale of both precipitation and PET anomalies with the highest correlation with annual  
209 alfalfa production is shown in Figure 4a. Most counties with significant sensitivity to precipitation anomalies  
210 had the greatest correlation with precipitation anomalies occurring in June ( $n = 39$ ) and July ( $n = 43$ ) over  
211 time-scales 10 - 13 months ( $n = 28$ ). All significant precipitation factors indicated a direct relationship  
212 between alfalfa production anomalies and precipitation anomalies. Sensitivity of annual alfalfa production

213 anomalies to precipitation anomalies generally increased moving east across the study area, until reaching  
214 maximum sensitivity around counties located in eastern Montana, eastern Wyoming, western North Dakota,  
215 and western South Dakota, and then decreased moving further east into eastern North Dakota and eastern  
216 South Dakota. Annual alfalfa production anomalies in west central North Dakota was the most sensitive  
217 to precipitation anomalies, with a max precipitation factor of 93% ( $R^2 : 0.75$ ), and was representative of  
218 surrounding counties in western North Dakota, eastern Montana, eastern Wyoming, and western South  
219 Dakota. Alfalfa production near eastern border of North Dakota was shown to be the least sensitive to  
220 precipitation anomalies, with a minimum precipitation factor of 13% ( $R^2 : 0.23$ ), and was also representative  
221 of counties located around the eastern border of South Dakota. The area wide mean precipitation factor for  
222 counties having significant precipitation factors was 53%, the highest among the three crops under study.  
223  $R^2$  values using Equation 1 ranged from 0.0 and 0.83, with a mean  $R^2$  of 0.38 in counties with significant  
224 precipitation factors.

225 Annual alfalfa production anomalies were significantly sensitive to PET anomalies in 149 counties, and  
226 the spatial distribution of significant PET factors was similar to that of precipitation factors. The timing of  
227 PET anomalies having the greatest correlation with annual alfalfa production anomalies was more spatially  
228 variable than with precipitation, however the most common month was June ( $n = 33$ ) over time-scales of 1 to  
229 5 months ( $n = 22$ ). Alfalfa production in north western South Dakota was most sensitive to PET anomalies,  
230 with a maximum PET factor of -81% ( $R^2 : 0.67$ ). Annual alfalfa production anomalies near the western Idaho  
231 border were least sensitive to PET anomalies with a minimum PET factor of -23% ( $R^2 : 0.23$ ). The area wide  
232 mean PET factor for counties having significant PET factors was -48%, which was significantly lower than  
233 the mean of significant precipitation factors. Therefore, precipitation anomalies were more important than  
234 PET anomalies in driving alfalfa production anomalies, although PET anomalies were still important. Alfalfa  
235 production anomalies were also significantly more sensitive to precipitation anomalies and PET anomalies  
236 than barley or winter wheat.  $R^2$  values using Equation 2 ranged from between 0.0 and 0.72, with a mean  
237  $R^2$  of 0.29 in counties with significant PET factors.

238 Price factors for alfalfa were mostly non-significant across the study area, except for in a relatively few  
239 scattered counties. Annual alfalfa production anomalies showed a inverse relationship with price anomalies  
240 in some counties, but a direct relationship in others. 15 of 25 counties which had significant price factors had  
241 an inverse relationship, or about 60%. The inverse relationship was strongest in near the southwest border of  
242 Idaho where the price factor was -65% ( $R^2 : 0.22$ ), and weakest in south-central Idaho where the price factor  
243 was -18% ( $R^2 : 0.37$ ). The mean price factor for counties with an inverse relationship with price was -35%.  
244 10 of the 25 counties with significant price factors had alfalfa production anomalies with a direct relationship  
245 with price, or about 40%. This relationship was greatest in south-central Montana with a price factor of 36%

246 ( $R^2 : 0.58$ ), and weakest at the south-eastern Idaho border with a price factor of 2% ( $R^2 : 0.63$ ). The mean  
247 price factor in counties with a direct relationship between alfalfa production anomalies and price anomalies  
248 was 27%. Price anomalies was least important to annual alfalfa production anomalies than precipitation  
249 anomalies and PET anomalies, and alfalfa was less sensitive to price anomalies than barley or winter wheat.

### 250 **3.0.2 Barley**

251 Total barley production was primarily irrigated in Idaho, western Montana, and Wyoming, and was primarily  
252 rain fed in eastern Montana, North Dakota, and South Dakota. Irrigation had minimal effect on annual barley  
253 production anomalies compared to rainfed annual production anomalies. The variance in annual barley  
254 production anomalies explained by Equations 1 and 2 in respect to sensitivity to climatological anomalies is  
255 shown in Figure 3b. The mean precipitation factor for counties with greater than 50% irrigated annual barley  
256 production, a direct relationship with precipitation and an indirect relationship with PET saw essentially no  
257 change in precipitation factors or PET factors. Counties with annual barley production anomalies with a  
258 inverse relationship with precipitation anomalies and a direct relationship with PET anomalies were only  
259 observed in one county with greater than 50% irrigation.

260 190 counties had adequate barley production over the study period to be considered in this study, with  
261 annual barley production anomalies in 120 of these counties having significant sensitivity to precipitation  
262 anomalies. The timing and time-scale of both precipitation and PET anomalies with the highest correlation  
263 with annual winter wheat production is shown in Figure 4b. Precipitation factors were found to be significant  
264 across much of Montana and southern Idaho, and non-significant across northern Idaho. The significance  
265 of precipitation factors in North Dakota, South Dakota, and Wyoming were mixed. Most counties with  
266 significant sensitivity to precipitation anomalies had the greatest correlation with precipitation anomalies  
267 occurring in July ( $n = 52$ ), however time-scales across counties were very mixed between 1 and 12 months.  
268 Annual barley production anomalies in counties with significant precipitation factors showed a direct rela-  
269 tionship with precipitation anomalies in 115 counties with significant precipitation factors, or about 96% of  
270 counties with significant precipitation factors. The direct relationship was strongest in the north-west corner  
271 of South Dakota with a maximum precipitation factor of 63% ( $R^2 : 0.42$ ), and the direct relationship was  
272 weakest near the eastern border of North Dakota with a minimum precipitation factor of 12% ( $R^2 : 0.04$ ).  
273 The mean precipitation factor of counties shown to have had a direct relationship between precipitation  
274 anomalies and barley production anomalies was 34%.  $R^2$  values using Equation 1 ranged from between  
275 0.0 and 0.48 in counties with significant precipitation factors and a direct relationship between annual bar-  
276 ley production anomalies and precipitation anomalies, with a mean  $R^2$  of 0.17. Annual barley production  
277 anomalies showed an inverse relationship with precipitation anomalies in 5 counties, or about 4% of coun-

278 ties with significant precipitation factors. All counties which showed a inverse relationship between annual  
279 barley production anomalies and precipitation anomalies occurred in August over a time-scale of one month,  
280 and were located around central and north-central North Dakota. The inverse relationship was strongest in  
281 north-central North Dakota with a maximum precipitation factor of -25% ( $R^2 : 0.14$ ), and weakest near the  
282 center of North Dakota with a minimum precipitation factor of -21% ( $R^2 : 0.01$ ).  $R^2$  values using Equation  
283 1 ranged between 0.0 and 0.24 for models of annual barley production anomalies in counties with significant  
284 precipitation factors and a indirect relationship with precipitation anomalies, with a mean  $R^2$  of 0.15.

285 Annual barley production anomalies were significantly sensitive to PET anomalies in 149 counties. PET  
286 factors for barley were significant in most counties in North Dakota, while the remaining states were a mix  
287 of counties with significant and non-significant PET factors. Most counties with significant sensitivity to  
288 PET anomalies had the greatest correlation with PET anomalies occurring in September ( $n = 36$ ) and July  
289 ( $n = 24$ ) over time-scales of 3 months ( $n = 19$ ) and 1 - 2 months ( $n = 21$ ) respectively. Barley production  
290 anomalies showed a direct relationship with PET anomalies in 10 of the 81 counties with significant PET  
291 factors, and were mostly located around eastern Montana with PET factors ranging from 16% to 22%  
292 and a mean of 19%.  $R^2$  values using Equation2 ranged between 0.0 and 0.16 for models of annual barley  
293 production anomalies in counties with significant PET factors and a direct relationship with PET, with  
294 a mean  $R^2$  of 0.03. The remaining 71 counties with significant PET factors had an inverse relationship,  
295 or around 88% of counties with significant PET factors. The greatest inverse relationship between barley  
296 production anomalies and PET anomalies was located near the center of North Dakota with a maximum  
297 PET factor of -45% ( $R^2 : 0.23$ ), and was weakest in northern Idaho with a PET factor of -15% ( $R^2 : 0.01$ ).  
298 The mean significant PET factor of counties which had an inverse relationship between barley production  
299 anomalies and PET anomalies was -32%.  $R^2$  values using Equation 2 ranged between 0.0 and 0.55 for models  
300 of annual barley production anomalies in counties with significant PET factors and a indirect relationship  
301 with PET, with a mean  $R^2$  of 0.18.

302 Barley production was more sensitive to price than alfalfa production, but less sensitive to price than  
303 winter wheat production. Price factors of barley production were significant in many counties in Montana,  
304 but were mixed across counties in Idaho, North Dakota, South Dakota, and Wyoming. Annual barley  
305 production anomalies showed a direct relationship with price in 114 of 126 counties with significant price  
306 factors, or about 90%. The direct relationship between barley production anomalies and price anomalies  
307 was greatest near the south eastern border of Idaho with a price factor of 53% ( $r^2 : 0.16$ ), and least in  
308 north-eastern Montana with a price factor of 0.16% ( $R^2 : 0.07$ ). The mean price factor for counties with a  
309 direct relationship between barley production anomalies and price anomalies was 27%. Barley production  
310 anomalies showed an inverse relationship with price anomalies in 12 of 126 counties, or about 10%. The

inverse relationship between barley production anomalies and price anomalies was greatest was near south-eastern North Dakota with a price factor of -54% ( $R^2 : 0.28$ ), and was the least in north-central South Dakota with a price factor of -10% ( $R^2 : 0.26$ ). The mean price factor for counties which had an inverse relationship between barley production anomalies and price anomalies was -39%.

### 3.0.3 Winter Wheat

Irrigated total winter wheat production was extensive in western Wyoming, moderate in southern Idaho, and present but light in Montana and eastern Wyoming. The variance in annual winter wheat production anomalies explained by Equations 1 and 2 in respect to sensitivity to climatological anomalies is shown in 3c. Counties with greater than 50% total irrigated winter wheat production had a mean precipitation factor of 31% and a mean PET factor of 30%, compared to a mean precipitation factor of 38% and a PET factor of 29% in counties with less than 50% total irrigated winter wheat production. The mean  $R^2$  value in counties with greater than 50% total irrigated winter wheat production was 0.20 for Equation 1 and 0.13 for Equation 2, compared to 0.26 and 0.18 in counties with less than 50% total irrigated production. Similar to annual barley production anomalies, no inverse relationship between annual winter wheat production anomalies and precipitation or direct relationship with PET anomalies was observed in any counties with greater than 50% total irrigated winter wheat production.

201 counties had adequate winter wheat production over the study period to be considered in this study, with 138 of these counties having significant sensitivity to precipitation anomalies. Winter wheat production was generally less sensitive to precipitation than alfalfa production, but more sensitive to precipitation than barley production. The timing and time-scale of both precipitation and PET anomalies with the highest correlation with annual winter wheat production is shown in Figure 4c. Most counties with significant sensitivity to precipitation anomalies had the greatest correlation with precipitation anomalies occurring in June ( $n = 30$ ) over time-scales of between 5 and 15 months ( $n = 24$ ). Precipitation factors for winter wheat production were significant across counties in Montana and Wyoming, and in many counties in South Dakota, while counties in Idaho and North Dakota were a mix of significant and non-significant precipitation factors. Winter wheat production anomalies showed a direct relationship with precipitation anomalies in 143 of the 144 counties where precipitation factors were significant, or about 99%. The direct relationship between winter wheat production anomalies and precipitation anomalies was greatest in south-central South Dakota with a maximum precipitation factor of 65% ( $R^2 : 0.41$ ), and least in the north-west corner of North Dakota with a minimum precipitation factor of 14% ( $R^2 : 0.19$ ). The mean precipitation factor for counties which had a significant and direct relationship with winter wheat production was 37%. Only one county located near the south-west corner of North Dakota had an inverse relationship between precipitation

343 anomalies and winter wheat production anomalies with a precipitation factor of -17% ( $R^2 : 0.18$ ).  $R^2$  values  
344 using Equation 1 ranged between 0.0 and 0.73, with a mean  $R^2$  of 0.26.

345 Significant PET factors were found across counties in Wyoming, central Montana, much of North Dakota,  
346 western South Dakota, and in counties on the southern border of Idaho. Winter wheat production anomalies  
347 showed a direct relationship with PET in 27 of the 99 counties where PET factors were significant, or  
348 about 27%. Counties with a direct relationship between winter wheat production anomalies and PET  
349 anomalies were largely found in North Dakota, with a few counties also found in eastern Montana. The  
350 direct relationship between winter wheat production anomalies and PET anomalies was greatest on the  
351 eastern border of Montana with a maximum PET factor of 40% ( $R^2 : 0.20$ ), and least in eastern North  
352 Dakota with a minimum PET factor of 11% ( $R^2 : 0.12$ ). Winter wheat production anomalies showed an  
353 inverse relationship with PET anomalies in 72 of the 99 counties where PET factors were significant, or  
354 about 73%. The inverse relationship between winter wheat production anomalies and PET anomalies was  
355 greatest in the south-east corner of Wyoming with a maximum PET factor of 60% ( $R^2 : 0.51$ ), and least  
356 in the south-east corner of Idaho with a minimum PET factor of -5% ( $R^2 : 0.0$ ). The mean PET factor  
357 for counties with a significant and indirect relationship between precipitation anomalies and annual winter  
358 wheat production anomalies was -29%.  $R^2$  values using Equation 2 ranged from 0.0 and 0.58, with a mean  
359  $R^2$  of 0.25.

360 Annual winter wheat production was more sensitive to price anomalies than alfalfa and barley. Price  
361 factors were significant in many counties across Montana, and most counties in North Dakota, although  
362 price factors were non-significant in most of Idaho, South Dakota, and Wyoming. Winter wheat production  
363 showed a direct relationship with price anomalies in 158 of 160 counties where price factors were significant,  
364 or about 99%. The direct relationship between winter wheat production anomalies and price anomalies was  
365 greatest near the western border of South Dakota with a maximum price factor of 100%, and least near the  
366 center of South Dakota with a minimum price factor of 9%. The mean price factor for counties which had  
367 a significant direct relationship with price was 46%. The two counties with significant factors showing an  
368 inverse relationship between price and winter production anomalies were both located in Idaho, with the  
369 greatest inverse relationship with a price factor of -0.25, and the least inverse relationship with a price factor  
370 of -0.09.

### 371 **3.0.4 Clustering Analysis**

372 The clustering analysis grouped counties with similar sensitivity of annual crop production anomalies to  
373 precipitation anomalies, PET anomalies, and price anomalies for each crop. An optimal number of three  
374 clusters was determined for all three crops. Counties cluster classifications and the distribution of factors

375 within each cluster are presented for alfalfa, barley, and winter wheat in Figures 7, 8, and 9 respectively.

376 Alfalfa production anomalies in cluster one counties had the greatest negative drought response to both  
377 precipitation anomalies and PET anomalies. Cluster one counties were also least sensitive to price, where  
378 price factors were generally weak and situated around zero. Counties classified by cluster one were mostly  
379 found in North Dakota, South Dakota, north-east Wyoming, and a few counties in eastern Montana; counties  
380 primarily rain-fed with little irrigation. Cluster two counties generally had the greatest positive response to  
381 price anomalies. Cluster two counties were generally less sensitive to precipitation and PET than counties in  
382 cluster one, but more sensitive than cluster three. Cluster two mainly described annual alfalfa production in  
383 Montana. Alfalfa production anomalies in counties classified in cluster three were generally least sensitive to  
384 precipitation anomalies and PET anomalies. Cluster three also described counties where alfalfa production  
385 anomalies had a negative response to positive price anomalies, indicating farmers increase alfalfa production  
386 after receiving lower prices the year prior. Cluster three mainly described counties in Idaho, Wyoming,  
387 counties toward the western boundaries of North Dakota and South Dakota. Alfalfa production in many  
388 counties in Idaho and western Wyoming is irrigated.

389 Barley production anomalies in cluster one counties was largely associated with a negative drought  
390 response in terms of both precipitation anomalies and PET anomalies. Price factors in cluster one were  
391 mostly positive and similar in magnitude to cluster three counties. Counties classified in cluster one were  
392 found in all states within the study area, describing most of Idaho, Wyoming, South Dakota, and western  
393 Montana. Cluster two largely described counties where barley production anomalies showed a positive  
394 response to negative price anomalies. Cluster two had high variability in terms of sensitivity to precipitation  
395 anomalies, where counties had both negative and positive drought response. Barley production anomalies  
396 in cluster two counties generally showed a negative drought response in terms of PET. Cluster two counties  
397 were largely located in North Dakota. Barley production anomalies in cluster three counties was unique in  
398 that most counties had a positive drought response in terms of PET, where increased atmospheric demand  
399 was associated with increased barley production. However, cluster three counties had a similar negative  
400 drought response to precipitation as cluster one. Annual barley production anomalies generally had a positive  
401 response to positive price anomalies. Cluster three counties were largely located in eastern Montana, but  
402 were also scattered around Idaho, North Dakota, and South Dakota.

403 Annual winter wheat production anomalies in counties characterized by cluster one were least impacted  
404 by anomalies in precipitation, PET, and price. Counties classified as cluster one were mostly found in  
405 Idaho and counties near the eastern borders of North Dakota and South Dakota. Cluster two had the  
406 greatest positive price response, and largely consisted of counties where annual winter wheat production  
407 had a positive response to higher atmospheric demand, with a few counties where a weak negative drought



408 response to positive PET anomalies was observed. Generally, annual winter wheat production showed  
409 a negative drought response to negative precipitation anomalies. Cluster two counties comprised much of  
410 North Dakota and eastern Montana, and northwest Montana. Annual alfalfa production anomalies in cluster  
411 three had the greatest negative drought response in terms of precipitation and PET, and had a weak and  
412 mostly positive response to price. These counties comprised annual wheat production in most of North  
413 Dakota, eastern Wyoming, west and central Montana, and parts of southern Idaho.

## 414 **4 Discussion**

415 A comprehensive understanding of the main drivers behind crop production variability is key to ensuring that  
416 resources are appropriately allocated to maximize the efficacy of future agricultural practices Lipper et al.  
417 (2014). This study focused on the sensitivity of annual crop production anomalies to climatological anomalies  
418 and price anomalies for three key crops produced in the northwestern United States. Our research differs  
419 from existing studies which focused specifically on yield, in that we focused on productivity to incorporate  
420 into our analysis both variability in yield and variability in farmer response through cropping area allocation.  
421 We found large spatial and temporal variability in sensitivities of annual crop production to precipitation,  
422 PET and price anomalies, indicating that small scale analysis (e.g., county scale) is optimal for understanding  
423 or predicting variability in annual crop production. Our research provided two simple models at the county  
424 scale using public data which can be implemented by agricultural producers and decision makers to quantify  
425 the impacts of climatological and economic fluctuations on annual crop production. Furthermore, we provide  
426 classifications of counties which describe the appropriateness of the models.

427 Multiscalar climatological indices have been used to identify the timing and time-scale of drought condi-  
428 tions that most impact crop productivity in several recent studies with relatively clear results. Zipper et al.  
429 (2016) showed how maize and soy yield anomalies in the US were most correlated with drought conditions  
430 occurring during July and August over time-scales of 1-3 months, or about 1 to 2 months prior to harvest.  
431 Vicente-Serrano et al. (2006) used a one and three month SPI in February, 4 months prior to harvest, to  
432 explain greater than 80% of temporal variability in wheat and barley production (defined as the proportion  
433 between sown and harvested crop) in north-east Spain. However, Peña-Gallardo et al. (2018) showed more  
434 spatial variability in the timing of SPEI for county scale barley and winter wheat yields in the US, with  
435 many counties being most sensitive over time-scales longer than three months. The highest correlation in this  
436 study often occurred at longer time-scales ( $> 7$  months), much longer than the shorter time-scales identified  
437 in Zipper et al. (2016) and Vicente-Serrano et al. (2006). This is likely due to our focus on production which  
438 is a function of both yield and cropping area, thus incorporates farmer decision making into the analysis.

439 Higher correlations at longer time-scales indicated that farmers likely considered current climate conditions,  
440 seasonal forecasts, or used traditional knowledge to estimate the possibility of drought conditions during  
441 the season when deciding cropping area, months before crops are sown. This relationship between farmer  
442 decision making early in the season and drought conditions occurring later in the season over long time-scales  
443 is supported by Haigh et al. (2015), who found that over 80% of producers in the US Corn Belt decided  
444 on cropping area between mid-fall and late-winter, and that over 50% of the same producers used current,  
445 monthly or seasonal drought forecasts to aid in their decisions. However, this largely speculation, as studies  
446 focusing on annual crop production in respect to the timing and time-scale of climatological anomalies is  
447 limited.

448 Sensitivity of annual crop production to precipitation and PET anomalies generally coincided with gradi-  
449 ents in precipitation, temperature, and soil moisture regimes moving across the study area. This is generally  
450 in agreement with Lobell et al. (2011), who showed that crop yields in warmer regions were generally more  
451 sensitive to climatological variability than cooler regions. Existing studies provide insight into how these  
452 sensitivities may affect future variability in annual crop production. Ficklin and Novick (2017) showed that  
453 vapor pressure deficit has decreased in eastern Montana and North Dakota from 1979-2013. This trend could  
454 not only impact annual crop production in terms of atmospheric water supply and demand, but may also  
455 have implications to changes in soil moisture regime. Salley et al. (2016) found that the soil transition from  
456 ustic (drier) to udic (wetter) soils is closely related to the isohyet running roughly north to south through  
457 western North Dakota and central South Dakota where precipitation equals PET. While precipitation trends  
458 within the study area over the same period are, to the best of our knowledge, not currently available in the  
459 literature, decreased VPD alone may be associated with the isohyet migrating west. This trend could have  
460 positive implications for alfalfa production in the region (e.g., counties described by cluster one), where  
461 alfalfa was most sensitive to atmospheric water demand. However, winter wheat production described by  
462 cluster two, and barley production described by cluster three showed a slightly positive production response  
463 to increased atmospheric water demand. It is therefore a reasonable expectation that production of winter  
464 wheat and barley production may decline with decrease in VPD. Furthermore, winter wheat production in  
465 cluster two and barley production in cluster three had greater sensitivity to price, likely made possible by  
466 lesser sensitivity to climatological anomalies. Decreases in VPD in the region may be cause for farmers to  
467 reassess future production strategies to put more emphasis on climatological variability. Ficklin and Novick  
468 (2017) also showed that VPD is increasing in many counties where crop production was least sensitive to  
469 PET and precipitation. These regions are buffered from climatological anomalies by irrigation and wetter  
470 soils. However increased VPD may stress irrigation supply and diminish soil moisture, thus increasing sen-  
471 sitivity to climatological anomalies and reducing production. Further work concerning historic sensitivity

472 to climatological anomalies in conjunction with historic trends in atmospheric water supply and demand,  
473 and if these relationships are changing, would provide useful insights into how the equilibrium between crop  
474 production and climate variability will shift moving into the future.

475 The positive crop production response to drought observed in this study for barley and winter wheat  
476 was also observed by Lobell and Asner (2003) and Zipper et al. (2016) for corn and soybean yields, where  
477 increased crop yields occurred during periods of below average precipitation or above average atmospheric  
478 water demand. Zipper et al. (2016) attributed negative drought sensitivity to shallow groundwater and poorly  
479 drained soils, or the presence of irrigation. We found in our study area that positive production response  
480 to drought occurred in rainfed areas where minimal irrigation was present, largely in eastern Montana and  
481 North Dakota. Our study indicated that negative drought sensitivity was primarily associated with a direct  
482 relationship between production and PET, and was less associated with an inverse relationship between  
483 annual production anomalies and precipitation anomalies. While irrigation can work to mitigate stress  
484 caused by above normal temperatures associated with above average PET by removing energy from the  
485 plant surface through latent heat (Asseng et al., 2011), irrigation would need to be continuously available to  
486 the plant surface over the entire course of the PET anomaly for the temperature mitigation affect to be fully  
487 realized, something not always possible due to water limitations often associated with periods of drought.  
488 Thus, the positive crop production response to drought observed for barley and winter wheat production is  
489 most likely due to areas with poorly drained soils where increased atmospheric water demand worked to dry  
490 soils to moistures more suitable for plant growth.

491 While the analysis in this study provided reasonable results in quantifying the sensitivity of annual  
492 crop production anomalies to anomalies in precipitation, PET, and price in primarily rainfed counties, it  
493 is important to note several limitations of the linear relationship proposed in our study. Overwhelming  
494 pluvial conditions would likely break the direct relationship between annual crop production anomalies and  
495 precipitation anomalies observed in most counties. These occurrences are rare in the semi-arid climate within  
496 our particular study area, however may be observed in wetter regions. Furthermore, isolated events such  
497 as hail storms or tornadoes may not produce adequate precipitation to result in an anomaly, but can result  
498 in serious crop damage and drastic decrease in annual crop productivity. Insect or disease outbreaks in  
499 croplands associated with drought may be present during some years and not others (Rosenzweig et al.,  
500 2001). While these phenomena are beyond the scope of this study, they are important considerations to  
501 understanding interannual variability in crop production and are generally poorly understood Iizumi and  
502 Ramankutty (2015).

## 503 4.1 Conclusion

504 This study quantified the sensitivity of annual crop production anomalies to climatological and price anomalies of three crops produced in the northwest US at time-scales most correlated with variability in annual  
505 crop production. Spatial variability of sensitivity to these driving factors were classified into three clusters  
506 for each crop. Annual alfalfa production was shown to be most sensitive to precipitation anomalies, particularly in rain-fed counties, and barley was least sensitive. Irrigation most reduced the sensitivity of alfalfa  
507 to climatological anomalies, while the effect of irrigation on barley production was less clear. Clustering  
508 analysis generally grouped counties spatially coincident with gradients in precipitation, temperature, and  
509 soil moisture regimes moving across the study area. Further study into changing sensitivity to climatological  
510 variability and changes in atmospheric water demand and supply may provide insight into how variability  
511 in annual crop production may change moving into the future. Our research provided simple models at the  
512 county scale using public data which can be implemented by agricultural producers and decision makers to  
513 quantify the impacts of climatological and economic fluctuations on annual crop production. Furthermore,  
514 we provide classifications of counties which describe the appropriateness of the models.  
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516

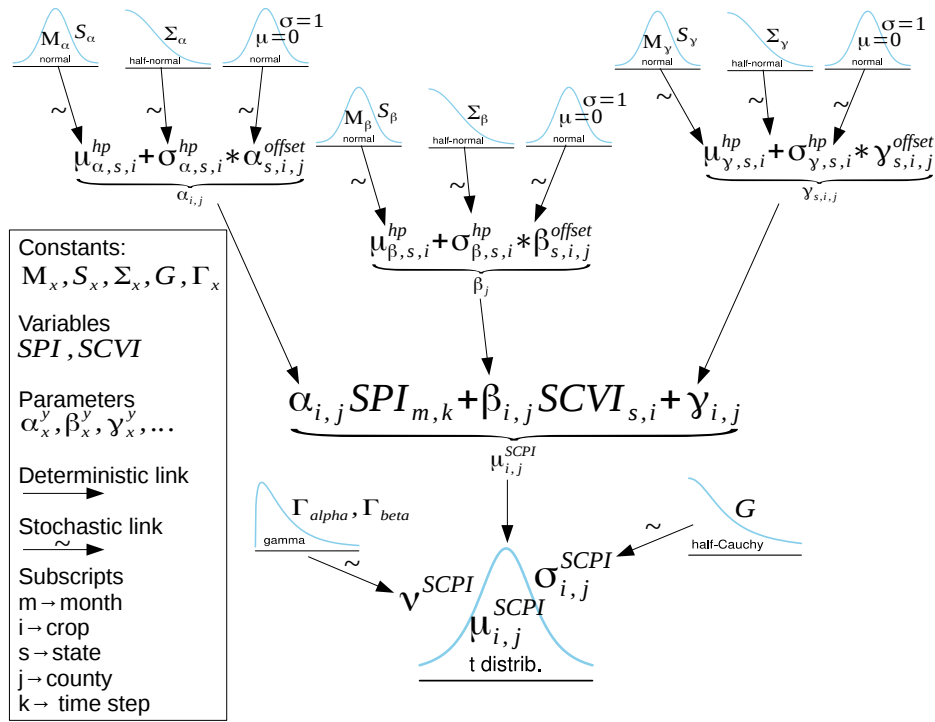


Figure 1: Kruschke style diagram of the Markov chain Monte Carlo hierarchical robust linear regression model showing the probability distributions used in Equation 1. The same model structure was used for Equation 2, except the EDDI index was used as the independent climatological variable.

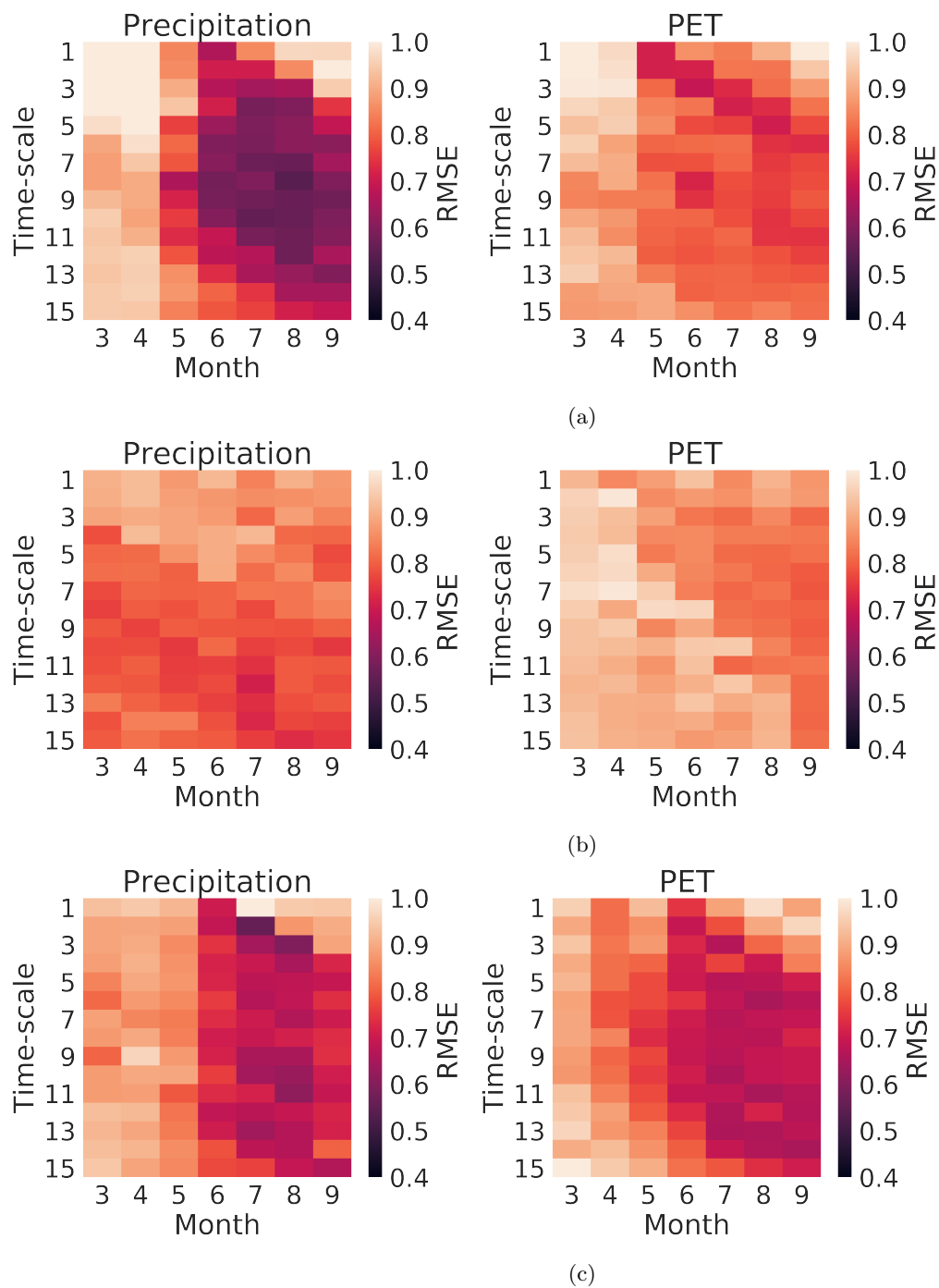
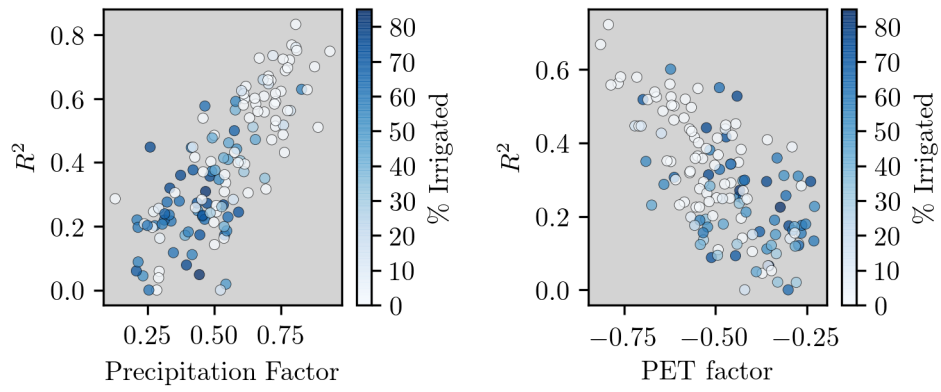
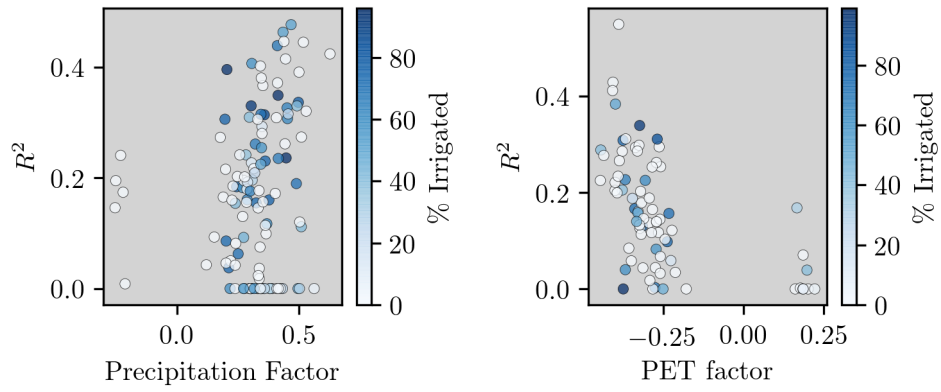


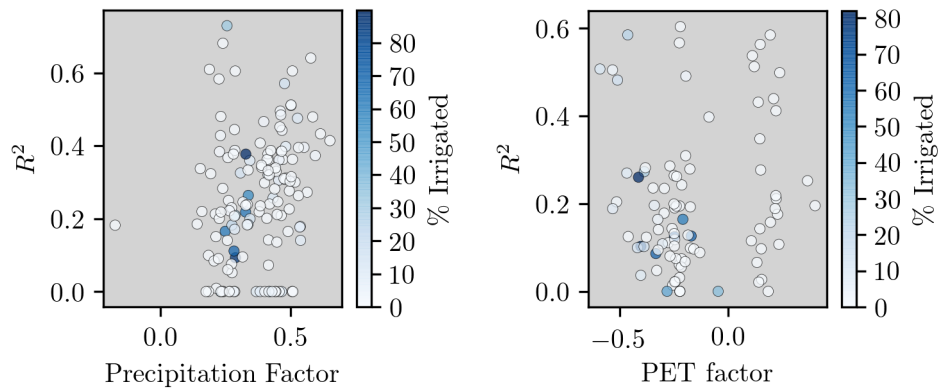
Figure 2: Heatmap examples showing root mean square error (RMSE) for months during the growing season using 1 (left) and 2 (right) for alfalfa (a), barley (b), and winter wheat (c).



(a)

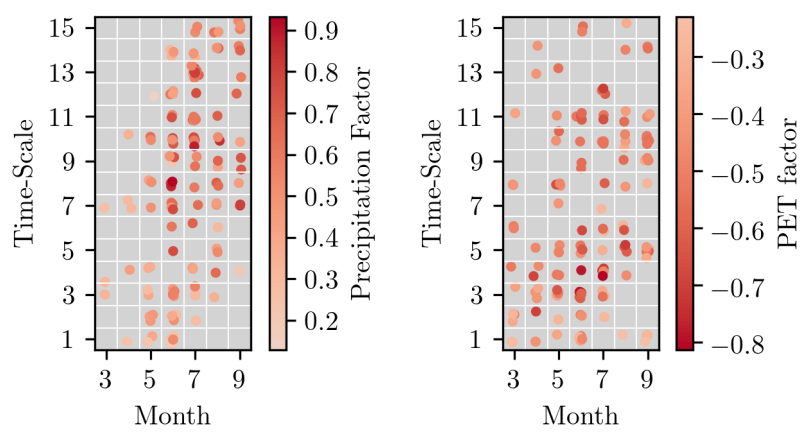


(b)

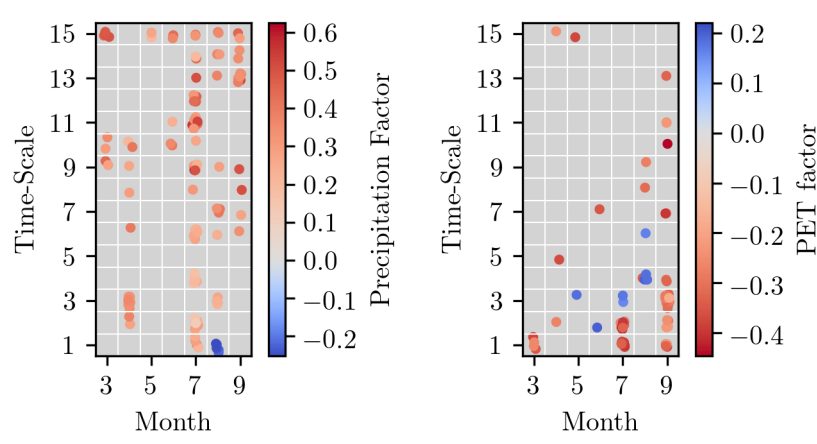


(c)

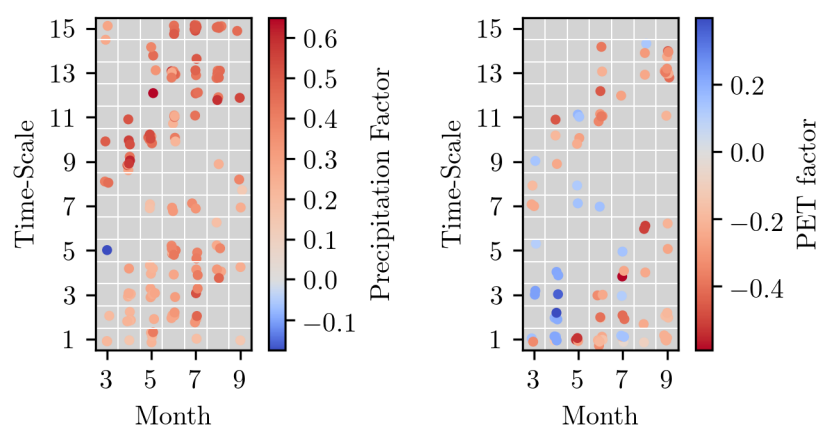
Figure 3: Plots showing the relationship between variance explained and climatological factors determined by 1 (left) and 2 (right) for alfalfa (a), barley (b), and winter wheat (c). Cooler colors indicate greater total irrigated production for the study period.



(a)



(b)



(c)

Figure 4: Plots showing the (randomly jittered) month and time scale having the highest correlation with annual crop production anomalies for each county, scaled by precipitation factors (left) and PET factors (right) for alfalfa (a), barley (b), and winter wheat (c). Warmer colors indicate a greater negative drought response, and cooler colors indicate a greater positive drought response.



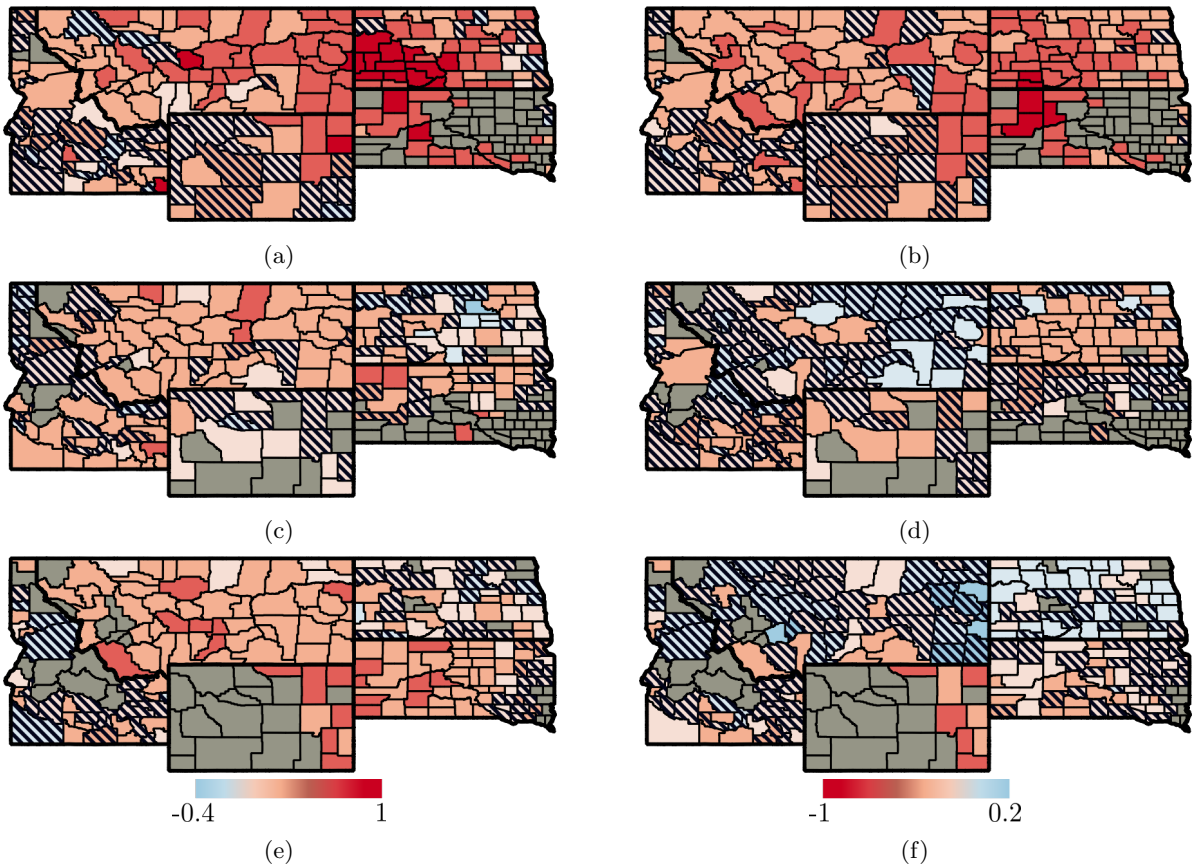


Figure 5: Spatial distribution of precipitation factors (left column) and PET factors (right column) for alfalfa (a) and (b), barley (c) and (d), and winter wheat (e) and (f). Warmer colors indicate a negative response in crop production anomalies to negative precipitation anomalies or positive PET anomalies (i.e., negative drought response), and cooler colors indicate a positive response in crop production anomalies to negative precipitation anomalies or positive PET anomalies (i.e., positive drought response). Diagonal lines across counties indicate non-significant factors.

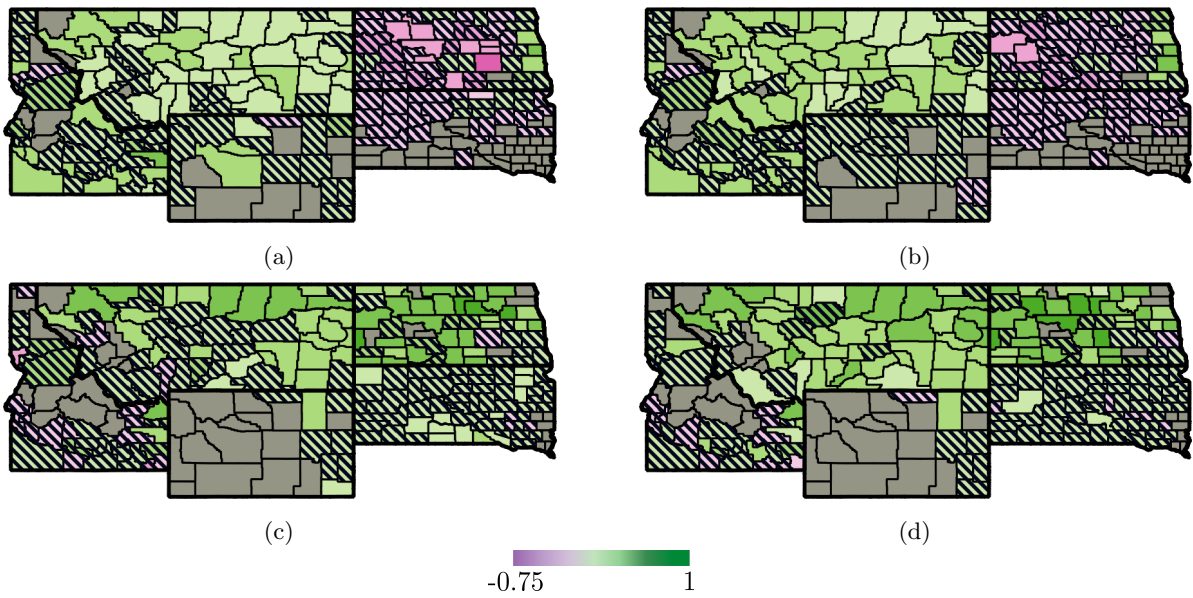


Figure 6: Spatial distribution of price factors derived from Equation 1 (left column) and Equation 2 (right column) for barley (a) and (b) and winter wheat (c) and (d). Purples indicate a negative response of crop production anomalies to positive price anomalies and greens indicate a positive response of crop production anomalies to positive price anomalies. Diagonal lines across counties indicate non-significant factors. Price factors for alfalfa were non-significant in most counties and so is not included.

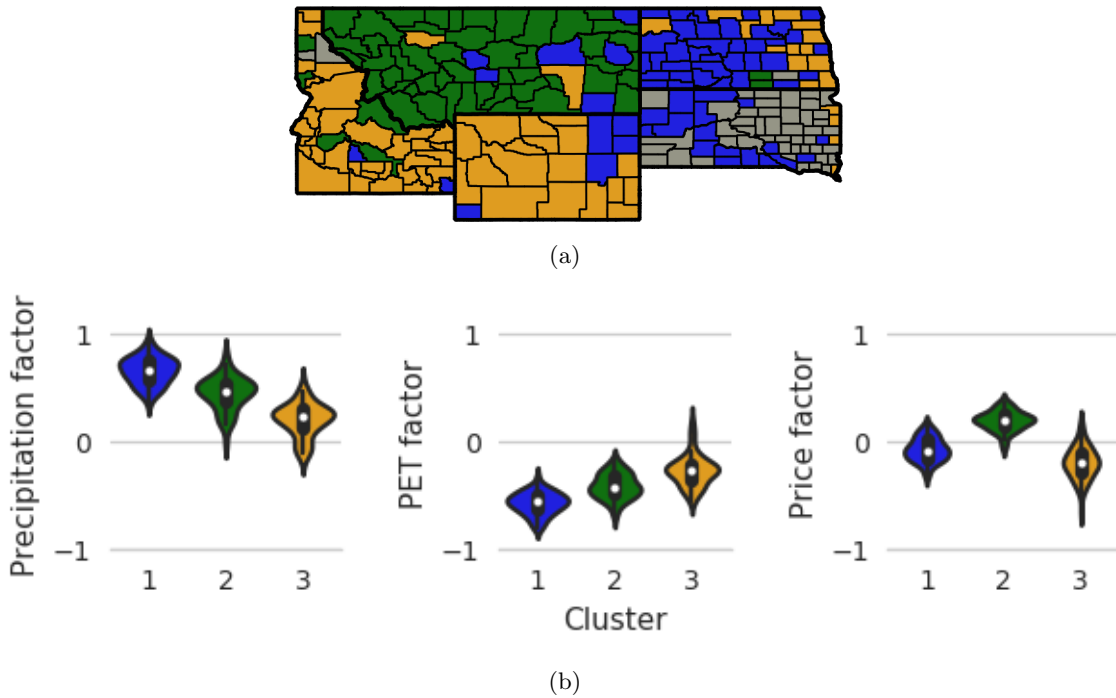
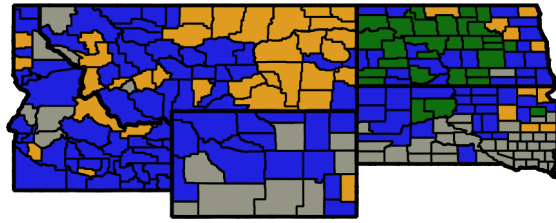
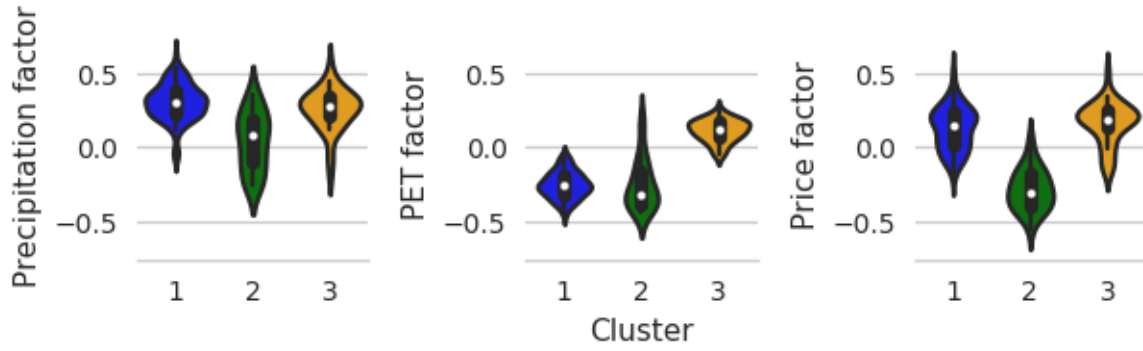


Figure 7: (a) is a map showing county classifications for alfalfa production based on clustering. (b) are violin plots showing the distribution of precipitation factors (left), PET factors, (middle), and price factors (right) for clusters 1 (blue), 2 (green) and 3 (orange).

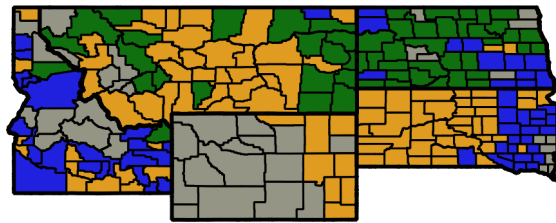


(a)



(b)

Figure 8: Same as Figure 7 but for barley.



(a)



(b)

Figure 9: Same as Figure 7 but for winter wheat.

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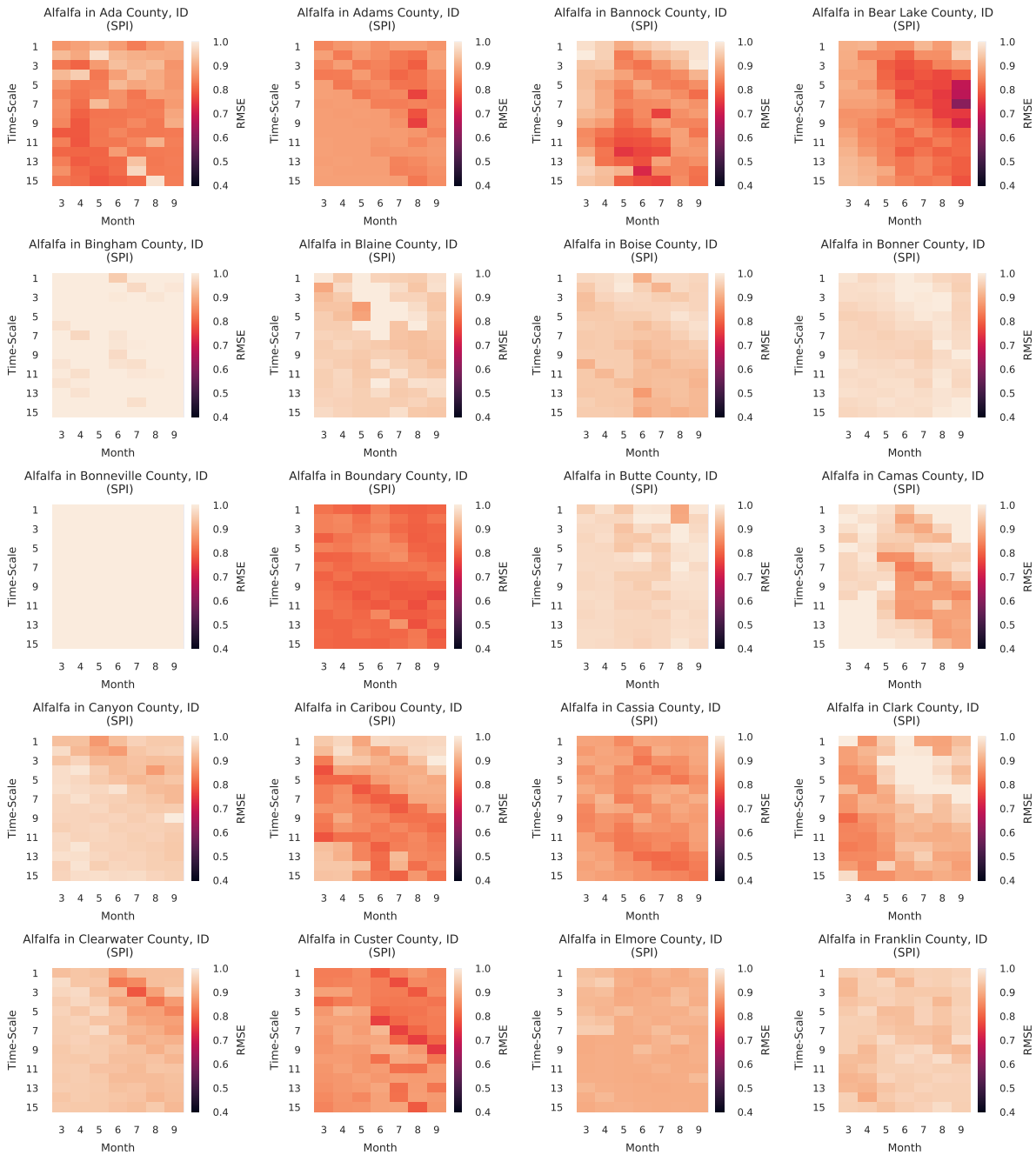
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608 **Appendix A RMSE from Equation 1 over months 3-9 and time-**  
609 **scales 1-15**

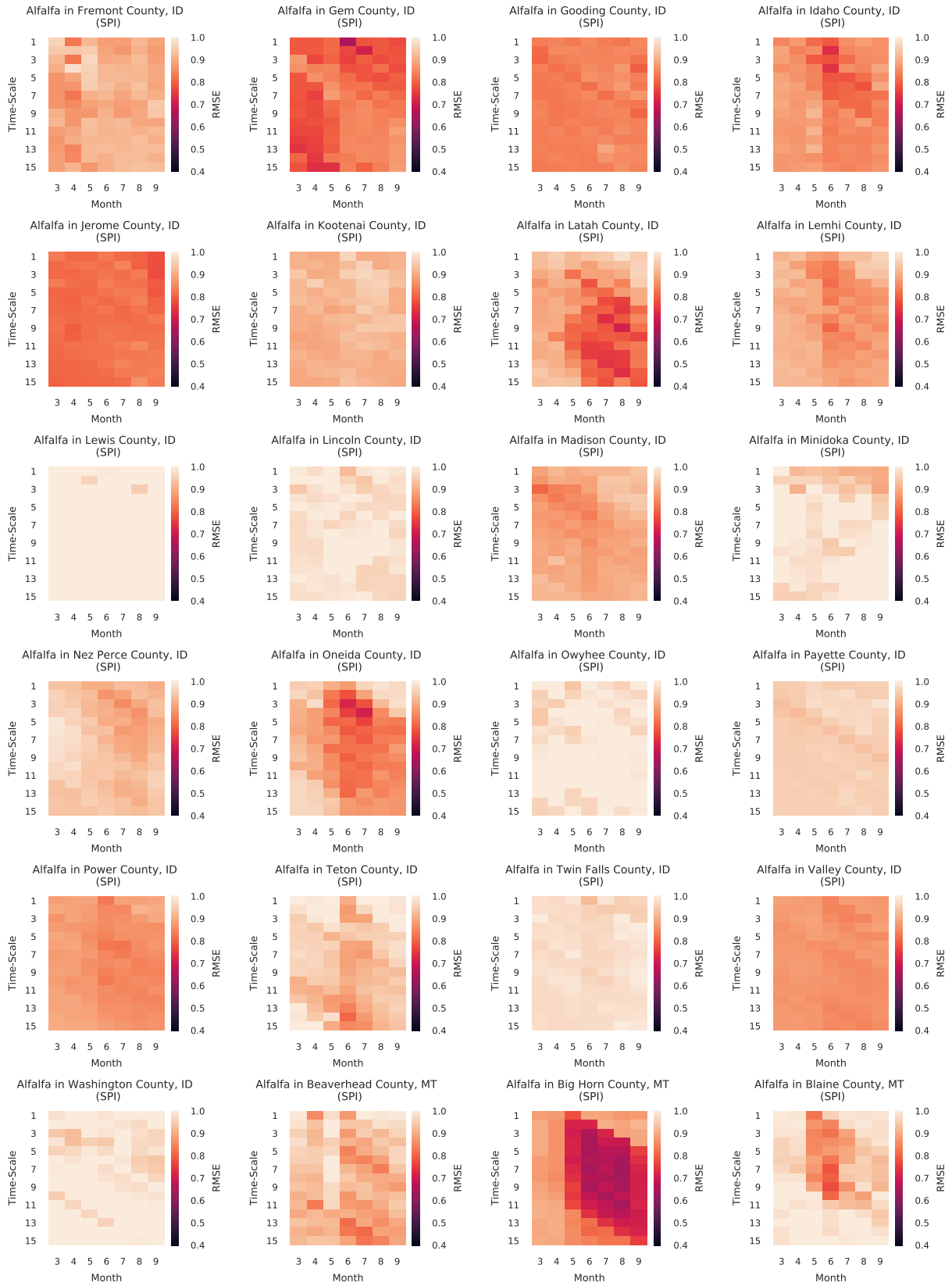
610 Root mean square error (RMSE) produced by Equation 1 from March-September over time-scales 1-15 for  
611 all counties and crops under study. Darker colors indicate lower RMSE.

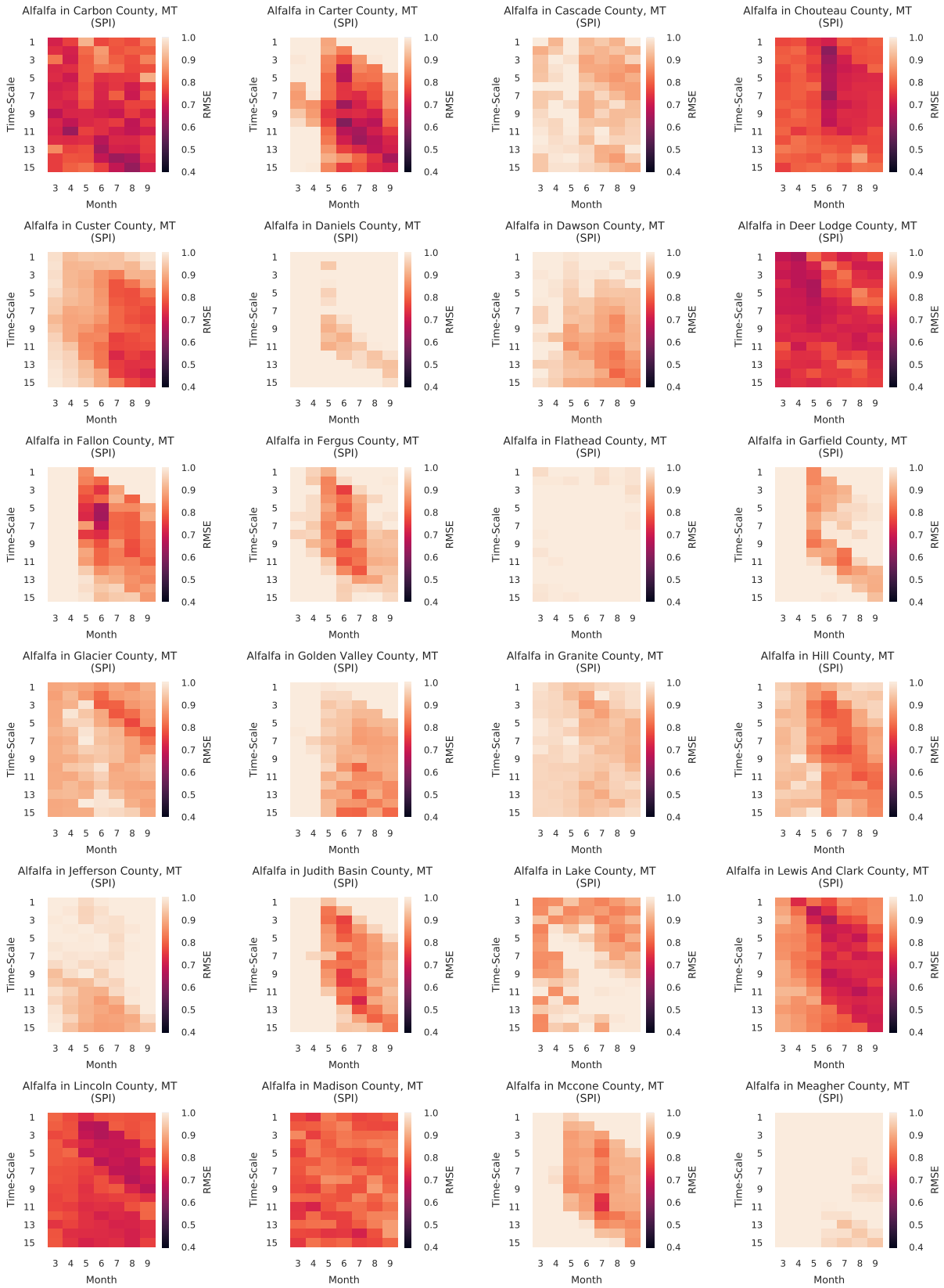


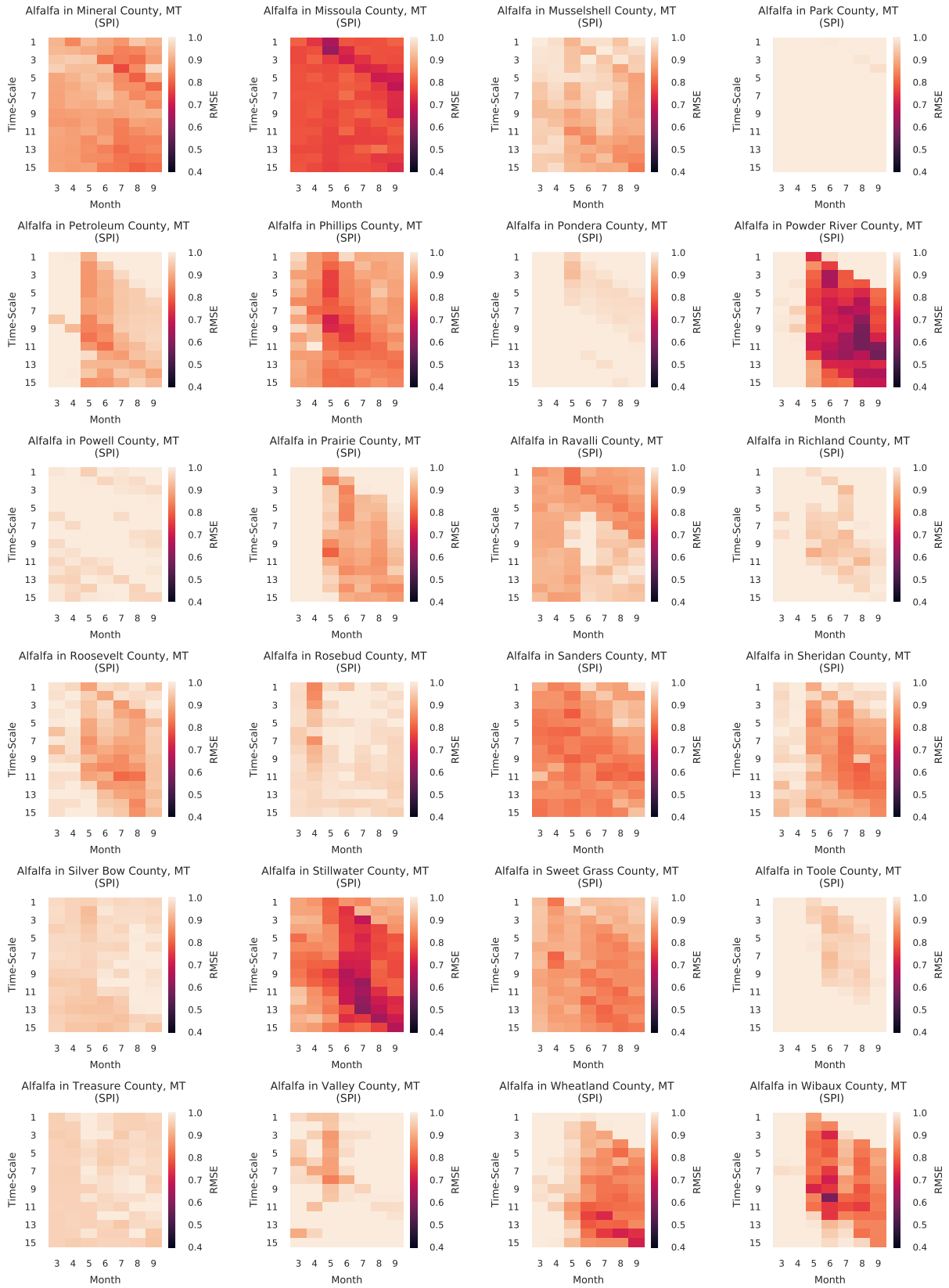
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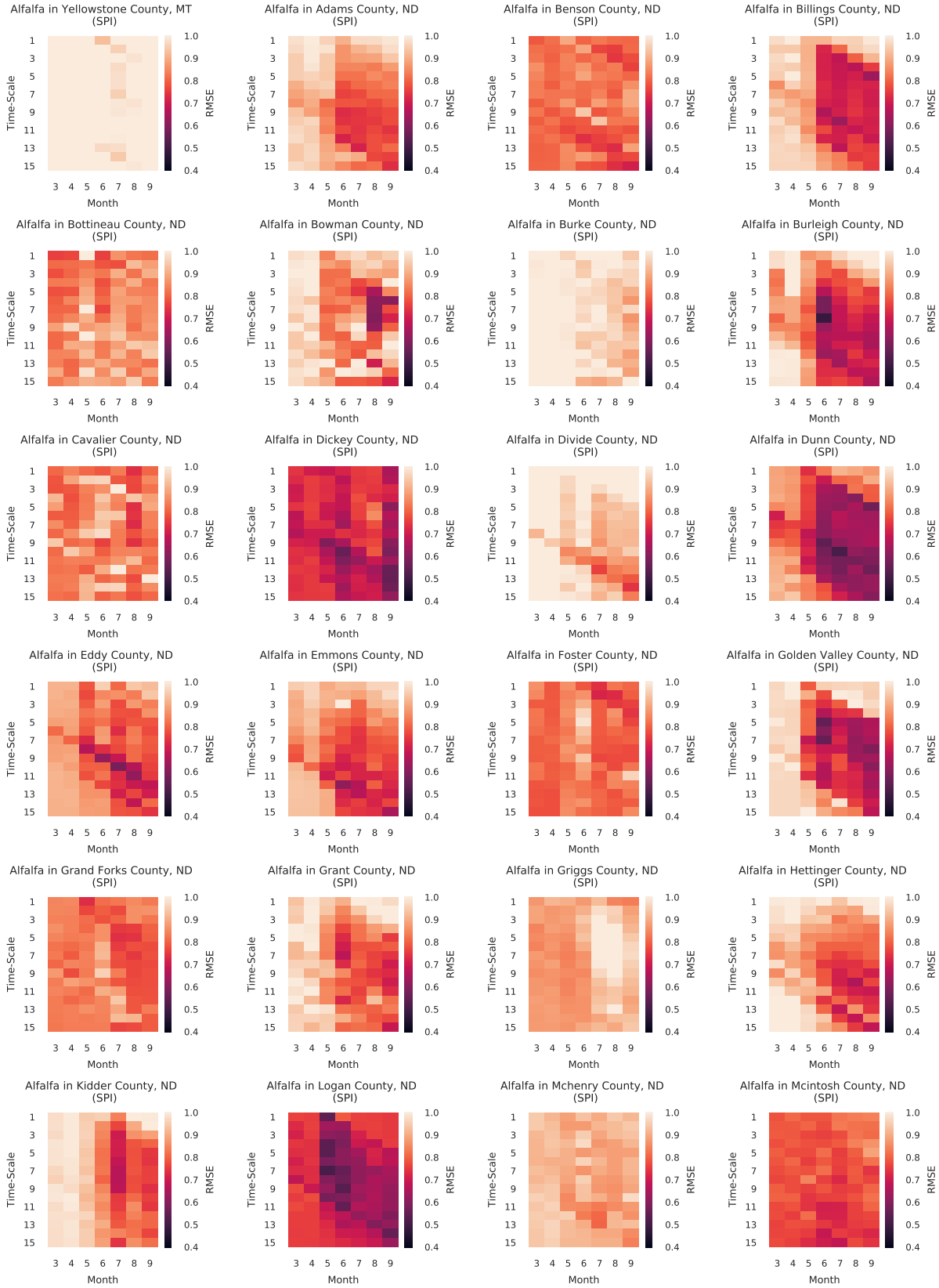
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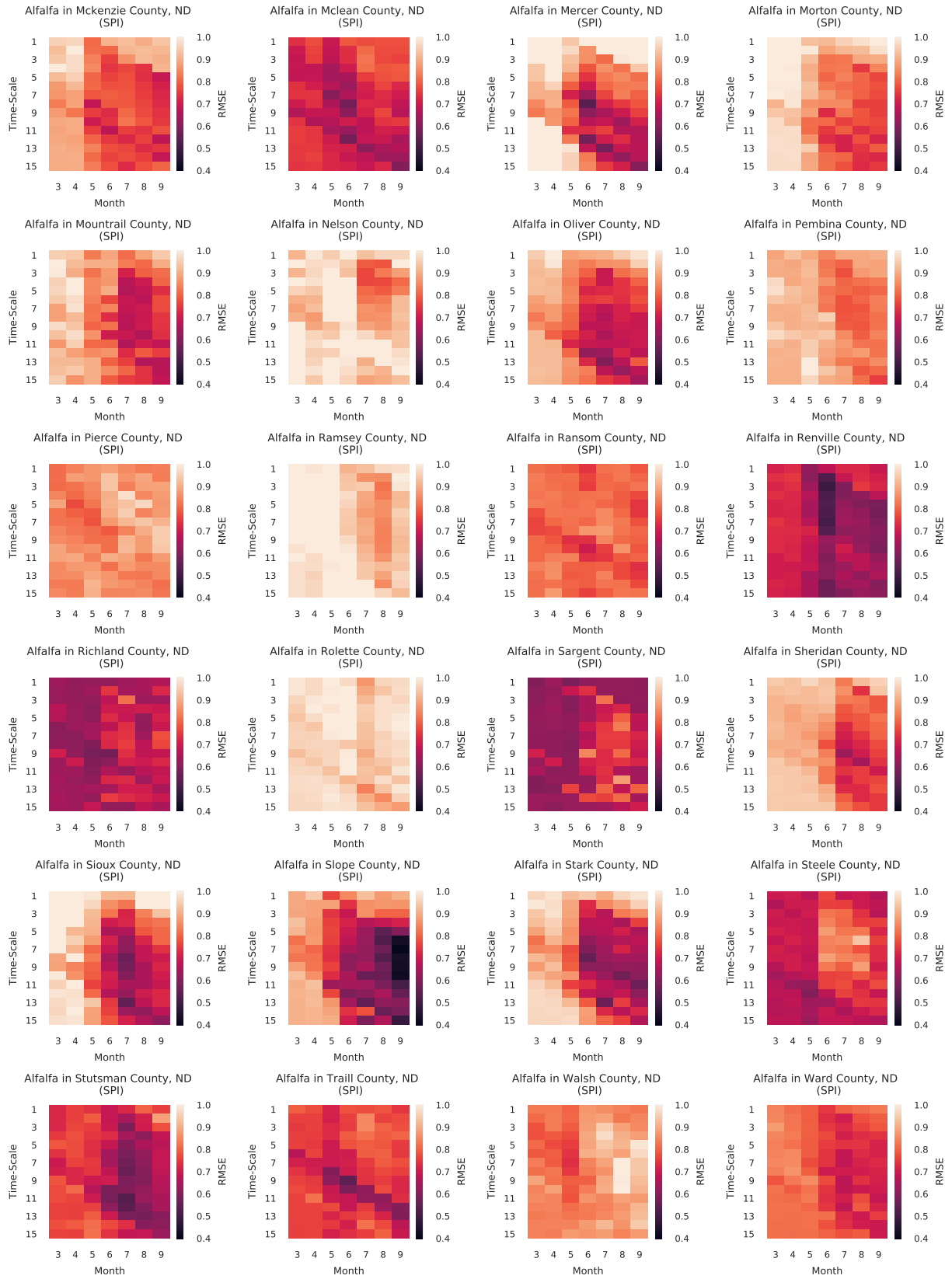


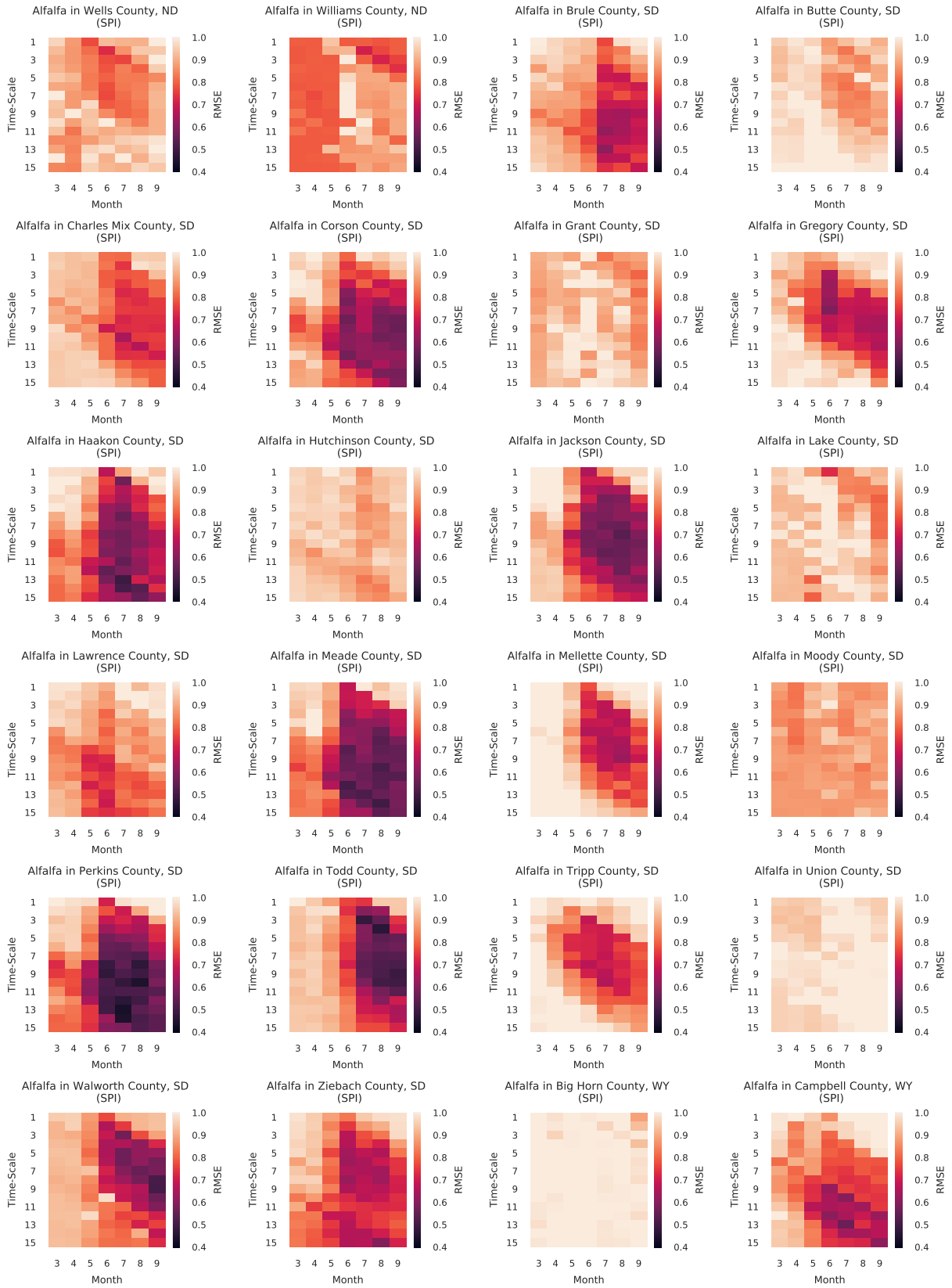


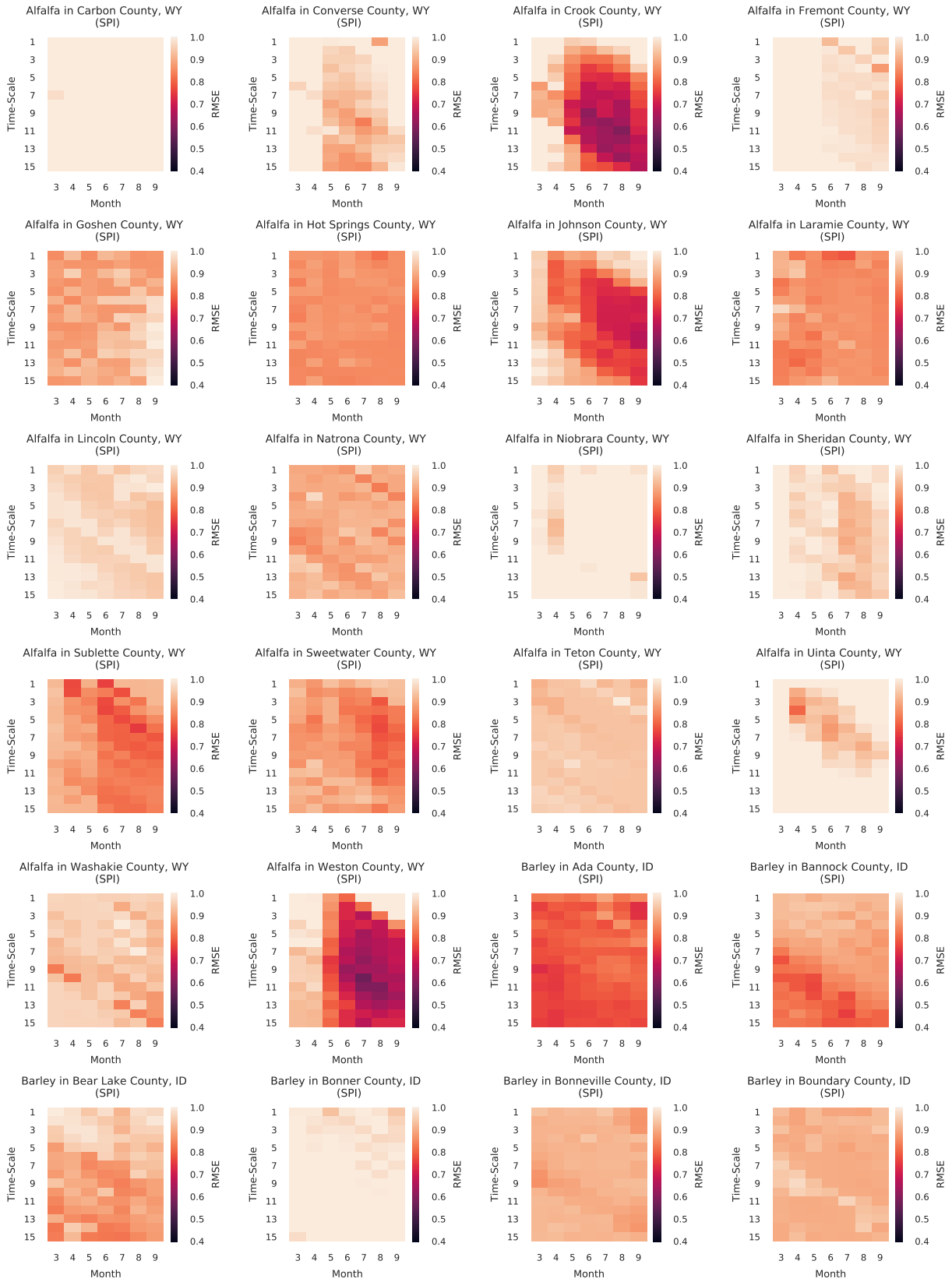


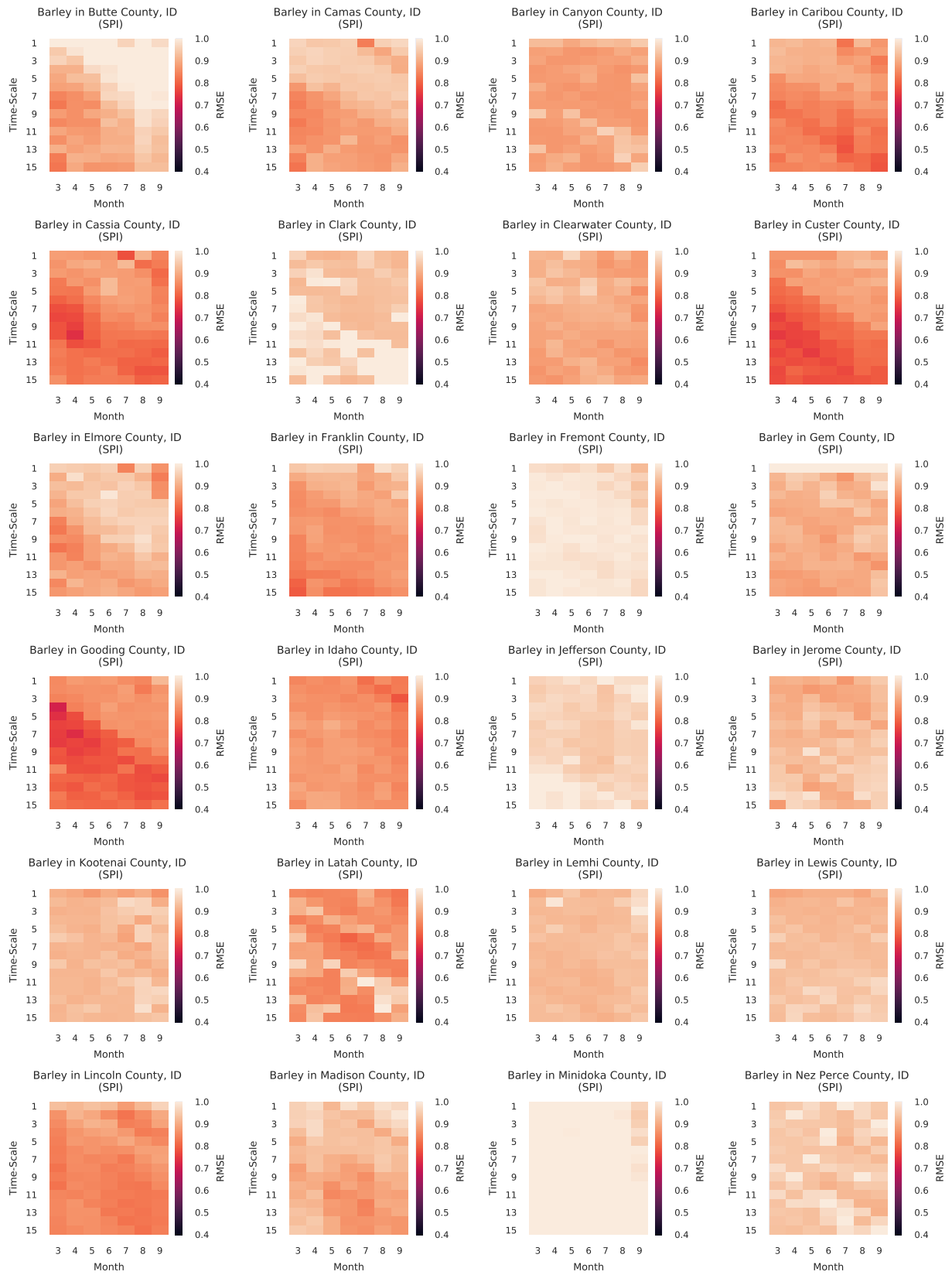




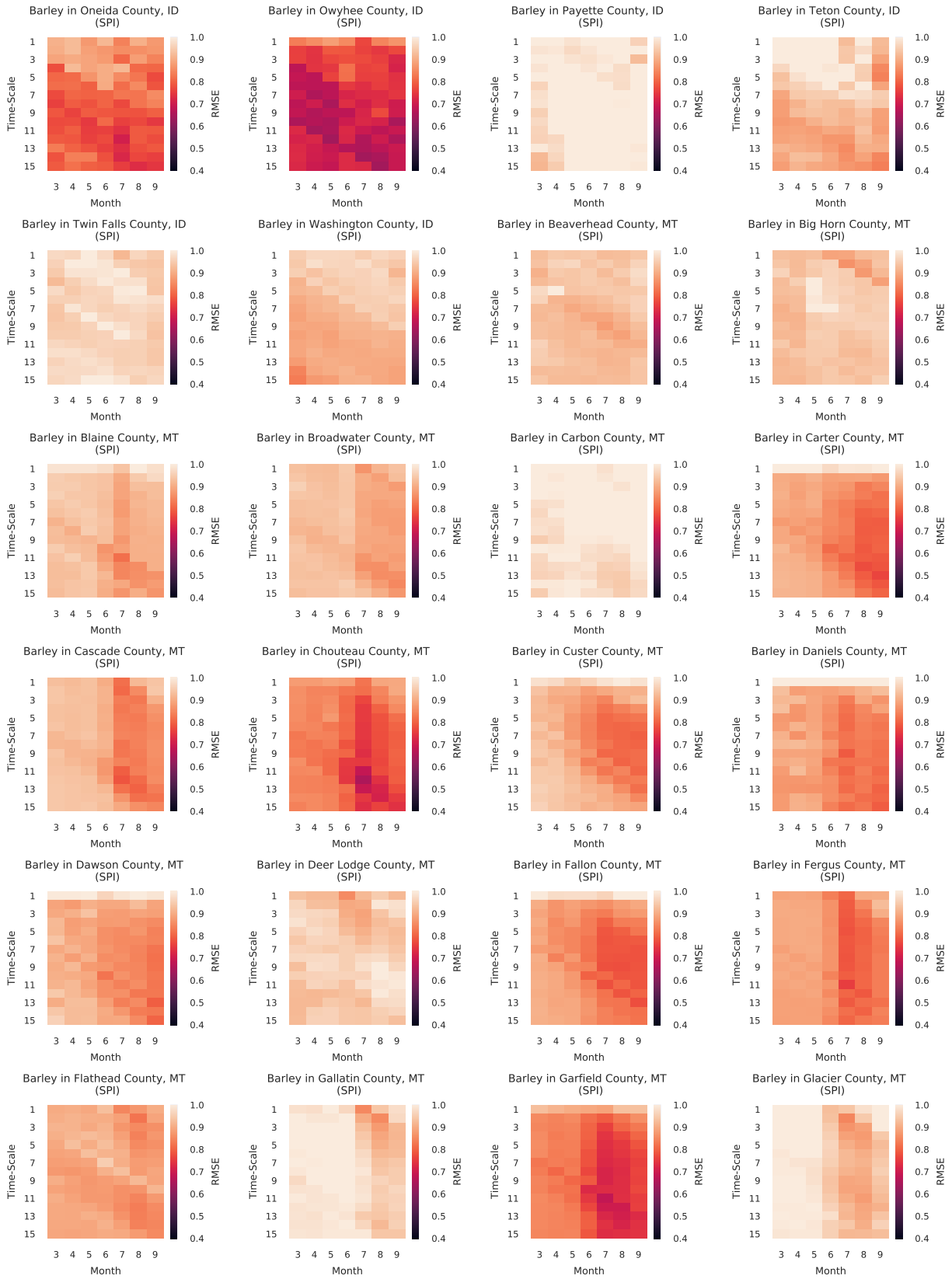


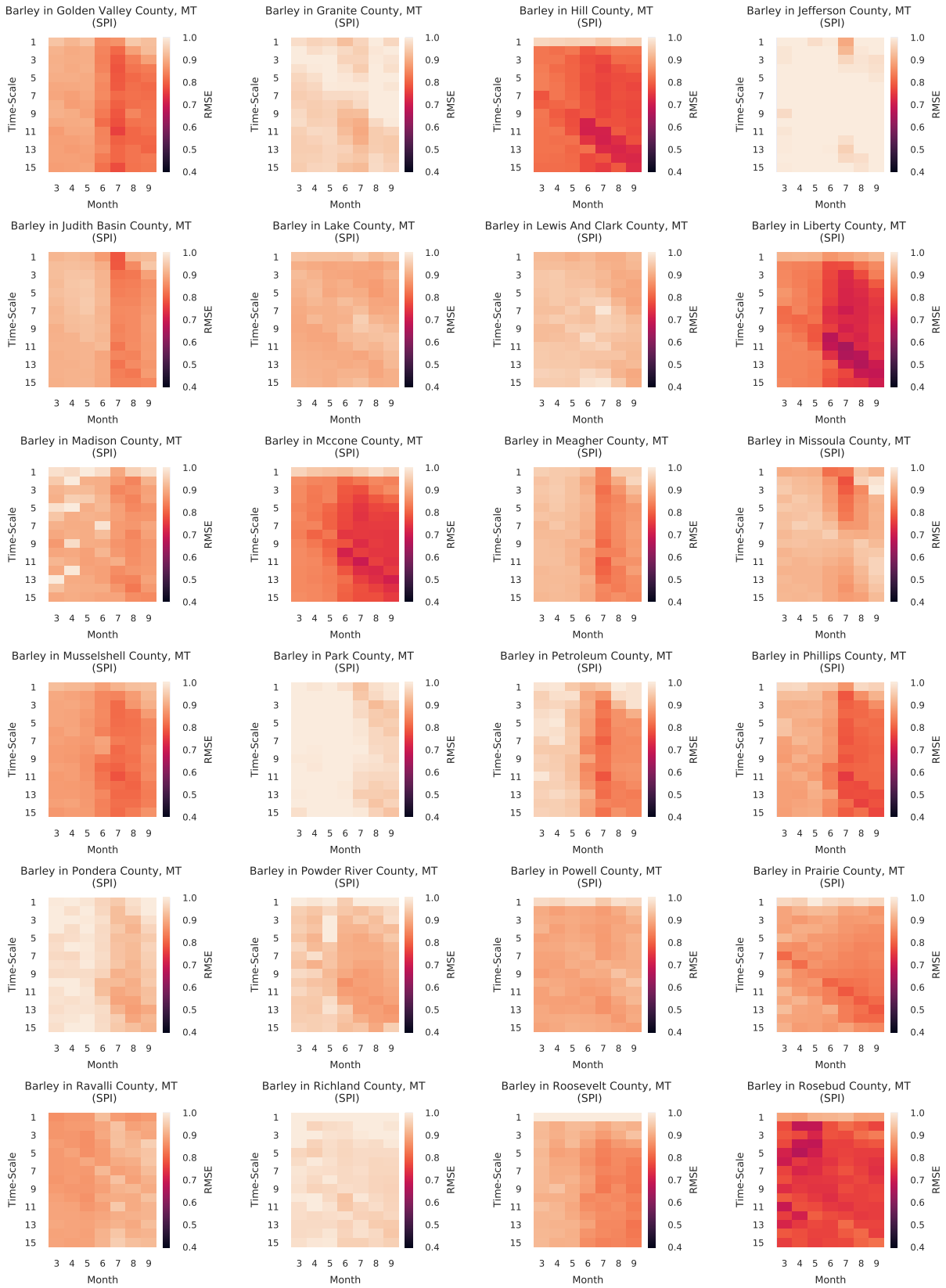


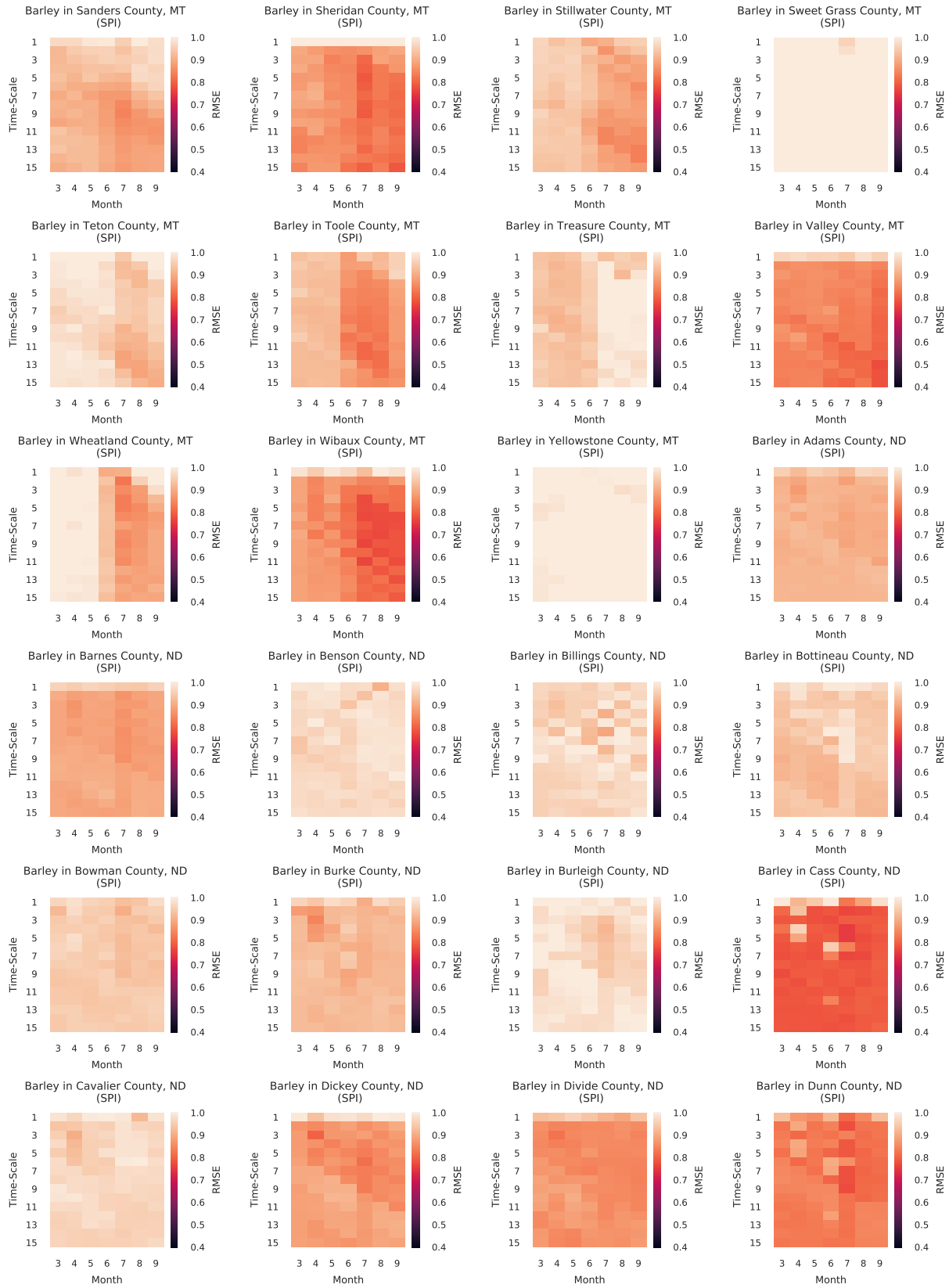


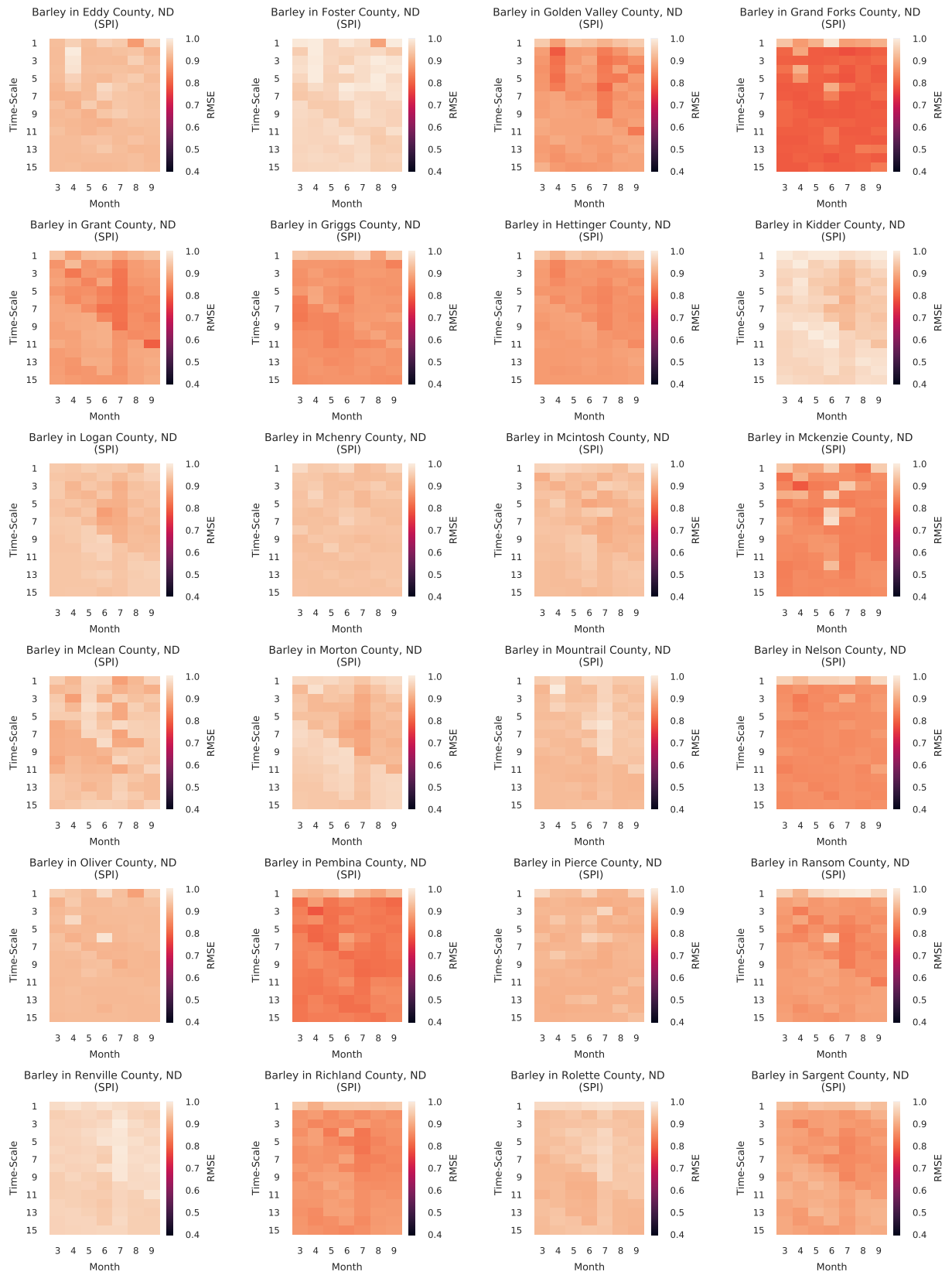


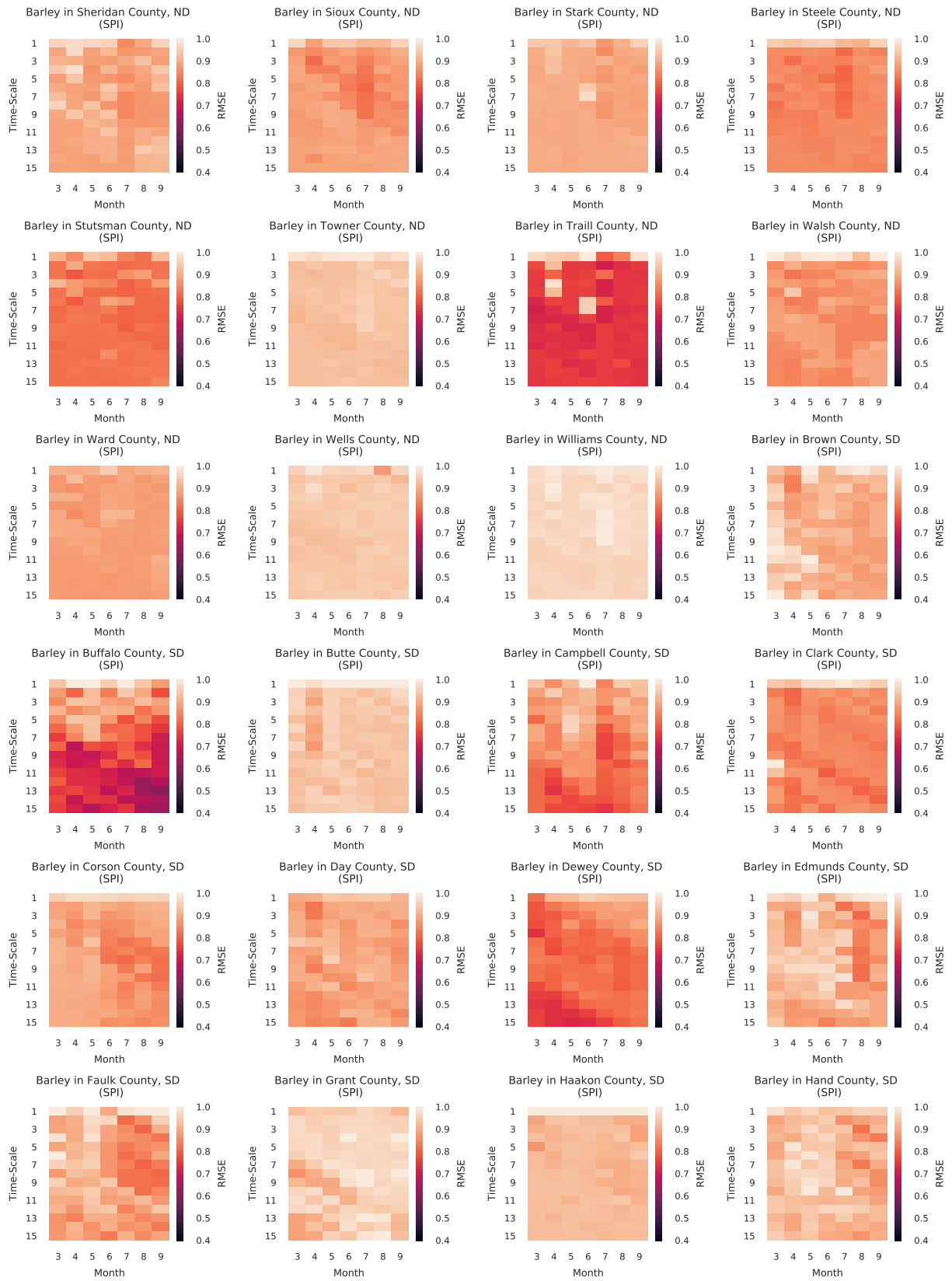


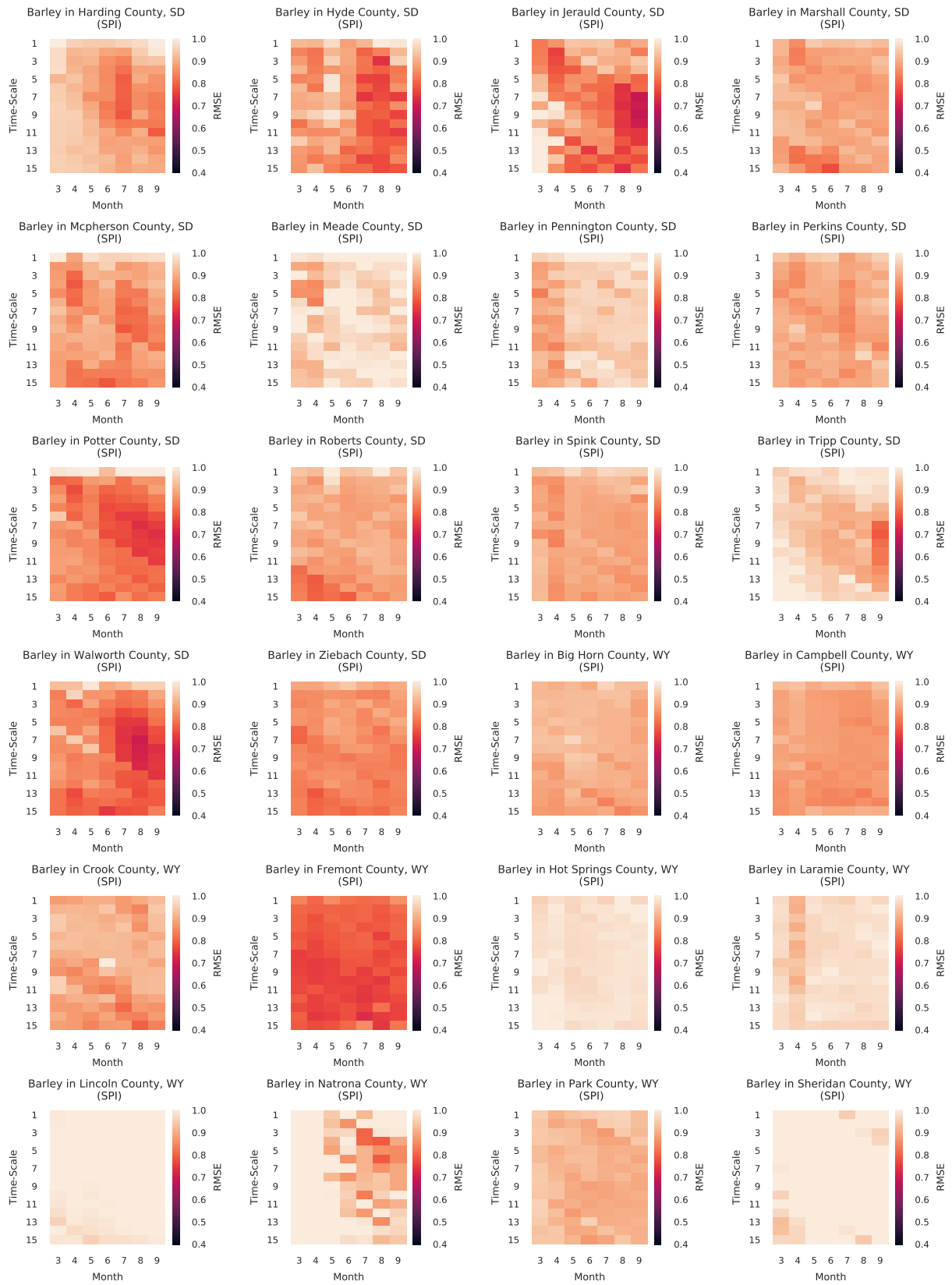


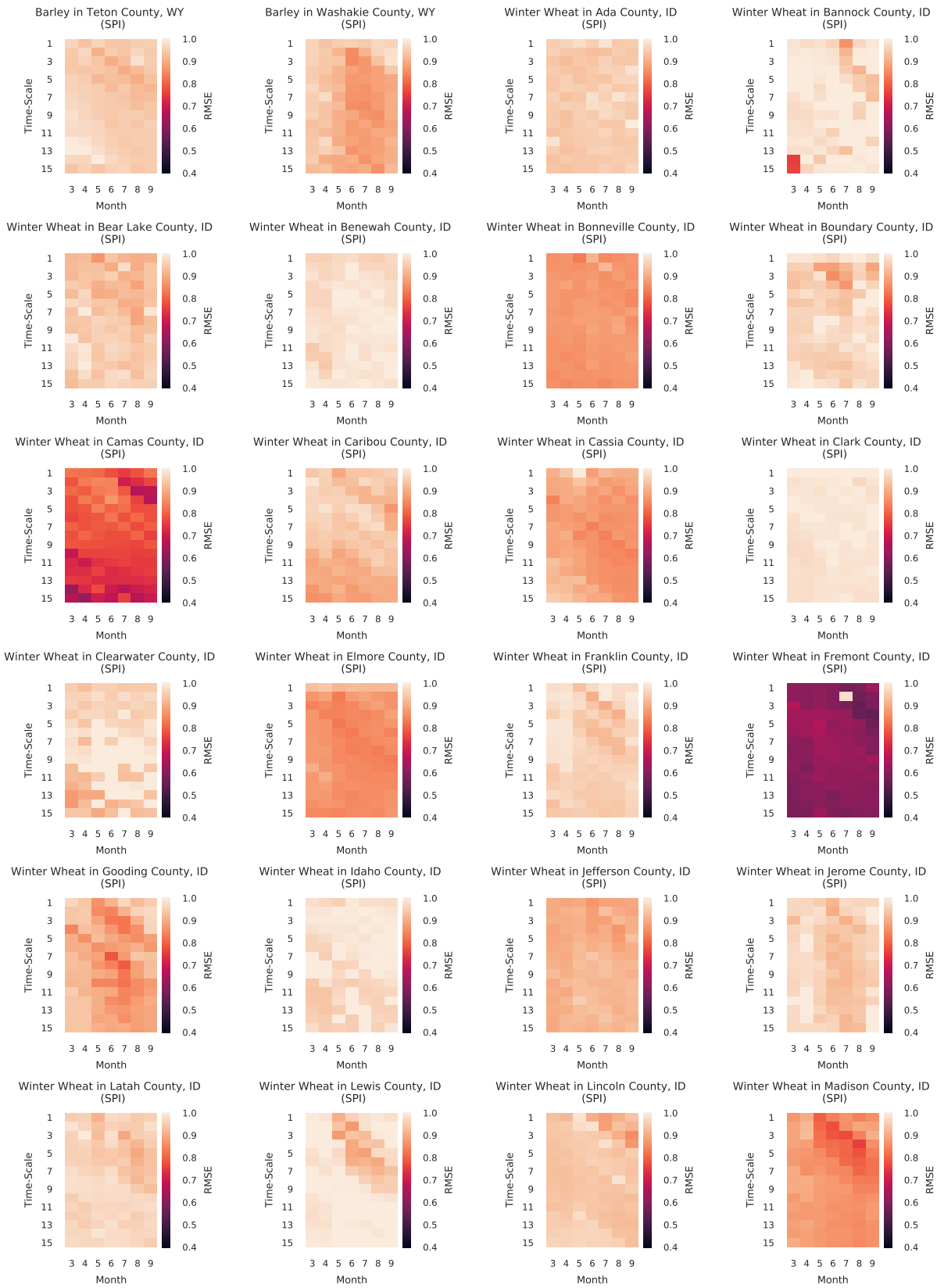


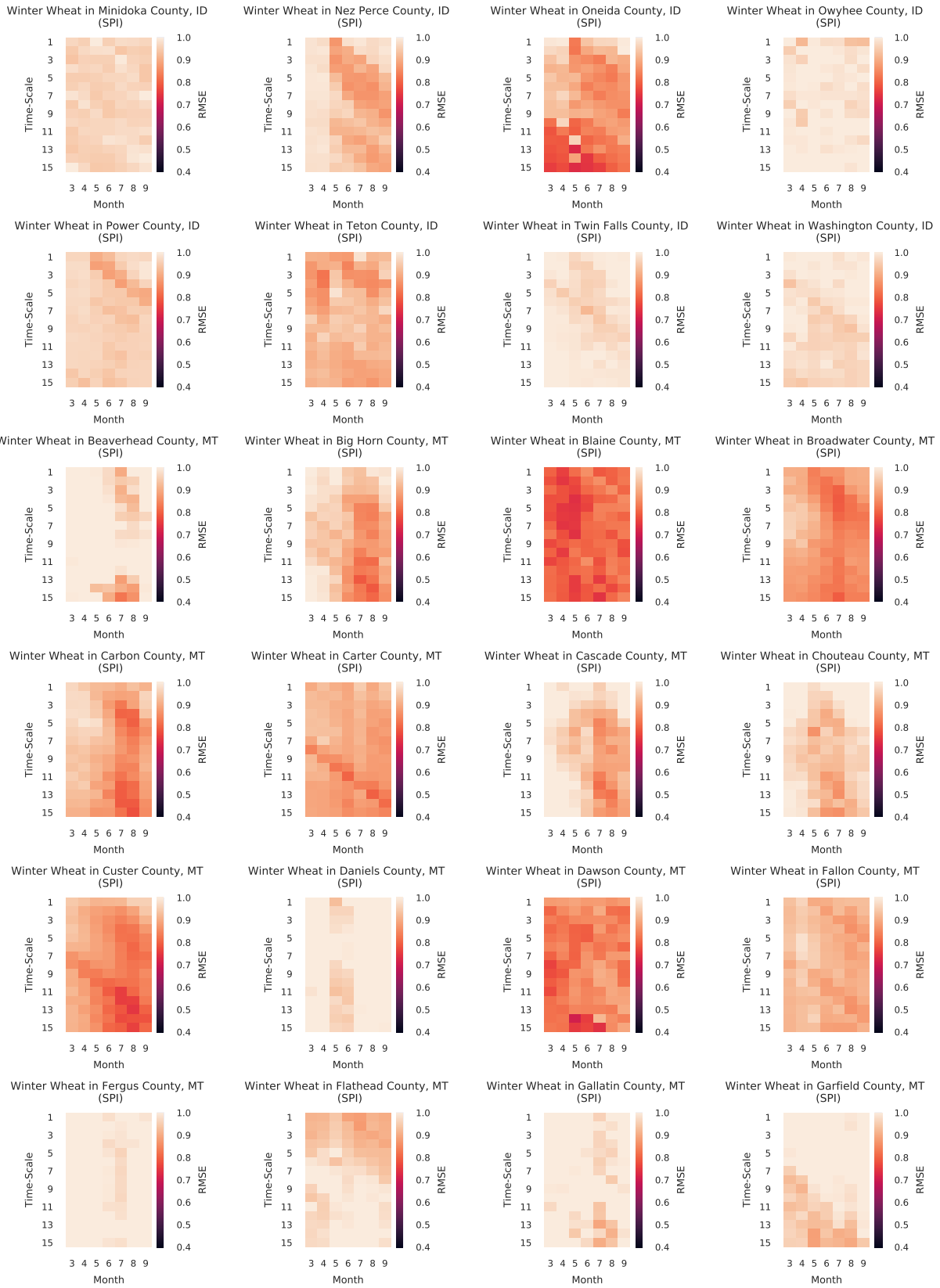




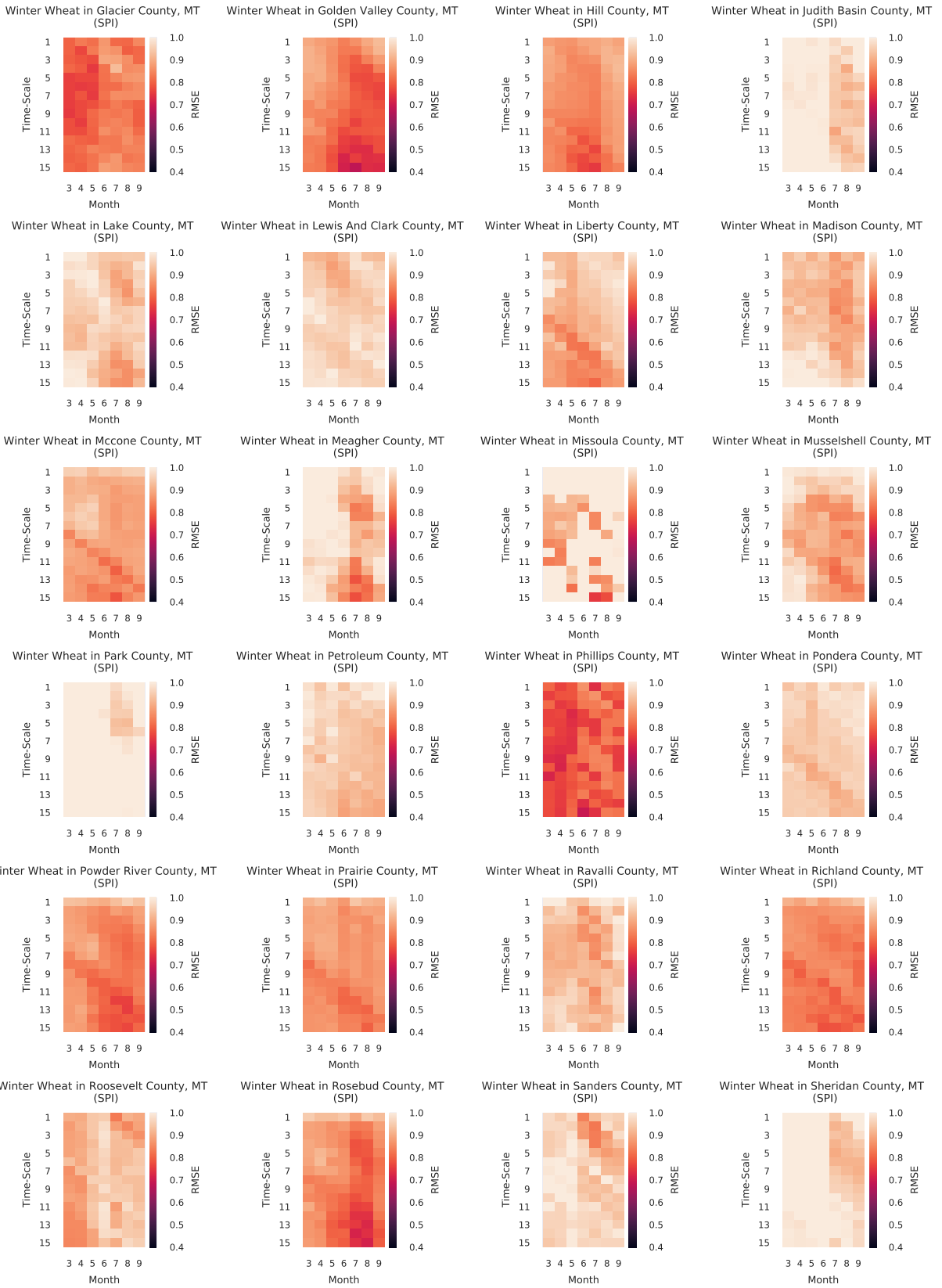


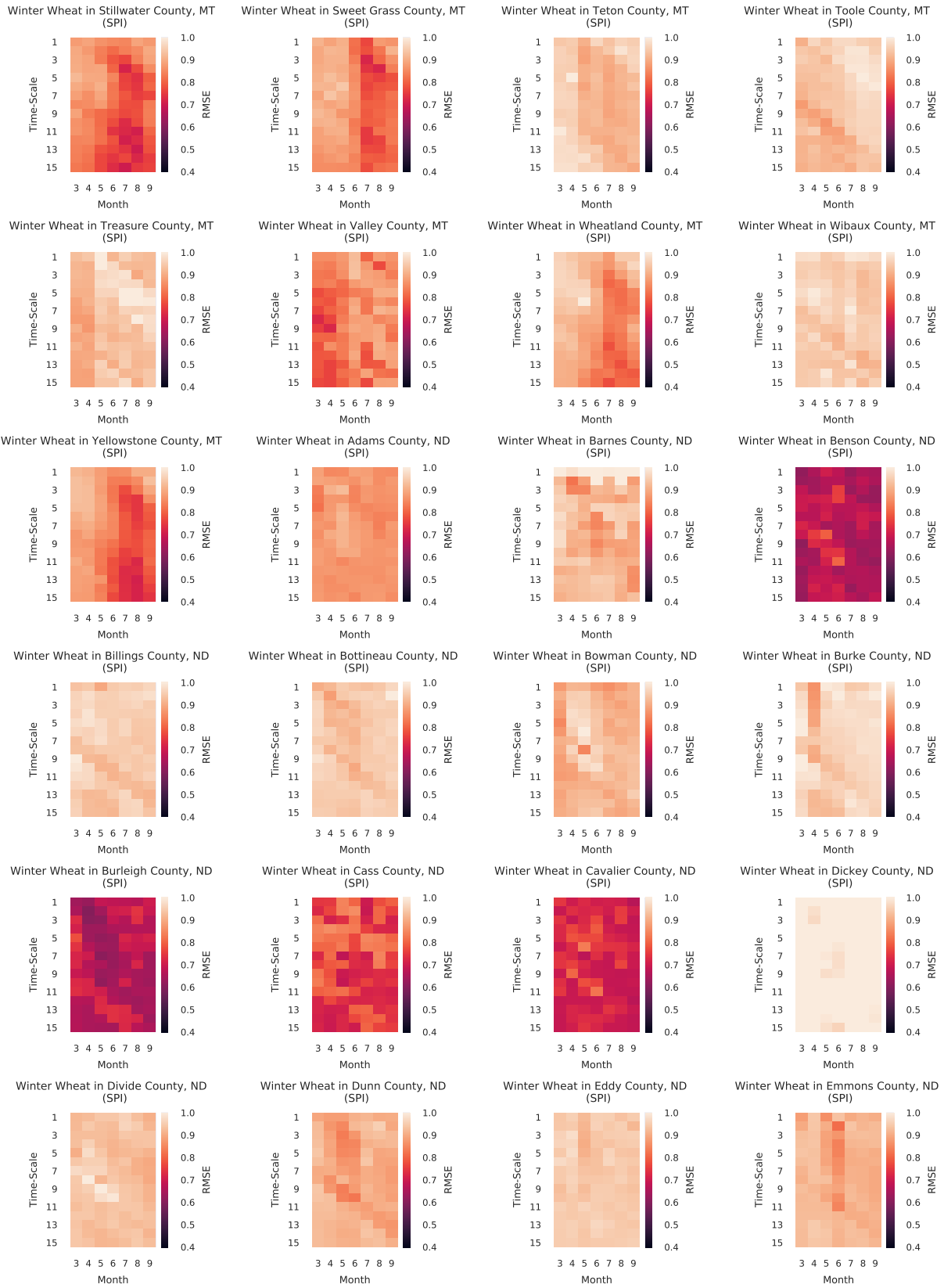




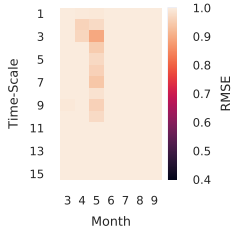




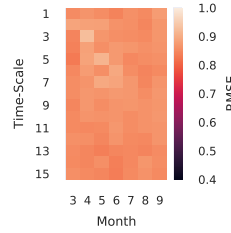




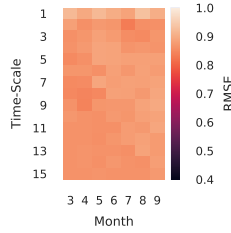
Winter Wheat in Foster County, ND (SPI)



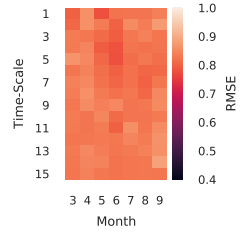
Winter Wheat in Golden Valley County, ND (SPI)



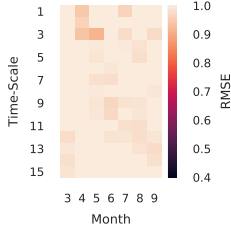
Winter Wheat in Grand Forks County, ND (SPI)



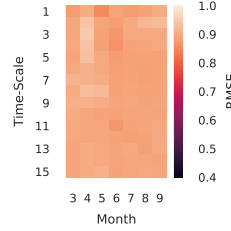
Winter Wheat in Grant County, ND (SPI)



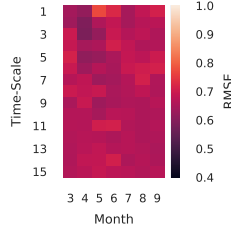
Winter Wheat in Griggs County, ND (SPI)



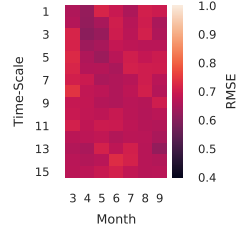
Winter Wheat in Hettinger County, ND (SPI)



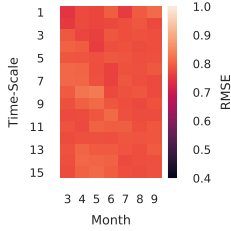
Winter Wheat in Kidder County, ND (SPI)



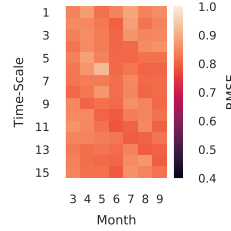
Winter Wheat in Mcherry County, ND (SPI)



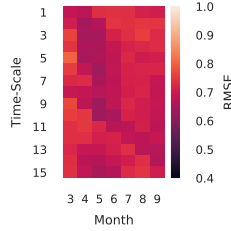
Winter Wheat in McIntosh County, ND (SPI)



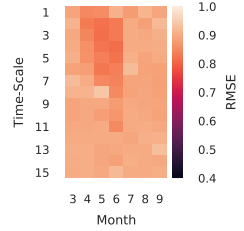
Winter Wheat in Mckenzie County, ND (SPI)



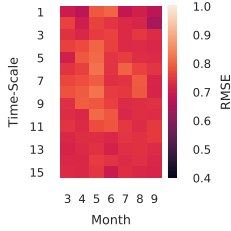
Winter Wheat in Mclean County, ND (SPI)



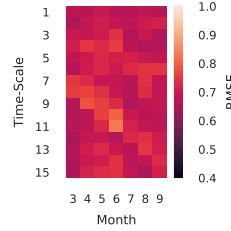
Winter Wheat in Morton County, ND (SPI)



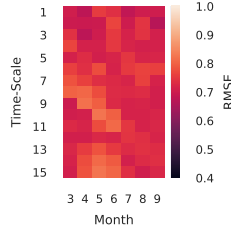
Winter Wheat in Mountrail County, ND (SPI)



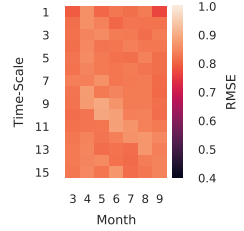
Winter Wheat in Nelson County, ND (SPI)



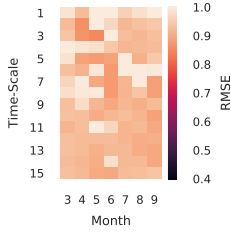
Winter Wheat in Pierce County, ND (SPI)



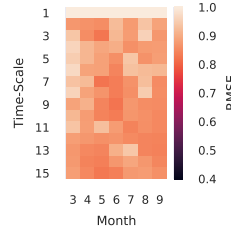
Winter Wheat in Ramsey County, ND (SPI)



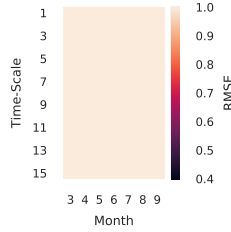
Winter Wheat in Ransom County, ND (SPI)



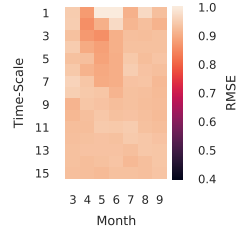
Winter Wheat in Richland County, ND (SPI)



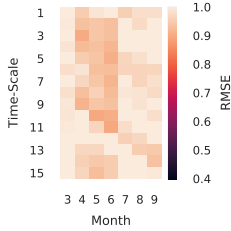
Winter Wheat in Sargent County, ND (SPI)



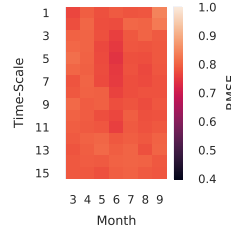
Winter Wheat in Sheridan County, ND (SPI)



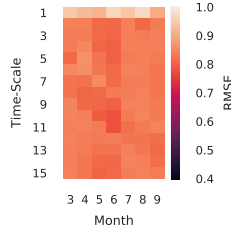
Winter Wheat in Sioux County, ND (SPI)



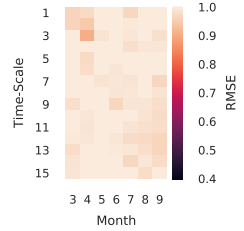
Winter Wheat in Stark County, ND (SPI)

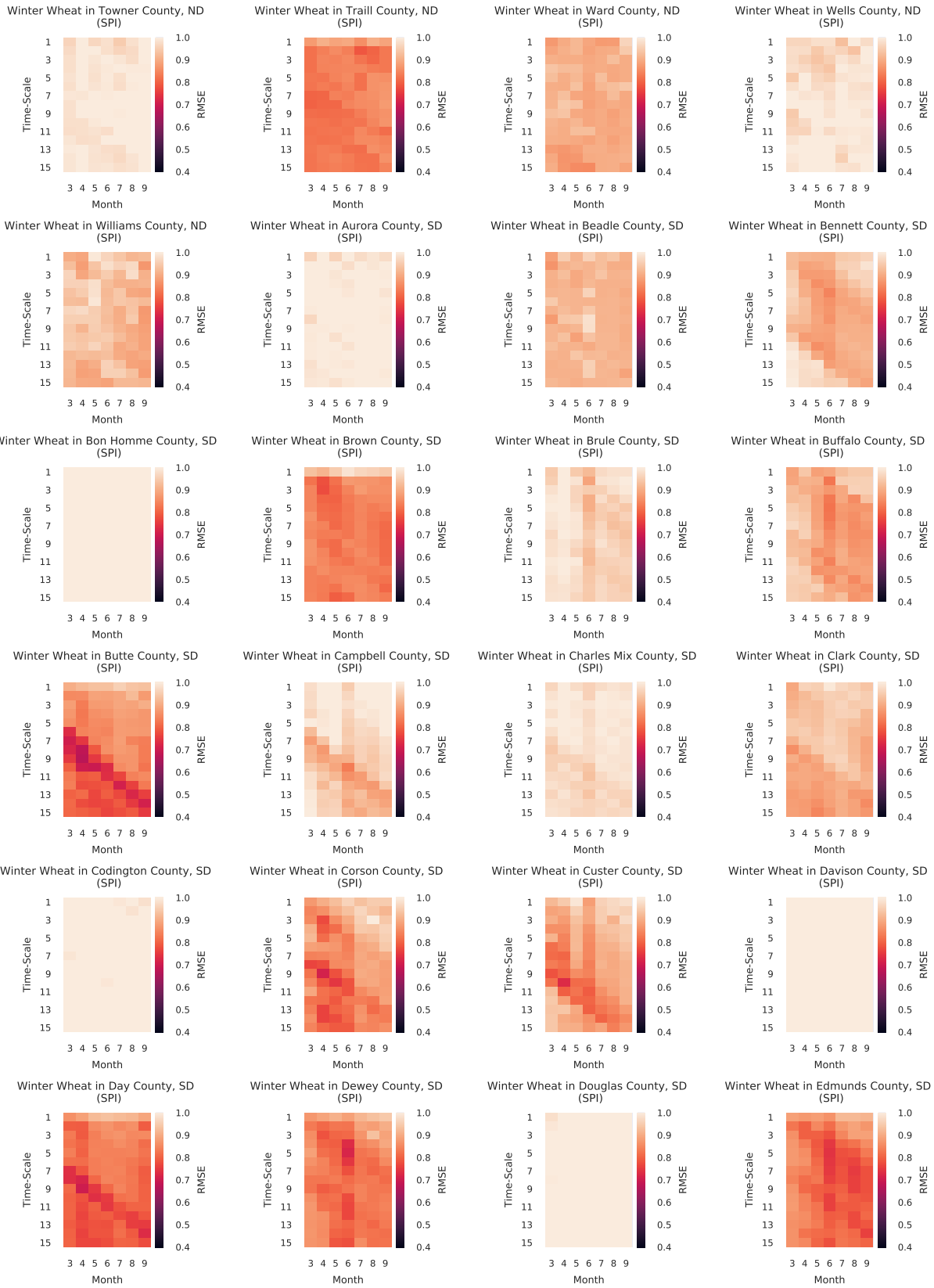


Winter Wheat in Steele County, ND (SPI)

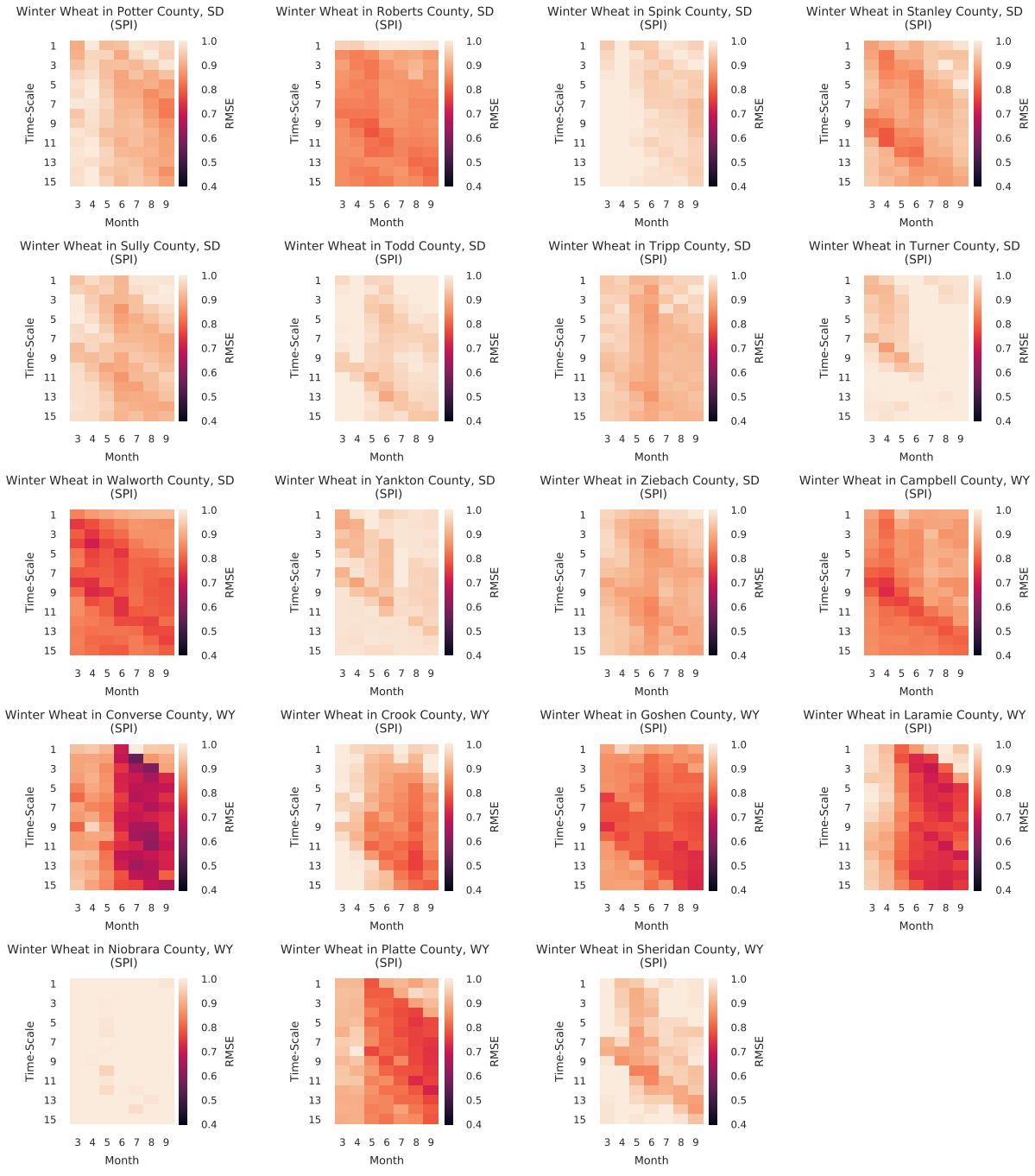


Winter Wheat in Stutsman County, ND (SPI)



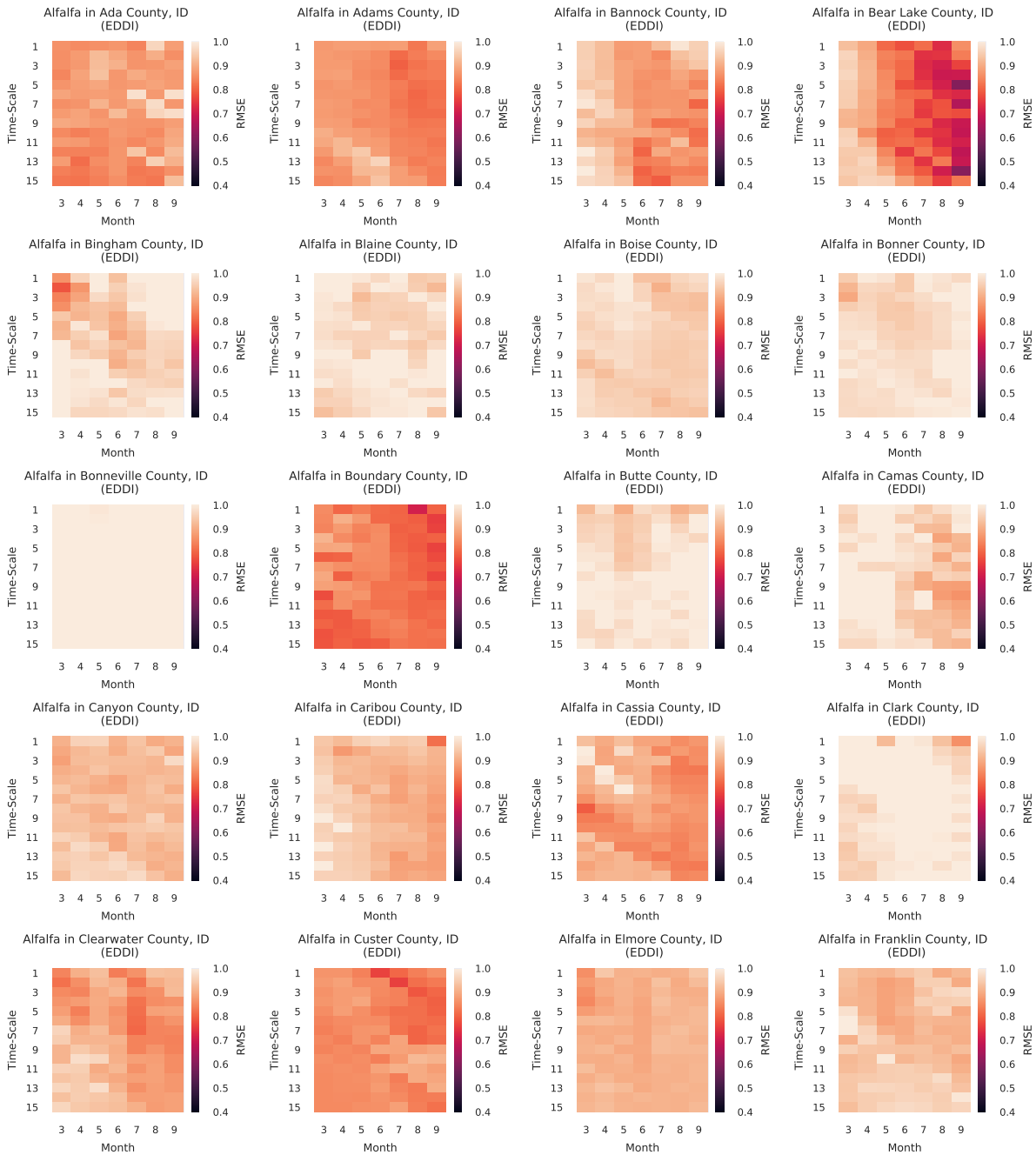






636 **Appendix B RMSE from Equation 2 over months 3-9 and time-**  
 637 **scales 1-15**

638 Root mean square error (RMSE) produced by Equation 2 from March-September over time-scales 1-15 for  
 639 all counties and crops under study. Darker colors indicate lower RMSE.



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