MA678 Final Project

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Abstract: This article is a prediction of fire occurrences in various counties in the United States, predicting the duration of fires and the number of fires. GLM models, Bayesian models, etc. were used, and the conclusion was that the variables provided in this article cannot predict the results well, but there is a certain relationship between some dependent variables and independent variables.

Introduction: In the United States, many fires occur every year, and the scale of the fires and the economic losses they cause are huge. In 2022, local fire departments responded to an estimated 1.5 million fires in the United States. These fires caused 3,790 civilian fire deaths and 13,250 reported civilian fire injuries. The property damage caused by these fires was estimated at $18 billion. On average, a fire department responded to a fire somewhere in the US every 21 seconds in 2022. A home structure fire was reported every 88 seconds, a home fire death occurred every three hours and fourteen minutes, and a home fire injury occurred every 53 minutes.[1] Above all, predicting fire is very necessary.
This article will try to explore the influencing factors of fires by combining land conditions, population, climate, drought degree, and other indicators. In this way, the intensity and duration of fires can be predicted, and the firefighting layout can be optimized.

Data Introduction: This article includes five main data, including soil conditions, weather, drought, population, and fire. Among them, the soil condition and weather dataset is from the Food and Agriculture Organization of the United Nations [2]. The drought dataset is from the U.S. Drought Monitor [3]. The population dataset is from the United States Census [4]. The fire dataset is from 2.3 Million US Wildfires (1992-2020) 6th Edition in Kaggle [5].

Data Preparing: All datasets will be combined by using a key variable, fips. This is a five-digit code established by the U.S. federal government. The first two represent the state, and the last three represent the counties under the state.
The selected variable is in Table 1.
First, choose a variable from the soil condition dataset. Since the slope includes 8 variables. Using the group median as the weight, combine the eight slopes into a weighted slope, where the group median of the last group is set to 50. Then, get variables from the weather dataset. Since the dataset is too big, about 2 G, using SQLite to get the dataset. Calculate each county's average QV2M, WS10M, WS50M, and PROCTOR between 2012 and 2020. Get drought conditions from the drought dataset. Because low-level drought must include high-level drought, this makes D0 must be greater than D1, D2, D3, and D4. This may lead to high collinearity in the model. Give different weights to different drought levels and add them up to get drought_value. Get population information form the population dataset and fire information from the fire dataset, calculate fire_last=(CONT_DOY - DISCOVERY_DOY) * 2400

[1] Fire loss in the United States | NFPA Research
[2] Harmonized world soil database v1.2 | FAO SOILS PORTAL | Food and Agriculture Organization of the United Nations
[3] Comprehensive Statistics | U.S. Drought Monitor (unl.edu)
[4] Index of /programs-surveys/popest/datasets/2010-2020/counties/totals (census.gov)
[5] 2.3 Million US Wildfires (1992-2020) 6th Edition (kaggle.com)

+as.numeric(substr(CONT_TIME, 1, 2)) * 60 + as.numeric(substr(CONT_TIME, 3, 4)) - as.numeric(substr(DISCOVERY_TIME, 1, 2)) * 60.

Table.1. Variable in this article

Variable name	Variable Meaning	Dataset From
fips	FIPS CODE	ALL
elevation	Median elevation(meters)	Soil conditions
Slope1,2,…,8	Different slope ratio	Soil conditions
WAT_LAND	Mapped water bodies	Soil conditions
NVG_LAND	Barren/ very sparsely vegetated land	Soil conditions
GRS_LAND	Grass/ scrub/woodland	Soil conditions
URB_LAND	Build-up land	Soil conditions
FOR_LAND	Forest land	Soil conditions
CULT_LAND	Total cultivate land	Soil conditions
date	Recording date	Weather
QV2M	Specific Humidity at 2 Meters(g/kg)	Weather
WS10M	Wind speed at 10m.(m/s)	Weather
WS50M	Wind speed at 50m.(m/s)	Weather
PRECTOR	Precipitation(mm/day)	Weather
None	No drought ratio	Drought
D0	Abnormally dry ratio	Drought
D1	Moderate drought ratio	Drought
D2	Severe drought ratio	Drought
D3	Extreme drought ratio	Drought
D4	Exceptional drought ratio	Drought
STNAME	State name	Population
CTYNAME	County name	Population
CENSUS2010POP	Population in 2010	Population
DISCOVER_DOY	Fire discover day in year	Fire
DISCOVER_TIME	Fire discover time (hhmm)	Fire
CONT_DOY	Fire end day in year	Fire
CONT_TIME	Fire end time (hhmm)	Fire
FIRE_YEAR	Fire occurrence year	Fire

EDA: Heatmap plotting fire duration and number of fire occurrences on a map of the United States. as shown in Figure.1 and Figure.2. Draw a correlation coefficient matrix diagram between different variables to help select variables that may be used in the model, as shown in Figure.3.
According to the information in the figure, we can see that fires mainly occur in the western United States, and the number and duration of fires vary greatly between different counties.

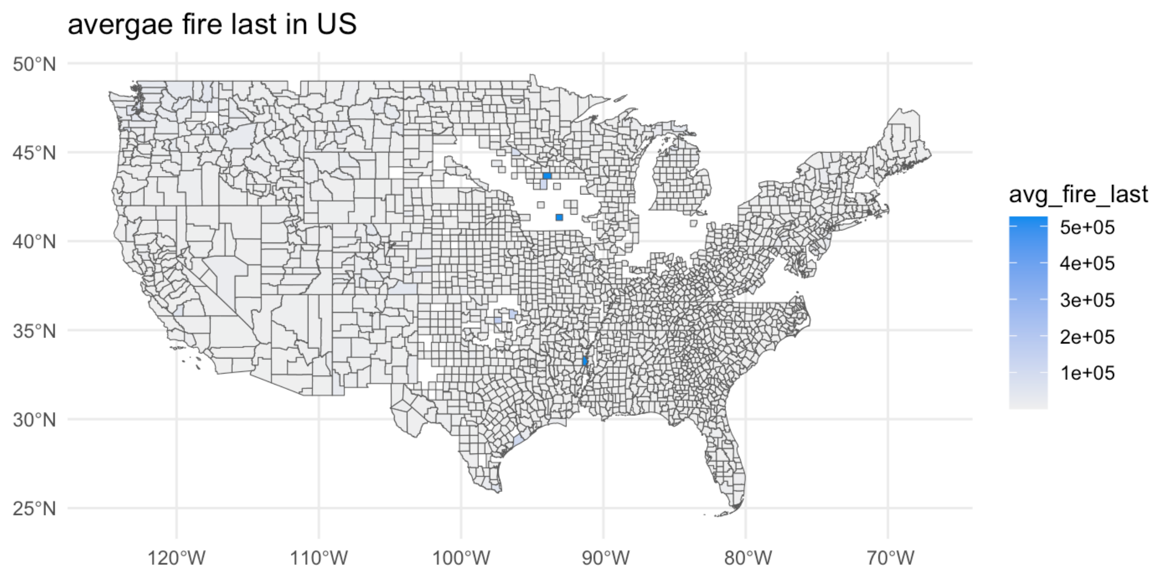

Figure.1. Average fire duration in U.S.

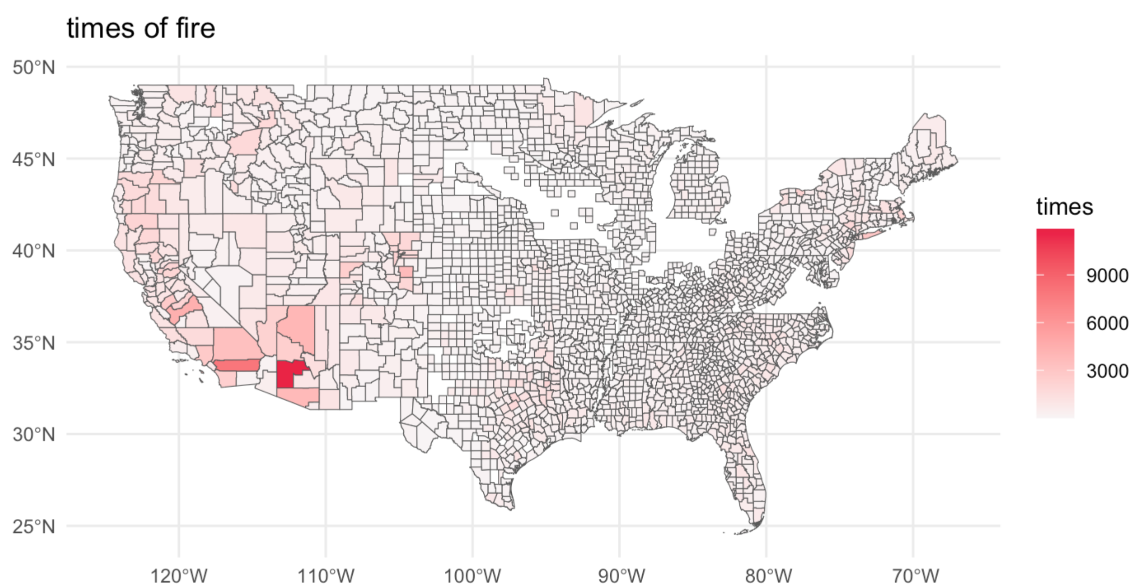

Figure.2. Times of fire in U.S.

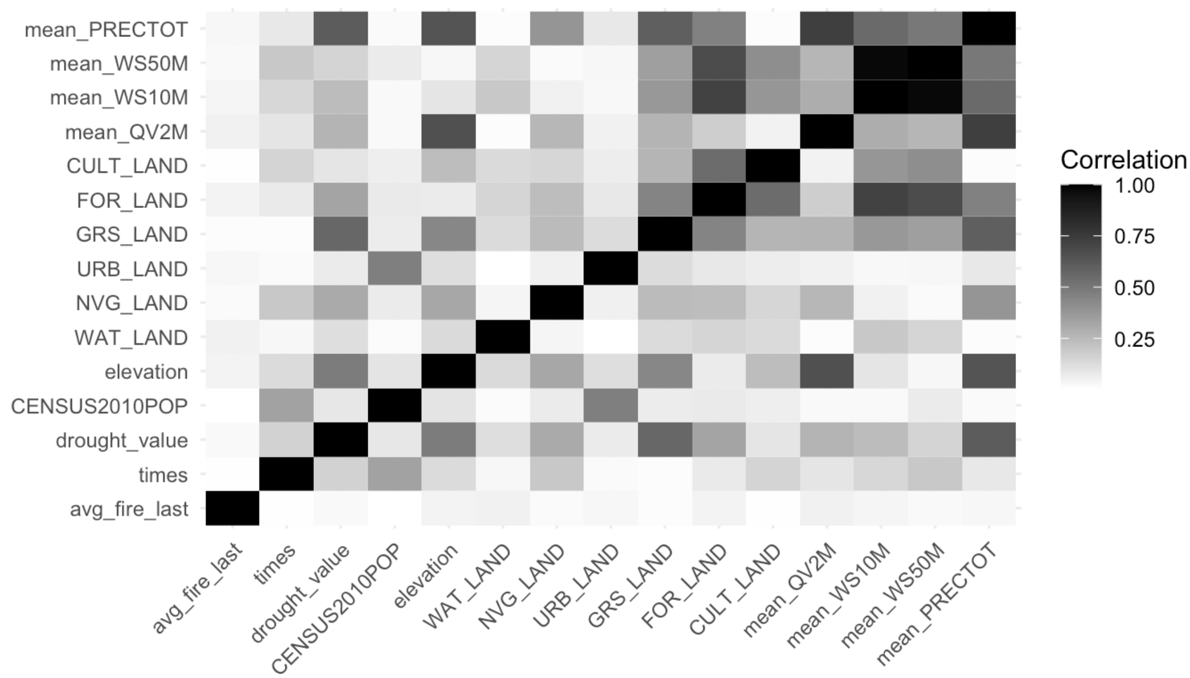

Figure.3. Correlation of different varibles

Model for fire duration:

1.Null Model:

```
Call:
lm(formula = avg_fire_last ~ 1, data = combined_data_last)

Residuals:
   Min     1Q Median     3Q    Max 
 -3405  -3270  -3073  -1292 522165 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   3435.0      432.1   7.949 2.79e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 21910 on 2570 degrees of freedom
```

The Result show that the residuals have a wide range of values, and the residual standard error is 21910, indicating some variability in the data that the model does not explain well.

2.GLM Model:

Remove the two variables population and cultivate land based on the results of the correlation coefficient matrix, and because there is overdispersion in the data, select the Gamma distribution, and the link is log.

Call:

```
glm(formula = avg_fire_last ~ drought_value + elevation + WAT_LAND +
    NVG_LAND + URB_LAND + GRS_LAND + FOR_LAND + slope + mean_QV2M +
    mean_WS10M + mean_WS50M + mean_PRECTOT, family = Gamma(link =
"log"),
    data = truncated_data_last)

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   10.720067   0.775836  13.817  < 2e-16 ***
drought_value -0.151530   0.079131  -1.915 0.055614 .
elevation      0.000171   0.000126   1.357 0.174846
WAT_LAND       0.008650   0.003436   2.518 0.011878 *
NVG_LAND       0.008686   0.006161   1.410 0.158680
URB_LAND       0.018535   0.004620   4.012 6.19e-05 ***
GRS_LAND       0.020491   0.002309   8.873  < 2e-16 ***
FOR_LAND       0.006791   0.001910   3.556 0.000384 ***
slopemedium   -0.423327   0.116476  -3.634 0.000284 ***
slopesmall    -0.249215   0.139237  -1.790 0.073598 .
mean_QV2M     -0.141189   0.033641  -4.197 2.80e-05 ***
mean_WS10M     1.610428   0.220570   7.301 3.81e-13 ***
mean_WS50M    -1.512523   0.203566  -7.430 1.48e-13 ***
mean_PRECTOT   0.118487   0.102868   1.152 0.249496
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Gamma family taken to be 4.152228)

    Null deviance: 6347.5  on 2518  degrees of freedom
```

Residual deviance: 4760.4 on 2505 degrees of freedom
AIC: 41857

Number of Fisher Scoring iterations: 12

The model's AIC is too large, and compared to Null model deviance, residual deviance is not significant small. It is considered that the results of the model are still not ideal and require further processing.
Check if there is collinearity in the variables of the model.

```
                  GVIF Df GVIF^(1/(2*Df))
drought_value 2.421935  1        1.556257
elevation     2.762665  1        1.662127
WAT_LAND      1.224788  1        1.106701
NVG_LAND      1.420104  1        1.191681
URB_LAND      1.075065  1        1.036853
```

```
GRS_LAND        2.215652  1         1.488507
FOR_LAND        2.724123  1         1.650492
slope           2.105186  2         1.204544
mean_QV2M       3.689340  1         1.920765
mean_WS10M     40.471483  1         6.361720
mean_WS50M     36.907567  1         6.075160
mean_PRECTOT    6.447560  1         2.539205
```

Variables such as mean_WS10M and mean_WS50M have very high GVIF values (40.47 and 36.91, respectively), which strongly suggest multicollinearity issues. This means that these variables are highly correlated with other predictors in the model. However, if we remove the variable mean_WS50M or mean_WS10M, the model fails to converge. This may because removing certain variables may change the overall stability of the model. For example, if mean_WS50M is correlated with other variables, its presence may help balance the model. After removing this variable, the model may become unstable, especially if the variability of avg_fire_last is not well explained by other variables.
According to the actual, we think that the coefficient of WAT_LAND is contrary to our common sense, and the same is true for mean_PRECTOR, so we remove this two variable and mean_WS10M.

```
Call:
glm(formula = avg_fire_last ~ elevation + NVG_LAND + URB_LAND + 
    GRS_LAND + FOR_LAND + slope + mean_QV2M + mean_WS50M, family = 
Gamma(link = "log"), 
    data = truncated_data_last)

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  8.6530393  0.4736755  18.268  < 2e-16 ***
elevation    0.0002718  0.0001182   2.299 0.021606 *  
NVG_LAND     0.0122712  0.0059136   2.075 0.038081 *  
URB_LAND     0.0165433  0.0046558   3.553 0.000387 ***
GRS_LAND     0.0133656  0.0020386   6.556 6.67e-11 ***
FOR_LAND     0.0026186  0.0018630   1.406 0.159976    
slopemedium -0.4076534  0.1167763  -3.491 0.000490 ***
slopesmall   0.1339208  0.1366281   0.980 0.327089    
mean_QV2M   -0.1314485  0.0271448  -4.842 1.36e-06 ***
mean_WS50M  -0.1187267  0.0549922  -2.159 0.030947 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Gamma family taken to be 4.23565)

    Null deviance: 6347.5  on 2518  degrees of freedom
```

```
Residual deviance: 5135.9  on 2509  degrees of freedom
AIC: 42091

Number of Fisher Scoring iterations: 24
```

To further observe the results of the model, draw the residual plot and QQ plot. As the Figure.4 shows.

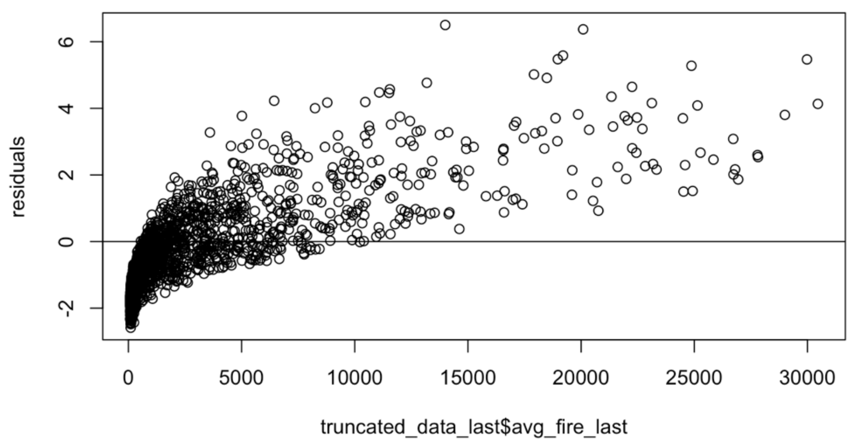

Figure.4.a. Residual plot of removing mean_WS10M, WAT_LAND, mean_PRECTOR

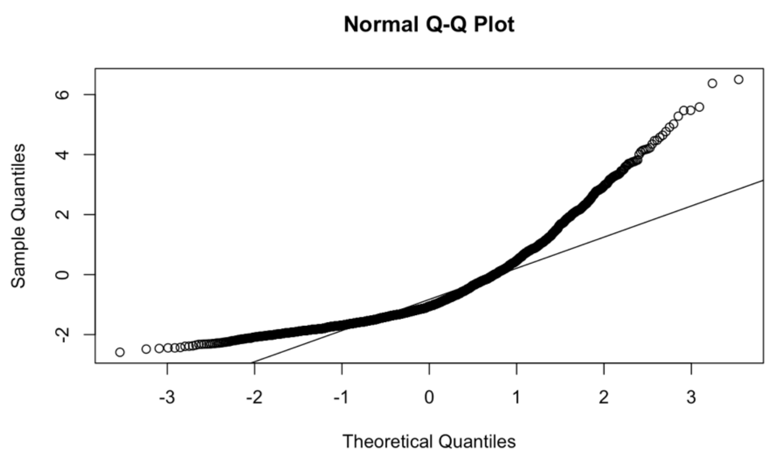

Figure 4.b QQ-plot of removing mean_WS10M, WAT_LAND, mean_PRECTOR

According to the change of the abscissa value in the residual plot, the absolute value of the residual is getting larger and larger, and it does not obey the normal distribution. At the same time, according to the results of the qq chart, the residual shows a curve, which shows that the model prediction results are poor and there may be heteroskedasticity.

The results of using WLS to solve heteroskedasticity are not ideal, so parameter transformation is used to try to solve the problem of heteroskedasticity. Replace avg_fire_last with log_avg_fire_last.

```
Call:
glm(formula = log_avg_fire_last ~ elevation + NVG_LAND + URB_LAND +
    GRS_LAND + FOR_LAND + slope + mean_QV2M + mean_WS50M, family =
Gamma(link = "log"),
    data = truncated_data_last)
    …
(Dispersion parameter for Gamma family taken to be 0.04275955)

    Null deviance: 135.799  on 2518  degrees of freedom
Residual deviance:  99.259  on 2509  degrees of freedom
AIC: 8272.3
```

From the comparison of AIC and deviation, we can see that the transformed model is better than the previous model. Further, draw the residual plot and QQ plot (as Figure.5 shows) to check whether the model is good.

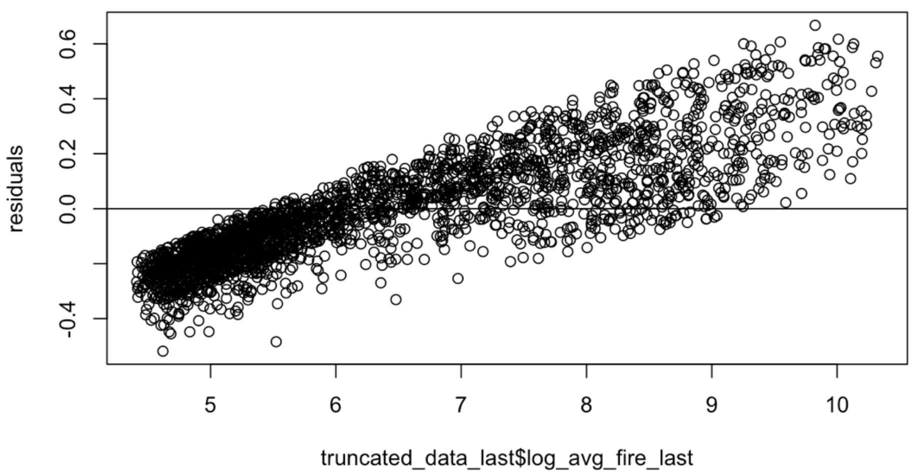

Figure.5a.Residual plot after using log_avg_fire_last

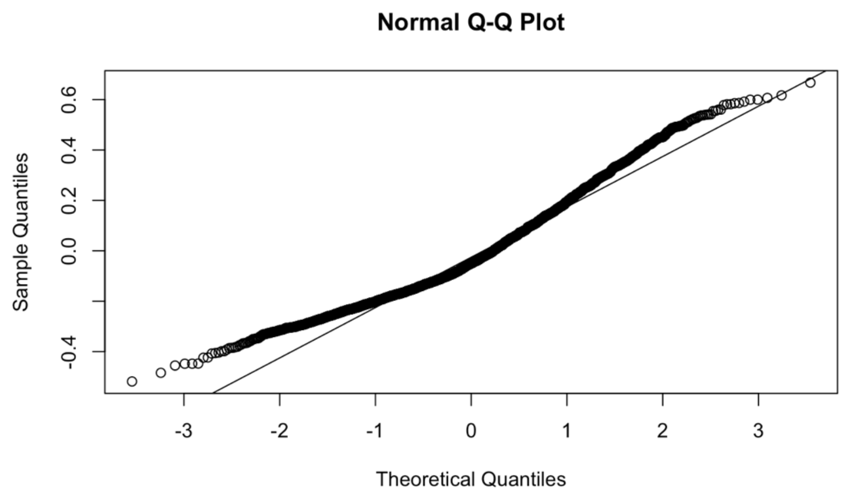

Figure 5.b. QQ- plot after using log_avg_fire_last

Although according to the residual plot and QQ plot, the performance of the model is not ideal. But this may be caused by the difference between the predicted variables being too large or the predictor variables not being able to predict the predicted variables well. Observing the model, it can be concluded that the performance of the model is not ideal based on the existing variables, which indicates that the duration of the fire may be controlled by other factors, but this variable is not included in the model. The significant variable results given by the model are as follows:

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.941e+00  4.759e-02  40.793  < 2e-16 ***
elevation    1.034e-04  1.188e-05   8.705  < 2e-16 ***
NVG_LAND     2.717e-03  5.942e-04   4.573 5.03e-06 ***
GRS_LAND     2.431e-03  2.048e-04  11.871  < 2e-16 ***
mean_WS50M  -2.851e-02  5.525e-03  -5.160 2.66e-07 ***
```

According to the result of the model, we get the following conclusion.
Intercept: The intercept term is 1.941e+00, which is the estimated log of the response variable when all predictor variables are zero.
elevation: The coefficient for the elevation variable is 1.034e-04. This means that for a one-unit increase in elevation, the log of the response variable is expected to increase by approximately 1.034e-04 units, holding all other variables constant.
NVG_LAND: The coefficient for NVG_LAND is 2.717e-03. This suggests that for a one-unit increase in NVG_LAND, the log of the response variable is expected to increase by approximately 2.717e-03 units, holding all other variables constant.
GRS_LAND: The coefficient for GRS_LAND is 2.431e-03. For a one-unit increase in GRS_LAND, the log of the response variable is expected to increase by approximately 2.431e-03 units, holding all other variables constant.

mean_WS50M: The coefficient for mean_WS50M is -2.851e-02. This indicates that for a one-unit increase in mean_WS50M, the log of the response variable is expected to decrease by approximately 2.851e-02 units, holding all other variables constant.
In short, as the altitude, Barren/very sparsely vegetated land, Grass/scrub/woodland and near-surface wind speed increase, the fire lasts longer, which means that the fire is more difficult to extinguish in a short time. This may be due to vegetation providing flammable materials for fire spread, and higher wind speeds causing fires to spread more easily. The reason why fires last too long due to high altitude may be due to factors such as difficulty in carrying out relevant firefighting work.
3. Partial Pooling Model.
When I try to build a partial pooling model, the program reports an error:

```
Warning: Model failed to converge with max|grad| = 0.755596 (tol =
0.002, component 1)Warning: Model is nearly unidentifiable: very large
eigenvalue
 - Rescale variables?;Model is nearly unidentifiable: large eigenvalue
ratio
 - Rescale variables?
```

This shows that the formula does not converge and it is difficult to predict the duration of the fire using the variables currently available.

Model for fire times:
1. Null Model

```
Call:
lm(formula = times ~ 1, data = time_data)

Residuals:
    Min      1Q  Median      3Q     Max
-163.16 -125.16  -60.16   66.84  632.84

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  167.157      3.499   47.77   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 169.1 on 2335 degrees of freedom
```

2. GLS Model
First, we need to choose variables. According to the boxplot of slope as Figure.6 shows and use the correlation matrix as Figure.3 shows, we choose variable drought_value, CENSUS2010POP, CULT_LAND, FOR_LAND, mean_QV2M, mean_WS10M, mean_WS50M, mean_PRECTOT into the model. Draw the hist graph of times as shown in Figure 7 to obtain the distribution of the

predicted variable and select an appropriate model. Since the distribution is right-skewed and affected by extreme values and times is a counting indicator, choose the family to build the model for Poisson.

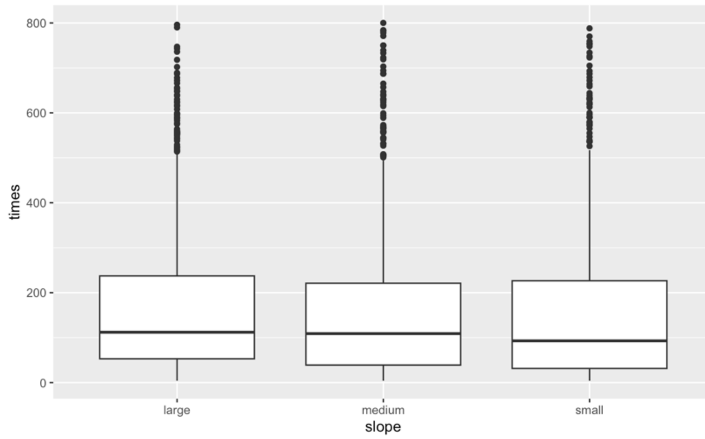

Figure.6. boxplot of slope and times

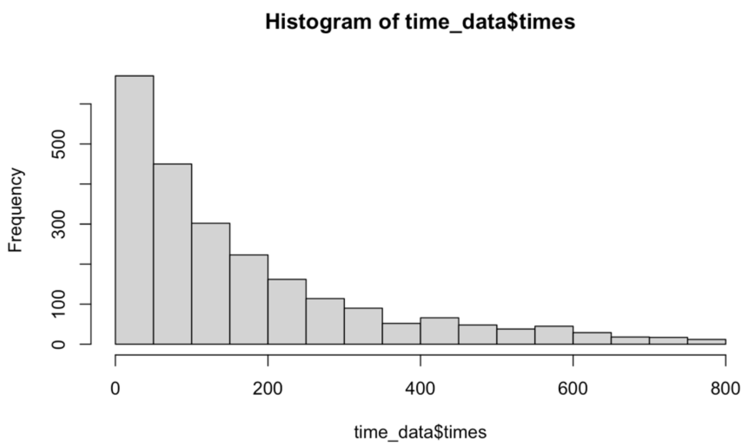

Figure.7. Frequency of times

```
Model Info:
 function:     stan_glm
 family:       poisson [log]
 formula:      times ~ drought_value + CENSUS2010POP + CULT_LAND +
FOR_LAND +
          mean_QV2M + mean_WS10M + mean_WS50M + mean_PRECTOT
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 2336
 predictors:   9

Estimates:
                mean   sd    10%   50%   90%
```

```
(Intercept)    5.72   0.03  5.69  5.72  5.75
drought_value  0.12   0.00  0.11  0.12  0.12
CENSUS2010POP  0.00   0.00  0.00  0.00  0.00
CULT_LAND      0.00   0.00  0.00  0.00  0.00
FOR_LAND       0.00   0.00  0.00  0.00  0.00
mean_QV2M      0.06   0.00  0.06  0.06  0.07
mean_WS10M     0.43   0.01  0.42  0.43  0.44
mean_WS50M    -0.53   0.01 -0.54 -0.53 -0.52
mean_PRECTOT  -0.10   0.00 -0.10 -0.10 -0.09

Fit Diagnostics:
           mean   sd     10%    50%    90%
mean_PPD 167.16   0.39 166.65 167.15 167.68

The mean_ppd is the sample average posterior predictive distribution
of the outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
              mcse Rhat n_eff
(Intercept)   0.00 1.00 1792
drought_value 0.00 1.00 2959
CENSUS2010POP 0.00 1.00 3775
CULT_LAND     0.00 1.00 4070
FOR_LAND      0.00 1.00 3103
mean_QV2M     0.00 1.00 3162
mean_WS10M    0.00 1.00  824
mean_WS50M    0.00 1.00  795
mean_PRECTOT  0.00 1.00 2692
mean_PPD      0.01 1.00 3665
log-posterior 0.06 1.01 1277
```

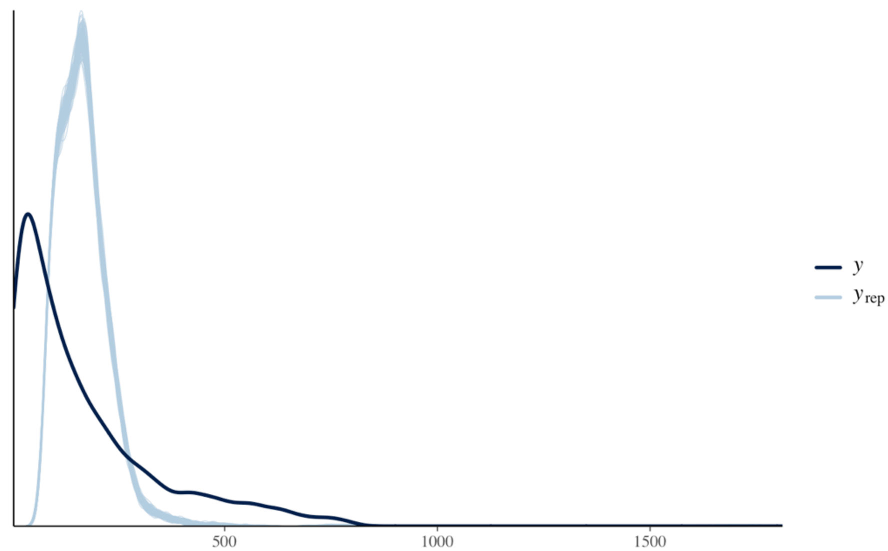

Figure.8. PPC chart of model STAN_GLM

According to Rhat, the model is convergent, and all parameters are significant. To further observe the model, draw the PPC chart and get the results as shown in the figure.8.

3.Partial Pooling Model

Establish the partial pooling model and draw its residual diagram and PPC diagram. The results are as shown in the figure.9 and figure.10. Since there are too many parameters in the model, the complete output results of the model are shown in Appendix 1.

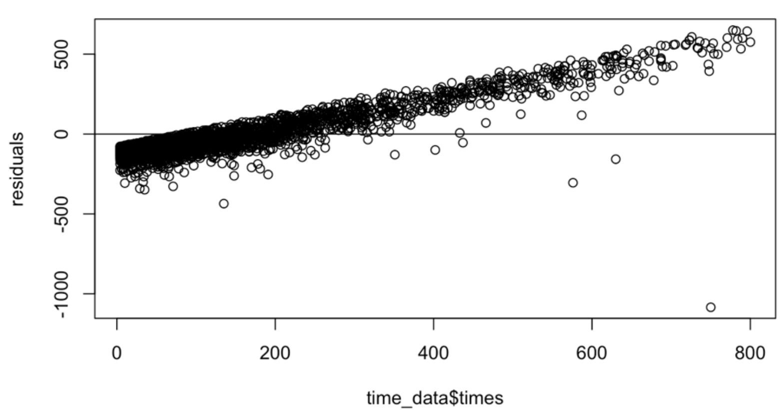

Figure.9. Partial pooling model redisual plot

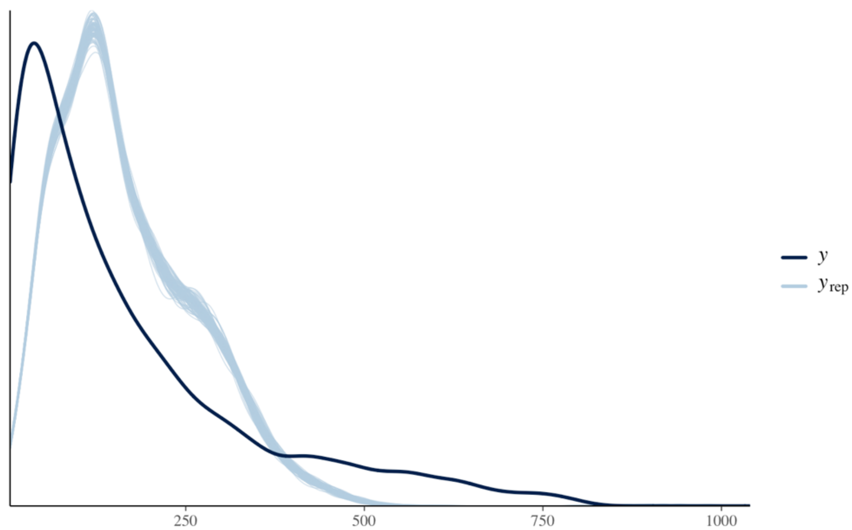

Figure.10. Paritial pooling model PPC plot

It can be seen that although the results of Partial Pooling are still not very ideal, compared with the results of Complete Pooling, its degree of fitting is better.

```
Estimates:
                                  mean   sd   10%   50%   90%
(Intercept)                      5.31  0.12  5.15  5.31  5.47
drought_value                   -0.07  0.01 -0.08 -0.07 -0.06
CENSUS2010POP                    0.00  0.00  0.00  0.00  0.00
CULT_LAND                        0.00  0.00  0.00  0.00  0.00
FOR_LAND                         0.00  0.00  0.00  0.00  0.00
mean_QV2M                        0.10  0.00  0.10  0.10  0.10
mean_WS10M                      -0.02  0.01 -0.03 -0.02 -0.01
mean_WS50M                      -0.15  0.01 -0.16 -0.15 -0.13
mean_PRECTOT                    -0.08  0.00 -0.09 -0.08 -0.08
```

(Intercept): The posterior mean for the intercept is approximately 5.31. This represents the estimated log of the expected count of times when all other predictor variables are zero. You can exponentiate this value to get an estimate of the expected count (e.g., exp(5.31) $\approx$ 202.61).
drought_value: The posterior mean for drought_value is approximately -0.07. It represents the estimated change in the log expected count of times for a one-unit increase in drought_value while holding all other predictors constant.
CENSUS2010POP: The posterior mean for CENSUS2010POP is approximately 0.00, indicating that there is essentially no estimated effect of CENSUS2010POP on the log expected count of times in your model.
CULT_LAND: The posterior mean for CULT_LAND is approximately 0.00, suggesting no estimated effect of CULT_LAND on the log expected count of times.
FOR_LAND: The posterior mean for FOR_LAND is approximately 0.00, indicating no estimated effect of FOR_LAND on the log expected count of times.

mean_QV2M: The posterior mean for mean_QV2M is approximately 0.10. This represents the estimated change in the log expected count of times for a one-unit increase in mean_QV2M while holding all other predictors constant.
mean_WS10M: The posterior mean for mean_WS10M is approximately -0.02. It represents the estimated change in the log expected count of times for a one-unit increase in mean_WS10M while holding all other predictors constant.
mean_WS50M: The posterior mean for mean_WS50M is approximately -0.15. This represents the estimated change in the log expected count of times for a one-unit increase in mean_WS50M while holding all other predictors constant.
mean_PRECTOT: The posterior mean for mean_PRECTOT is approximately -0.08. It represents the estimated change in the log expected count of times for a one-unit increase in mean_PRECTOT while holding all other predictors constant.

4. No Pooling Model

The results of the established no pooling model are shown in Appendix 2. When the Rhat diagram was drawn as Figure.11 shows, it showed that Rhat is much larger than 1, which means the model is not good.

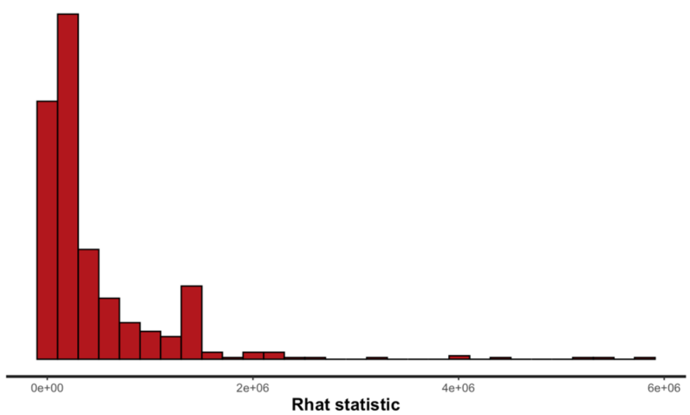

Figure.10. Rhat plot of no pooling model

Discussion:

According to the results, it can be concluded that it is difficult to achieve very good results in predicting the duration of fires and the number of fire occurrences in this article. But at the same time, the occurrence of fires on the map is not random, and it can be seen that there is a clear influence of geographical distribution. Perhaps future research should emphasize the impact of topography on fires, and comprehensively consider the causes and duration of fires from factors such as ocean currents and atmospheric circulation, so as to further predict the occurrence of fires and reduce economic and life losses. loss.

Appendix:

1.Partial Pooling Model result

```
Model Info:
```

```
 function:     stan_glmer
 family:       poisson [log]
 formula:      times ~ drought_value + CENSUS2010POP * CULT_LAND + FOR_LAND + 
	 mean_QV2M + mean_WS10M + mean_WS50M + mean_PRECTOT + (1 | 
	 STNAME)
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 2336
 groups:       STNAME (48)

Estimates:
                                       mean   sd     10%    50%    90% 
(Intercept)                           5.309  0.125  5.146  5.311  5.469
drought_value                        -0.071  0.006 -0.078 -0.071 -0.064
CENSUS2010POP                         0.000  0.000  0.000  0.000  0.000
CULT_LAND                             0.001  0.000  0.000  0.001  0.001
FOR_LAND                              0.004  0.000  0.004  0.004  0.004
mean_QV2M                             0.098  0.002  0.095  0.098  0.101
mean_WS10M                           -0.020  0.012 -0.035 -0.020 -0.005
mean_WS50M                           -0.146  0.012 -0.161 -0.146 -0.131
mean_PRECTOT                         -0.082  0.004 -0.088 -0.082 -0.077
CENSUS2010POP:CULT_LAND               0.000  0.000  0.000  0.000  0.000
b[(Intercept) STNAME:Alabama]         0.080  0.119 -0.071  0.080  0.232
b[(Intercept) STNAME:Arizona]         1.246  0.120  1.093  1.246  1.400
b[(Intercept) STNAME:Arkansas]       -0.977  0.119 -1.129 -0.978 -0.826
b[(Intercept) STNAME:California]      0.923  0.120  0.771  0.922  1.077
b[(Intercept) STNAME:Colorado]        0.679  0.119  0.527  0.678  0.832
b[(Intercept) STNAME:Connecticut]     0.499  0.120  0.344  0.499  0.652
b[(Intercept) STNAME:Delaware]       -0.703  0.171 -0.927 -0.702 -0.485
b[(Intercept) STNAME:Florida]         0.157  0.119  0.006  0.155  0.309
b[(Intercept) STNAME:Georgia]        -0.104  0.119 -0.256 -0.106  0.047
b[(Intercept) STNAME:Idaho]           0.316  0.119  0.162  0.314  0.470
b[(Intercept) STNAME:Illinois]       -1.687  0.122 -1.843 -1.689 -1.528
b[(Intercept) STNAME:Indiana]        -2.315  0.143 -2.502 -2.314 -2.134
b[(Intercept) STNAME:Iowa]           -0.779  0.126 -0.940 -0.781 -0.615
b[(Intercept) STNAME:Kansas]          0.456  0.119  0.306  0.455  0.610
b[(Intercept) STNAME:Kentucky]       -0.614  0.119 -0.766 -0.615 -0.462
b[(Intercept) STNAME:Louisiana]      -0.232  0.119 -0.384 -0.232 -0.080
b[(Intercept) STNAME:Maine]           0.827  0.119  0.673  0.826  0.981
b[(Intercept) STNAME:Maryland]       -1.211  0.121 -1.365 -1.211 -1.057
b[(Intercept) STNAME:Massachusetts]   0.837  0.120  0.685  0.836  0.989
b[(Intercept) STNAME:Michigan]        0.186  0.119  0.034  0.185  0.338
b[(Intercept) STNAME:Minnesota]       0.366  0.119  0.215  0.366  0.522
b[(Intercept) STNAME:Mississippi]    -0.306  0.119 -0.458 -0.307 -0.154
b[(Intercept) STNAME:Missouri]       -0.612  0.119 -0.763 -0.613 -0.460
b[(Intercept) STNAME:Montana]         0.595  0.118  0.443  0.595  0.748
b[(Intercept) STNAME:Nebraska]       -0.609  0.120 -0.760 -0.610 -0.454
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b[(Intercept) STNAME:Nevada]            0.940  0.120  0.788  0.939  1.092
b[(Intercept) STNAME:New_Hampshire]     0.091  0.125 -0.070  0.089  0.253
b[(Intercept) STNAME:New_Jersey]        0.693  0.119  0.540  0.691  0.844
b[(Intercept) STNAME:New_Mexico]        0.984  0.119  0.833  0.984  1.137
b[(Intercept) STNAME:New_York]          0.877  0.119  0.726  0.877  1.030
b[(Intercept) STNAME:North_Carolina]    0.534  0.119  0.382  0.533  0.687
b[(Intercept) STNAME:North_Dakota]     -0.187  0.120 -0.338 -0.187 -0.030
b[(Intercept) STNAME:Ohio]             -0.491  0.120 -0.644 -0.493 -0.335
b[(Intercept) STNAME:Oklahoma]         -0.105  0.120 -0.257 -0.105  0.052
b[(Intercept) STNAME:Oregon]            0.703  0.119  0.552  0.703  0.859
b[(Intercept) STNAME:Pennsylvania]     -0.445  0.119 -0.598 -0.445 -0.293
b[(Intercept) STNAME:Rhode_Island]     -0.380  0.127 -0.542 -0.382 -0.220
b[(Intercept) STNAME:South_Carolina]    0.297  0.119  0.145  0.296  0.448
b[(Intercept) STNAME:South_Dakota]      0.516  0.120  0.363  0.516  0.672
b[(Intercept) STNAME:Tennessee]        -0.839  0.119 -0.988 -0.839 -0.685
b[(Intercept) STNAME:Texas]             0.502  0.119  0.350  0.501  0.654
b[(Intercept) STNAME:Utah]              1.073  0.119  0.922  1.071  1.225
b[(Intercept) STNAME:Vermont]          -1.110  0.124 -1.268 -1.110 -0.948
b[(Intercept) STNAME:Virginia]         -1.187  0.121 -1.343 -1.188 -1.029
b[(Intercept) STNAME:Washington]        0.338  0.119  0.186  0.338  0.491
b[(Intercept) STNAME:West_Virginia]    -0.588  0.119 -0.741 -0.589 -0.436
b[(Intercept) STNAME:Wisconsin]         0.287  0.119  0.134  0.286  0.443
b[(Intercept) STNAME:Wyoming]           1.235  0.119  1.081  1.235  1.391
Sigma[STNAME:(Intercept),(Intercept)]   0.661  0.137  0.503  0.643  0.835

Fit Diagnostics:
           mean    sd      10%     50%     90%
mean_PPD 167.151   0.374 166.671 167.153 167.628

The mean_ppd is the sample average posterior predictive distribution of the
outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
                                      mcse  Rhat  n_eff
(Intercept)                           0.006 1.009  394
drought_value                         0.000 1.000 4055
CENSUS2010POP                         0.000 1.000 4302
CULT_LAND                             0.000 1.000 4176
FOR_LAND                              0.000 1.000 4471
mean_QV2M                             0.000 1.001 3662
mean_WS10M                            0.000 1.000 2126
mean_WS50M                            0.000 1.000 2124
mean_PRECTOT                          0.000 1.000 4060
CENSUS2010POP:CULT_LAND               0.000 0.999 4442
b[(Intercept) STNAME:Alabama]         0.006 1.009  367
b[(Intercept) STNAME:Arizona]         0.006 1.008  372
b[(Intercept) STNAME:Arkansas]        0.006 1.009  367
b[(Intercept) STNAME:California]      0.006 1.010  369
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b[(Intercept) STNAME:Colorado]       0.006 1.010  362
b[(Intercept) STNAME:Connecticut]    0.006 1.008  372
b[(Intercept) STNAME:Delaware]       0.007 1.005  644
b[(Intercept) STNAME:Florida]        0.006 1.009  370
b[(Intercept) STNAME:Georgia]        0.006 1.009  366
b[(Intercept) STNAME:Idaho]          0.006 1.009  360
b[(Intercept) STNAME:Illinois]       0.006 1.009  372
b[(Intercept) STNAME:Indiana]        0.006 1.006  540
b[(Intercept) STNAME:Iowa]           0.006 1.008  404
b[(Intercept) STNAME:Kansas]         0.006 1.009  362
b[(Intercept) STNAME:Kentucky]       0.006 1.009  364
b[(Intercept) STNAME:Louisiana]      0.006 1.008  371
b[(Intercept) STNAME:Maine]          0.006 1.009  367
b[(Intercept) STNAME:Maryland]       0.006 1.008  382
b[(Intercept) STNAME:Massachusetts]  0.006 1.009  369
b[(Intercept) STNAME:Michigan]       0.006 1.009  365
b[(Intercept) STNAME:Minnesota]      0.006 1.009  362
b[(Intercept) STNAME:Mississippi]    0.006 1.009  367
b[(Intercept) STNAME:Missouri]       0.006 1.009  368
b[(Intercept) STNAME:Montana]        0.006 1.009  361
b[(Intercept) STNAME:Nebraska]       0.006 1.009  367
b[(Intercept) STNAME:Nevada]         0.006 1.010  367
b[(Intercept) STNAME:New_Hampshire]  0.006 1.008  399
b[(Intercept) STNAME:New_Jersey]     0.006 1.009  362
b[(Intercept) STNAME:New_Mexico]     0.006 1.010  360
b[(Intercept) STNAME:New_York]       0.006 1.009  360
b[(Intercept) STNAME:North_Carolina] 0.006 1.009  362
b[(Intercept) STNAME:North_Dakota]   0.006 1.009  371
b[(Intercept) STNAME:Ohio]           0.006 1.009  368
b[(Intercept) STNAME:Oklahoma]       0.006 1.009  371
b[(Intercept) STNAME:Oregon]         0.006 1.009  363
b[(Intercept) STNAME:Pennsylvania]   0.006 1.009  363
b[(Intercept) STNAME:Rhode_Island]   0.006 1.007  419
b[(Intercept) STNAME:South_Carolina] 0.006 1.009  365
b[(Intercept) STNAME:South_Dakota]   0.006 1.009  364
b[(Intercept) STNAME:Tennessee]      0.006 1.009  365
b[(Intercept) STNAME:Texas]          0.006 1.009  364
b[(Intercept) STNAME:Utah]           0.006 1.009  363
b[(Intercept) STNAME:Vermont]        0.006 1.008  397
b[(Intercept) STNAME:Virginia]       0.006 1.008  376
b[(Intercept) STNAME:Washington]     0.006 1.009  368
b[(Intercept) STNAME:West_Virginia]  0.006 1.009  366
b[(Intercept) STNAME:Wisconsin]      0.006 1.009  365
b[(Intercept) STNAME:Wyoming]        0.006 1.009  359
Sigma[STNAME:(Intercept),(Intercept)] 0.007 1.018  418
mean_PPD                             0.006 1.000 3878
log-posterior                        0.315 1.014  524
```

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence Rhat=1).

2.No Pooling Model result

```
Model Info:
 function:     stan_glmer
 family:       Gamma [inverse]
 formula:      times ~ drought_value + CENSUS2010POP * CULT_LAND + FOR_LAND + 
               mean_QV2M + mean_WS10M + mean_WS50M + mean_PRECTOT + (1 + 
               drought_value + CENSUS2010POP * CULT_LAND + FOR_LAND + mean_QV2M + 
               mean_WS10M + mean_WS50M + mean_PRECTOT | STNAME)
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 2336
 groups:       STNAME (48)

Estimates:
                                                   mean      sd        10%       50%       90%    
(Intercept)                                    2897773.3 3836064.3   53477.7 1063135.8 9411617.6
drought_value                                        0.7       2.6      -1.7      -0.1       4.8
CENSUS2010POP                                        0.0       0.0       0.0       0.0       0.0
CULT_LAND                                            0.0       0.1      -0.1       0.0       0.1
FOR_LAND                                             0.0       0.0       0.0       0.0       0.1
mean_QV2M                                            0.8       0.9      -0.4       0.8       1.7
mean_WS10M                                           0.3       2.6      -3.0       0.5       3.4
mean_WS50M                                           0.1       2.1      -2.9       0.1       3.1
mean_PRECTOT                                         0.3       2.9      -3.5       0.1       4.6
CENSUS2010POP:CULT_LAND                              0.0       0.0       0.0       0.0       0.0
b[(Intercept) STNAME:Alabama]                       -0.1       0.2      -0.4       0.0       0.0
b[drought_value STNAME:Alabama]                     -0.2       0.3      -0.7       0.0       0.0
b[CENSUS2010POP STNAME:Alabama]                      0.0       0.0       0.0       0.0       0.0
b[CULT_LAND STNAME:Alabama]                          0.0       0.1      -0.1       0.0       0.1
b[FOR_LAND STNAME:Alabama]                          -0.1       0.3      -0.6       0.0       0.1
b[mean_QV2M STNAME:Alabama]                          0.0       0.1       0.0       0.0       0.1
b[mean_WS10M STNAME:Alabama]                         0.0       0.0       0.0       0.0       0.1
b[mean_WS50M STNAME:Alabama]                        -0.1       0.1      -0.3       0.0       0.0
b[mean_PRECTOT STNAME:Alabama]                       0.0       0.1      -0.1       0.0       0.1
b[CENSUS2010POP:CULT_LAND STNAME:Alabama]            0.1       0.1       0.0       0.0       0.2
b[(Intercept) STNAME:Arizona]                        0.1       0.2       0.0       0.0       0.4
b[drought_value STNAME:Arizona]                      0.2       0.4       0.0       0.0       0.8
b[CENSUS2010POP STNAME:Arizona]                     -0.1       0.1      -0.3       0.0       0.0
b[CULT_LAND STNAME:Arizona]                          0.1       0.2      -0.1       0.0       0.5
b[FOR_LAND STNAME:Arizona]                          -0.1       0.1      -0.2       0.0       0.0
b[mean_QV2M STNAME:Arizona]                         -0.2       0.4      -1.0       0.0       0.0
b[mean_WS10M STNAME:Arizona]                        -0.1       0.1      -0.3       0.0       0.0
b[mean_WS50M STNAME:Arizona]                        -0.2       0.3      -0.8       0.0       0.1
b[mean_PRECTOT STNAME:Arizona]                       0.1       0.3      -0.1       0.0       0.6
b[CENSUS2010POP:CULT_LAND STNAME:Arizona]           -0.1       0.1      -0.2      -0.1       0.0
b[(Intercept) STNAME:Arkansas]                       0.0       0.1      -0.1       0.0       0.1
b[drought_value STNAME:Arkansas]                     0.1       0.2       0.0       0.0       0.4
b[CENSUS2010POP STNAME:Arkansas]                     0.0       0.1      -0.2       0.0       0.1
b[CULT_LAND STNAME:Arkansas]                         0.1       0.1       0.0       0.0       0.3
b[FOR_LAND STNAME:Arkansas]                          0.1       0.2       0.0       0.0       0.5
b[mean_QV2M STNAME:Arkansas]                        -0.1       0.1      -0.3       0.0       0.0
b[mean_WS10M STNAME:Arkansas]                        0.2       0.2       0.0       0.0       0.6
b[mean_WS50M STNAME:Arkansas]                        0.1       0.3      -0.1       0.0       0.7
b[mean_PRECTOT STNAME:Arkansas]                     -0.1       0.3      -0.6       0.0       0.0
b[CENSUS2010POP:CULT_LAND STNAME:Arkansas]           0.0       0.1      -0.1       0.0       0.2
b[(Intercept) STNAME:California]                    -0.1       0.1      -0.2      -0.1       0.0
b[drought_value STNAME:California]                  -0.1       0.3      -0.6       0.0       0.1
b[CENSUS2010POP STNAME:California]                   0.2       0.2       0.0       0.1       0.5
b[CULT_LAND STNAME:California]                      -0.1       0.2      -0.5       0.0       0.0
b[FOR_LAND STNAME:California]                        0.0       0.1       0.0       0.0       0.2
b[mean_QV2M STNAME:California]                       0.1       0.2       0.0       0.0       0.5
b[mean_WS10M STNAME:California]                      0.0       0.0       0.0       0.0       0.1
b[mean_WS50M STNAME:California]                      0.1       0.2       0.0       0.0       0.5
b[mean_PRECTOT STNAME:California]                    0.0       0.1      -0.1       0.0       0.1
b[CENSUS2010POP:CULT_LAND STNAME:California]         0.1       0.1       0.0       0.0       0.3
b[(Intercept) STNAME:Colorado]                       0.1       0.1       0.0       0.1       0.3
```

b[drought_value STNAME:Colorado]	0.1	0.1	0.0	0.0	0.3
b[CENSUS2010POP STNAME:Colorado]	0.0	0.0	0.0	0.0	0.0
b[CULT_LAND STNAME:Colorado]	-0.1	0.2	-0.4	0.0	0.1
b[FOR_LAND STNAME:Colorado]	-0.1	0.2	-0.4	0.0	0.0
b[mean_QV2M STNAME:Colorado]	0.2	0.3	0.0	0.0	0.7
b[mean_WS10M STNAME:Colorado]	0.1	0.2	-0.1	0.0	0.4
b[mean_WS50M STNAME:Colorado]	0.1	0.2	0.0	0.0	0.4
b[mean_PRECTOT STNAME:Colorado]	0.0	0.0	-0.1	0.0	0.0
b[CENSUS2010POP:CULT_LAND STNAME:Colorado]	0.1	0.1	0.0	0.0	0.3
b[(Intercept) STNAME:Connecticut]	-0.1	0.1	-0.3	-0.1	0.0
b[drought_value STNAME:Connecticut]	-0.1	0.3	-0.6	0.0	0.0
b[CENSUS2010POP STNAME:Connecticut]	0.0	0.1	0.0	0.0	0.1
b[CULT_LAND STNAME:Connecticut]	-0.1	0.1	-0.3	0.0	0.0
b[FOR_LAND STNAME:Connecticut]	0.2	0.3	0.0	0.0	0.6
b[mean_QV2M STNAME:Connecticut]	0.0	0.1	-0.1	0.0	0.0
b[mean_WS10M STNAME:Connecticut]	0.0	0.1	-0.2	0.0	0.0
b[mean_WS50M STNAME:Connecticut]	-0.3	0.5	-1.2	0.0	0.0
b[mean_PRECTOT STNAME:Connecticut]	0.0	0.1	0.0	0.0	0.2
b[CENSUS2010POP:CULT_LAND STNAME:Connecticut]	0.1	0.1	0.0	0.0	0.2
b[(Intercept) STNAME:Delaware]	0.0	0.1	-0.1	0.0	0.0
b[drought_value STNAME:Delaware]	0.2	0.3	0.0	0.1	0.8
b[CENSUS2010POP STNAME:Delaware]	-0.1	0.3	-0.6	0.0	0.1
b[CULT_LAND STNAME:Delaware]	0.2	0.3	-0.1	0.0	0.7
b[FOR_LAND STNAME:Delaware]	0.3	0.5	0.0	0.0	1.2
b[mean_QV2M STNAME:Delaware]	-0.2	0.2	-0.6	0.0	0.0
b[mean_WS10M STNAME:Delaware]	0.1	0.1	0.0	0.0	0.3
b[mean_WS50M STNAME:Delaware]	-0.3	0.4	-0.9	-0.1	0.0
b[mean_PRECTOT STNAME:Delaware]	-0.2	0.2	-0.5	-0.1	0.0
b[CENSUS2010POP:CULT_LAND STNAME:Delaware]	0.0	0.0	0.0	0.0	0.0
b[(Intercept) STNAME:Florida]	-0.1	0.1	-0.2	0.0	0.0
b[drought_value STNAME:Florida]	0.1	0.2	-0.1	0.0	0.5
b[CENSUS2010POP STNAME:Florida]	-0.1	0.1	-0.3	0.0	0.0
b[CULT_LAND STNAME:Florida]	0.0	0.0	0.0	0.0	0.1
b[FOR_LAND STNAME:Florida]	-0.1	0.1	-0.2	0.0	0.0
b[mean_QV2M STNAME:Florida]	0.2	0.4	0.0	0.0	1.0
b[mean_WS10M STNAME:Florida]	-0.2	0.4	-0.9	0.0	0.1
b[mean_WS50M STNAME:Florida]	-0.2	0.3	-0.8	0.0	0.0
b[mean_PRECTOT STNAME:Florida]	0.2	0.2	0.0	0.1	0.5
b[CENSUS2010POP:CULT_LAND STNAME:Florida]	0.1	0.1	0.0	0.1	0.3
b[(Intercept) STNAME:Georgia]	0.1	0.1	0.0	0.1	0.3
b[drought_value STNAME:Georgia]	0.2	0.2	0.0	0.0	0.5
b[CENSUS2010POP STNAME:Georgia]	0.0	0.0	-0.1	0.0	0.0
b[CULT_LAND STNAME:Georgia]	0.1	0.1	0.0	0.0	0.3
b[FOR_LAND STNAME:Georgia]	-0.2	0.5	-1.0	0.0	0.1
b[mean_QV2M STNAME:Georgia]	0.1	0.1	0.0	0.0	0.3
b[mean_WS10M STNAME:Georgia]	0.1	0.1	0.0	0.0	0.3
b[mean_WS50M STNAME:Georgia]	0.3	0.4	0.0	0.0	1.0
b[mean_PRECTOT STNAME:Georgia]	-0.1	0.2	-0.4	0.0	0.0
b[CENSUS2010POP:CULT_LAND STNAME:Georgia]	-0.1	0.1	-0.3	0.0	0.0
b[(Intercept) STNAME:Idaho]	0.1	0.2	-0.1	0.0	0.4
b[drought_value STNAME:Idaho]	0.4	0.8	-0.2	0.0	1.8
b[CENSUS2010POP STNAME:Idaho]	-0.3	0.5	-1.2	0.0	0.0
b[CULT_LAND STNAME:Idaho]	0.0	0.0	0.0	0.0	0.1
b[FOR_LAND STNAME:Idaho]	0.1	0.2	0.0	0.0	0.4
b[mean_QV2M STNAME:Idaho]	0.0	0.1	-0.2	0.0	0.1
b[mean_WS10M STNAME:Idaho]	0.2	0.3	0.0	0.0	0.7
b[mean_WS50M STNAME:Idaho]	0.1	0.1	0.0	0.0	0.2
b[mean_PRECTOT STNAME:Idaho]	0.2	0.2	0.0	0.1	0.6
b[CENSUS2010POP:CULT_LAND STNAME:Idaho]	-0.1	0.1	-0.2	0.0	0.0
b[(Intercept) STNAME:Illinois]	0.0	0.1	-0.2	0.0	0.2
b[drought_value STNAME:Illinois]	0.1	0.2	-0.1	0.0	0.5
b[CENSUS2010POP STNAME:Illinois]	0.0	0.0	0.0	0.0	0.1
b[CULT_LAND STNAME:Illinois]	-0.1	0.1	-0.3	0.0	0.0
b[FOR_LAND STNAME:Illinois]	0.2	0.4	0.0	0.0	0.9
b[mean_QV2M STNAME:Illinois]	0.0	0.1	0.0	0.0	0.1
b[mean_WS10M STNAME:Illinois]	0.1	0.2	0.0	0.0	0.4
b[mean_WS50M STNAME:Illinois]	0.2	0.3	0.0	0.0	0.8
b[mean_PRECTOT STNAME:Illinois]	0.0	0.0	0.0	0.0	0.1
b[CENSUS2010POP:CULT_LAND STNAME:Illinois]	0.0	0.1	-0.1	0.0	0.1
b[(Intercept) STNAME:Indiana]	0.0	0.1	0.0	0.0	0.1
b[drought_value STNAME:Indiana]	-0.1	0.2	-0.4	0.0	0.1
b[CENSUS2010POP STNAME:Indiana]	0.1	0.1	0.0	0.0	0.3
b[CULT_LAND STNAME:Indiana]	-0.1	0.3	-0.7	0.0	0.1
b[FOR_LAND STNAME:Indiana]	-0.1	0.2	-0.5	0.0	0.0

b[mean_QV2M STNAME:Indiana]	0.1	0.1	0.0	0.0	0.3
b[mean_WS10M STNAME:Indiana]	-0.1	0.2	-0.5	0.0	0.0
b[mean_WS50M STNAME:Indiana]	0.2	0.3	0.0	0.0	0.7
b[mean_PRECTOT STNAME:Indiana]	0.2	0.3	0.0	0.0	0.7
b[CENSUS2010POP:CULT_LAND STNAME:Indiana]	0.0	0.0	-0.1	0.0	0.0
b[(Intercept) STNAME:Iowa]	-0.1	0.2	-0.4	0.0	0.2
b[drought_value STNAME:Iowa]	-0.4	0.6	-1.5	0.0	0.0
b[CENSUS2010POP STNAME:Iowa]	0.2	0.4	-0.1	0.0	0.8
b[CULT_LAND STNAME:Iowa]	0.1	0.1	0.0	0.0	0.3
b[FOR_LAND STNAME:Iowa]	0.1	0.1	0.0	0.0	0.3
b[mean_QV2M STNAME:Iowa]	-0.2	0.5	-1.1	0.0	0.1
b[mean_WS10M STNAME:Iowa]	-0.2	0.3	-0.6	0.0	0.0
b[mean_WS50M STNAME:Iowa]	-0.1	0.2	-0.5	0.0	0.0
b[mean_PRECTOT STNAME:Iowa]	0.0	0.1	-0.2	0.0	0.0
b[CENSUS2010POP:CULT_LAND STNAME:Iowa]	-0.1	0.1	-0.3	0.0	0.0
b[(Intercept) STNAME:Kansas]	0.1	0.1	0.0	0.0	0.2
b[drought_value STNAME:Kansas]	0.3	0.4	0.0	0.1	0.9
b[CENSUS2010POP STNAME:Kansas]	-0.2	0.4	-0.8	0.0	0.0
b[CULT_LAND STNAME:Kansas]	-0.2	0.3	-0.6	0.0	0.0
b[FOR_LAND STNAME:Kansas]	0.0	0.1	-0.1	0.0	0.1
b[mean_QV2M STNAME:Kansas]	0.2	0.4	0.0	0.0	1.0
b[mean_WS10M STNAME:Kansas]	0.1	0.1	0.0	0.1	0.2
b[mean_WS50M STNAME:Kansas]	0.1	0.1	0.0	0.0	0.3
b[mean_PRECTOT STNAME:Kansas]	0.2	0.3	0.0	0.0	0.7
b[CENSUS2010POP:CULT_LAND STNAME:Kansas]	0.0	0.0	0.0	0.0	0.1
b[(Intercept) STNAME:Kentucky]	0.1	0.1	0.0	0.1	0.2
b[drought_value STNAME:Kentucky]	0.2	0.4	0.0	0.0	0.8
b[CENSUS2010POP STNAME:Kentucky]	-0.2	0.2	-0.6	0.0	0.0
b[CULT_LAND STNAME:Kentucky]	0.1	0.1	0.0	0.0	0.3
b[FOR_LAND STNAME:Kentucky]	0.0	0.1	-0.2	0.0	0.0
b[mean_QV2M STNAME:Kentucky]	-0.1	0.1	-0.2	0.0	0.0
b[mean_WS10M STNAME:Kentucky]	-0.1	0.2	-0.5	0.0	0.1
b[mean_WS50M STNAME:Kentucky]	-0.2	0.4	-1.0	0.0	0.0
b[mean_PRECTOT STNAME:Kentucky]	0.2	0.2	0.0	0.1	0.5
b[CENSUS2010POP:CULT_LAND STNAME:Kentucky]	0.0	0.0	0.0	0.0	0.1
b[(Intercept) STNAME:Louisiana]	0.0	0.0	0.0	0.0	0.1
b[drought_value STNAME:Louisiana]	0.2	0.3	0.0	0.0	0.8
b[CENSUS2010POP STNAME:Louisiana]	-0.2	0.4	-0.8	0.0	0.0
b[CULT_LAND STNAME:Louisiana]	0.1	0.2	-0.1	0.0	0.3
b[FOR_LAND STNAME:Louisiana]	-0.2	0.3	-0.8	0.0	0.0
b[mean_QV2M STNAME:Louisiana]	0.1	0.2	0.0	0.0	0.4
b[mean_WS10M STNAME:Louisiana]	-0.2	0.3	-0.8	0.0	0.0
b[mean_WS50M STNAME:Louisiana]	-0.2	0.4	-0.9	0.0	0.0
b[mean_PRECTOT STNAME:Louisiana]	0.2	0.3	0.0	0.0	0.7
b[CENSUS2010POP:CULT_LAND STNAME:Louisiana]	0.0	0.0	0.0	0.0	0.1
b[(Intercept) STNAME:Maine]	0.0	0.2	-0.2	0.0	0.3
b[drought_value STNAME:Maine]	0.4	0.8	-0.1	0.0	1.9
b[CENSUS2010POP STNAME:Maine]	-0.3	0.5	-1.2	0.0	0.0
b[CULT_LAND STNAME:Maine]	0.2	0.3	-0.1	0.0	0.8
b[FOR_LAND STNAME:Maine]	0.2	0.5	-0.1	0.0	1.0
b[mean_QV2M STNAME:Maine]	-0.2	0.4	-0.9	0.0	0.0
b[mean_WS10M STNAME:Maine]	0.1	0.2	0.0	0.0	0.4
b[mean_WS50M STNAME:Maine]	-0.1	0.1	-0.3	0.0	0.0
b[mean_PRECTOT STNAME:Maine]	0.0	0.0	0.0	0.0	0.1
b[CENSUS2010POP:CULT_LAND STNAME:Maine]	0.0	0.1	-0.2	0.0	0.0
b[(Intercept) STNAME:Maryland]	-0.1	0.2	-0.3	0.0	0.1
b[drought_value STNAME:Maryland]	-0.1	0.3	-0.7	0.0	0.1
b[CENSUS2010POP STNAME:Maryland]	0.1	0.2	0.0	0.0	0.4
b[CULT_LAND STNAME:Maryland]	0.2	0.3	0.0	0.0	0.6
b[FOR_LAND STNAME:Maryland]	0.3	0.5	0.0	0.0	1.2
b[mean_QV2M STNAME:Maryland]	-0.4	0.6	-1.4	0.0	0.0
b[mean_WS10M STNAME:Maryland]	0.1	0.2	0.0	0.0	0.5
b[mean_WS50M STNAME:Maryland]	0.0	0.0	0.0	0.0	0.0
b[mean_PRECTOT STNAME:Maryland]	-0.3	0.5	-1.2	0.0	0.1
b[CENSUS2010POP:CULT_LAND STNAME:Maryland]	0.1	0.1	0.0	0.0	0.3
b[(Intercept) STNAME:Massachusetts]	-0.1	0.1	-0.2	0.0	0.0
b[drought_value STNAME:Massachusetts]	-0.3	0.6	-1.3	0.0	0.0
b[CENSUS2010POP STNAME:Massachusetts]	0.3	0.4	0.0	0.0	1.0
b[CULT_LAND STNAME:Massachusetts]	0.0	0.0	0.0	0.0	0.0
b[FOR_LAND STNAME:Massachusetts]	0.2	0.4	-0.1	0.0	0.8
b[mean_QV2M STNAME:Massachusetts]	-0.2	0.4	-0.8	0.0	0.0
b[mean_WS10M STNAME:Massachusetts]	0.0	0.0	0.0	0.0	0.0
b[mean_WS50M STNAME:Massachusetts]	0.1	0.2	-0.1	0.0	0.3
b[mean_PRECTOT STNAME:Massachusetts]	-0.3	0.5	-1.0	0.0	0.0

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b[CENSUS2010POP:CULT_LAND STNAME:Massachusetts]                     0.1       0.1       0.0       0.0       0.3
 [ reached getOption("max.print") -- omitted 346 rows ]

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 0.0    0.0  0.0   0.0   0.0

The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for details see
help('summary.stanreg')).

MCMC diagnostics
                                                             mcse         Rhat         n_eff
(Intercept)                                                  2.711829e+06 6.974440e+04    2
drought_value                                                1.800000e+00 2.269077e+06    2
CENSUS2010POP                                                0.000000e+00 4.044605e+06    2
CULT_LAND                                                    1.000000e-01 5.336771e+06    2
FOR_LAND                                                     0.000000e+00 2.207566e+06    2
mean_QV2M                                                    6.000000e-01 3.229442e+06    2
mean_WS10M                                                   1.800000e+00 5.811113e+06    2
mean_WS50M                                                   1.500000e+00 4.424691e+06    2
mean_PRECTOT                                                 2.000000e+00 5.180544e+06    2
CENSUS2010POP:CULT_LAND                                      0.000000e+00 3.940950e+06    2
b[(Intercept) STNAME:Alabama]                                1.000000e-01 2.386437e+05    2
b[drought_value STNAME:Alabama]                              2.000000e-01 5.356663e+05    2
b[CENSUS2010POP STNAME:Alabama]                              0.000000e+00 1.491730e+04    2
b[CULT_LAND STNAME:Alabama]                                  0.000000e+00 2.717265e+05    2
b[FOR_LAND STNAME:Alabama]                                   2.000000e-01 7.956060e+04    2
b[mean_QV2M STNAME:Alabama]                                  0.000000e+00 1.212376e+05    2
b[mean_WS10M STNAME:Alabama]                                 0.000000e+00 1.520110e+04    2
b[mean_WS50M STNAME:Alabama]                                 1.000000e-01 7.770720e+04    2
b[mean_PRECTOT STNAME:Alabama]                               1.000000e-01 1.670351e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:Alabama]                    0.000000e+00 9.962450e+04    2
b[(Intercept) STNAME:Arizona]                                1.000000e-01 1.082190e+05    2
b[drought_value STNAME:Arizona]                              3.000000e-01 7.027153e+05    2
b[CENSUS2010POP STNAME:Arizona]                              1.000000e-01 1.874414e+05    2
b[CULT_LAND STNAME:Arizona]                                  2.000000e-01 3.902526e+05    2
b[FOR_LAND STNAME:Arizona]                                   0.000000e+00 4.483730e+04    2
b[mean_QV2M STNAME:Arizona]                                  3.000000e-01 2.623056e+06    2
b[mean_WS10M STNAME:Arizona]                                 1.000000e-01 1.210642e+05    2
b[mean_WS50M STNAME:Arizona]                                 2.000000e-01 1.431710e+05    2
b[mean_PRECTOT STNAME:Arizona]                               2.000000e-01 1.159337e+06    2
b[CENSUS2010POP:CULT_LAND STNAME:Arizona]                    1.000000e-01 8.566580e+04    2
b[(Intercept) STNAME:Arkansas]                               1.000000e-01 1.278781e+05    2
b[drought_value STNAME:Arkansas]                             1.000000e-01 4.000006e+05    2
b[CENSUS2010POP STNAME:Arkansas]                             1.000000e-01 3.022118e+05    2
b[CULT_LAND STNAME:Arkansas]                                 1.000000e-01 1.232442e+05    2
b[FOR_LAND STNAME:Arkansas]                                  2.000000e-01 6.103830e+04    2
b[mean_QV2M STNAME:Arkansas]                                 1.000000e-01 4.812000e+04    2
b[mean_WS10M STNAME:Arkansas]                                2.000000e-01 1.100357e+05    2
b[mean_WS50M STNAME:Arkansas]                                2.000000e-01 2.924717e+05    2
b[mean_PRECTOT STNAME:Arkansas]                              2.000000e-01 6.646872e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:Arkansas]                   1.000000e-01 1.542290e+05    2
b[(Intercept) STNAME:California]                             1.000000e-01 1.794327e+05    2
b[drought_value STNAME:California]                           2.000000e-01 1.101920e+06    2
b[CENSUS2010POP STNAME:California]                           1.000000e-01 2.492822e+05    2
b[CULT_LAND STNAME:California]                               2.000000e-01 2.669141e+05    2
b[FOR_LAND STNAME:California]                                1.000000e-01 2.896780e+04    2
b[mean_QV2M STNAME:California]                               1.000000e-01 1.008310e+05    2
b[mean_WS10M STNAME:California]                              0.000000e+00 5.260350e+04    2
b[mean_WS50M STNAME:California]                              2.000000e-01 2.329486e+05    2
b[mean_PRECTOT STNAME:California]                            0.000000e+00 8.608740e+04    2
b[CENSUS2010POP:CULT_LAND STNAME:California]                 1.000000e-01 1.549493e+05    2
b[(Intercept) STNAME:Colorado]                               1.000000e-01 1.365450e+05    2
b[drought_value STNAME:Colorado]                             1.000000e-01 4.477481e+05    2
b[CENSUS2010POP STNAME:Colorado]                             0.000000e+00 2.612600e+04    2
b[CULT_LAND STNAME:Colorado]                                 1.000000e-01 1.486130e+05    2
b[FOR_LAND STNAME:Colorado]                                  1.000000e-01 4.909160e+04    2
b[mean_QV2M STNAME:Colorado]                                 2.000000e-01 6.320518e+05    2
b[mean_WS10M STNAME:Colorado]                                1.000000e-01 2.079876e+05    2
b[mean_WS50M STNAME:Colorado]                                1.000000e-01 1.115701e+05    2
b[mean_PRECTOT STNAME:Colorado]                              0.000000e+00 1.385859e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:Colorado]                   1.000000e-01 1.593391e+05    2
b[(Intercept) STNAME:Connecticut]                            1.000000e-01 2.140092e+05    2
b[drought_value STNAME:Connecticut]                          2.000000e-01 1.356323e+06    2
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b[CENSUS2010POP STNAME:Connecticut]	0.000000e+00	9.647860e+04	2
b[CULT_LAND STNAME:Connecticut]	1.000000e-01	1.478309e+05	2
b[FOR_LAND STNAME:Connecticut]	2.000000e-01	1.960817e+05	2
b[mean_QV2M STNAME:Connecticut]	0.000000e+00	3.439270e+04	2
b[mean_WS10M STNAME:Connecticut]	0.000000e+00	5.954790e+04	2
b[mean_WS50M STNAME:Connecticut]	4.000000e-01	6.481213e+05	2
b[mean_PRECTOT STNAME:Connecticut]	0.000000e+00	1.088534e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Connecticut]	1.000000e-01	5.945870e+04	2
b[(Intercept) STNAME:Delaware]	0.000000e+00	8.509190e+04	2
b[drought_value STNAME:Delaware]	2.000000e-01	5.790458e+05	2
b[CENSUS2010POP STNAME:Delaware]	2.000000e-01	6.347238e+05	2
b[CULT_LAND STNAME:Delaware]	2.000000e-01	4.628225e+05	2
b[FOR_LAND STNAME:Delaware]	4.000000e-01	1.711396e+05	2
b[mean_QV2M STNAME:Delaware]	2.000000e-01	1.399973e+05	2
b[mean_WS10M STNAME:Delaware]	1.000000e-01	1.825037e+05	2
b[mean_WS50M STNAME:Delaware]	3.000000e-01	7.305652e+05	2
b[mean_PRECTOT STNAME:Delaware]	1.000000e-01	2.419539e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Delaware]	0.000000e+00	3.548520e+04	2
b[(Intercept) STNAME:Florida]	0.000000e+00	1.138991e+05	2
b[drought_value STNAME:Florida]	2.000000e-01	8.562545e+05	2
b[CENSUS2010POP STNAME:Florida]	1.000000e-01	4.116917e+05	2
b[CULT_LAND STNAME:Florida]	0.000000e+00	9.826930e+04	2
b[FOR_LAND STNAME:Florida]	1.000000e-01	4.760450e+04	2
b[mean_QV2M STNAME:Florida]	3.000000e-01	1.407302e+06	2
b[mean_WS10M STNAME:Florida]	3.000000e-01	7.318162e+05	2
b[mean_WS50M STNAME:Florida]	2.000000e-01	4.248170e+05	2
b[mean_PRECTOT STNAME:Florida]	1.000000e-01	1.417751e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Florida]	1.000000e-01	3.792123e+05	2
b[(Intercept) STNAME:Georgia]	1.000000e-01	1.273358e+05	2
b[drought_value STNAME:Georgia]	2.000000e-01	2.981258e+05	2
b[CENSUS2010POP STNAME:Georgia]	0.000000e+00	7.393040e+04	2
b[CULT_LAND STNAME:Georgia]	1.000000e-01	9.335470e+04	2
b[FOR_LAND STNAME:Georgia]	3.000000e-01	1.565358e+05	2
b[mean_QV2M STNAME:Georgia]	1.000000e-01	1.300063e+05	2
b[mean_WS10M STNAME:Georgia]	1.000000e-01	6.234510e+04	2
b[mean_WS50M STNAME:Georgia]	3.000000e-01	2.814077e+05	2
b[mean_PRECTOT STNAME:Georgia]	1.000000e-01	1.032082e+06	2
b[CENSUS2010POP:CULT_LAND STNAME:Georgia]	1.000000e-01	1.094608e+05	2
b[(Intercept) STNAME:Idaho]	1.000000e-01	1.750017e+05	2
b[drought_value STNAME:Idaho]	6.000000e-01	2.040881e+06	2
b[CENSUS2010POP STNAME:Idaho]	4.000000e-01	8.596576e+05	2
b[CULT_LAND STNAME:Idaho]	0.000000e+00	7.126340e+04	2
b[FOR_LAND STNAME:Idaho]	1.000000e-01	1.105242e+05	2
b[mean_QV2M STNAME:Idaho]	1.000000e-01	9.926270e+04	2
b[mean_WS10M STNAME:Idaho]	2.000000e-01	1.677633e+05	2
b[mean_WS50M STNAME:Idaho]	1.000000e-01	8.395160e+04	2
b[mean_PRECTOT STNAME:Idaho]	2.000000e-01	4.813175e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Idaho]	1.000000e-01	1.908455e+05	2
b[(Intercept) STNAME:Illinois]	1.000000e-01	3.988843e+05	2
b[drought_value STNAME:Illinois]	2.000000e-01	3.956756e+05	2
b[CENSUS2010POP STNAME:Illinois]	0.000000e+00	3.510360e+04	2
b[CULT_LAND STNAME:Illinois]	1.000000e-01	7.813300e+04	2
b[FOR_LAND STNAME:Illinois]	3.000000e-01	1.410663e+05	2
b[mean_QV2M STNAME:Illinois]	0.000000e+00	4.150660e+04	2
b[mean_WS10M STNAME:Illinois]	1.000000e-01	2.362066e+05	2
b[mean_WS50M STNAME:Illinois]	2.000000e-01	5.311231e+05	2
b[mean_PRECTOT STNAME:Illinois]	0.000000e+00	6.653780e+04	2
b[CENSUS2010POP:CULT_LAND STNAME:Illinois]	1.000000e-01	1.166020e+05	2
b[(Intercept) STNAME:Indiana]	0.000000e+00	1.569935e+05	2
b[drought_value STNAME:Indiana]	1.000000e-01	2.566135e+05	2
b[CENSUS2010POP STNAME:Indiana]	1.000000e-01	1.051270e+05	2
b[CULT_LAND STNAME:Indiana]	2.000000e-01	2.384136e+05	2
b[FOR_LAND STNAME:Indiana]	2.000000e-01	8.308150e+04	2
b[mean_QV2M STNAME:Indiana]	1.000000e-01	8.707770e+04	2
b[mean_WS10M STNAME:Indiana]	2.000000e-01	1.499687e+05	2
b[mean_WS50M STNAME:Indiana]	2.000000e-01	1.755616e+05	2
b[mean_PRECTOT STNAME:Indiana]	2.000000e-01	1.874147e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Indiana]	0.000000e+00	1.163987e+05	2
b[(Intercept) STNAME:Iowa]	1.000000e-01	1.258769e+05	2
b[drought_value STNAME:Iowa]	4.000000e-01	1.918745e+06	2
b[CENSUS2010POP STNAME:Iowa]	3.000000e-01	3.502309e+05	2
b[CULT_LAND STNAME:Iowa]	1.000000e-01	1.601224e+05	2
b[FOR_LAND STNAME:Iowa]	1.000000e-01	3.085800e+04	2
b[mean_QV2M STNAME:Iowa]	3.000000e-01	1.383071e+05	2

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b[mean_WS10M STNAME:Iowa]                                      2.000000e-01 9.595020e+04     2
b[mean_WS50M STNAME:Iowa]                                      2.000000e-01 1.018638e+05     2
b[mean_PRECTOT STNAME:Iowa]                                    1.000000e-01 8.885280e+04     2
b[CENSUS2010POP:CULT_LAND STNAME:Iowa]                         1.000000e-01 2.140836e+05     2
b[(Intercept) STNAME:Kansas]                                   1.000000e-01 4.380750e+04     2
b[drought_value STNAME:Kansas]                                 3.000000e-01 5.380855e+05     2
b[CENSUS2010POP STNAME:Kansas]                                 3.000000e-01 3.698398e+05     2
b[CULT_LAND STNAME:Kansas]                                     2.000000e-01 1.990224e+05     2
b[FOR_LAND STNAME:Kansas]                                      0.000000e+00 2.925970e+04     2
b[mean_QV2M STNAME:Kansas]                                     3.000000e-01 8.852933e+05     2
b[mean_WS10M STNAME:Kansas]                                    1.000000e-01 3.389190e+04     2
b[mean_WS50M STNAME:Kansas]                                    1.000000e-01 6.883180e+04     2
b[mean_PRECTOT STNAME:Kansas]                                  2.000000e-01 5.250351e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Kansas]                       0.000000e+00 9.452000e+04     2
b[(Intercept) STNAME:Kentucky]                                 1.000000e-01 2.292592e+05     2
b[drought_value STNAME:Kentucky]                               3.000000e-01 1.381001e+06     2
b[CENSUS2010POP STNAME:Kentucky]                               2.000000e-01 3.300729e+05     2
b[CULT_LAND STNAME:Kentucky]                                   1.000000e-01 2.340818e+05     2
b[FOR_LAND STNAME:Kentucky]                                    1.000000e-01 1.459050e+05     2
b[mean_QV2M STNAME:Kentucky]                                   1.000000e-01 1.096348e+05     2
b[mean_WS10M STNAME:Kentucky]                                  2.000000e-01 3.761485e+05     2
b[mean_WS50M STNAME:Kentucky]                                  3.000000e-01 4.176123e+05     2
b[mean_PRECTOT STNAME:Kentucky]                                1.000000e-01 2.017838e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Kentucky]                     0.000000e+00 1.464243e+05     2
b[(Intercept) STNAME:Louisiana]                                0.000000e+00 2.201330e+04     2
b[drought_value STNAME:Louisiana]                              2.000000e-01 1.615937e+06     2
b[CENSUS2010POP STNAME:Louisiana]                              3.000000e-01 9.933204e+05     2
b[CULT_LAND STNAME:Louisiana]                                  1.000000e-01 3.718980e+05     2
b[FOR_LAND STNAME:Louisiana]                                   2.000000e-01 1.417782e+05     2
b[mean_QV2M STNAME:Louisiana]                                  1.000000e-01 1.211238e+05     2
b[mean_WS10M STNAME:Louisiana]                                 2.000000e-01 1.973156e+05     2
b[mean_WS50M STNAME:Louisiana]                                 3.000000e-01 2.436454e+05     2
b[mean_PRECTOT STNAME:Louisiana]                               2.000000e-01 2.861994e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Louisiana]                    0.000000e+00 1.353548e+05     2
b[(Intercept) STNAME:Maine]                                    1.000000e-01 1.182070e+05     2
b[drought_value STNAME:Maine]                                  6.000000e-01 1.224768e+06     2
b[CENSUS2010POP STNAME:Maine]                                  4.000000e-01 7.937589e+05     2
b[CULT_LAND STNAME:Maine]                                      2.000000e-01 2.063020e+05     2
b[FOR_LAND STNAME:Maine]                                       3.000000e-01 5.999248e+05     2
b[mean_QV2M STNAME:Maine]                                      3.000000e-01 3.126577e+05     2
b[mean_WS10M STNAME:Maine]                                     1.000000e-01 8.610440e+04     2
b[mean_WS50M STNAME:Maine]                                     1.000000e-01 7.796430e+04     2
b[mean_PRECTOT STNAME:Maine]                                   0.000000e+00 5.326610e+04     2
b[CENSUS2010POP:CULT_LAND STNAME:Maine]                        1.000000e-01 2.150389e+05     2
b[(Intercept) STNAME:Maryland]                                 1.000000e-01 1.033257e+05     2
b[drought_value STNAME:Maryland]                               2.000000e-01 9.240546e+05     2
b[CENSUS2010POP STNAME:Maryland]                               1.000000e-01 5.138720e+05     2
b[CULT_LAND STNAME:Maryland]                                   2.000000e-01 1.531860e+05     2
b[FOR_LAND STNAME:Maryland]                                    4.000000e-01 7.474680e+05     2
b[mean_QV2M STNAME:Maryland]                                   4.000000e-01 2.379189e+05     2
b[mean_WS10M STNAME:Maryland]                                  2.000000e-01 1.722408e+05     2
b[mean_WS50M STNAME:Maryland]                                  0.000000e+00 1.412060e+04     2
b[mean_PRECTOT STNAME:Maryland]                                4.000000e-01 9.157357e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Maryland]                     1.000000e-01 1.590341e+05     2
b[(Intercept) STNAME:Massachusetts]                            0.000000e+00 1.221807e+05     2
b[drought_value STNAME:Massachusetts]                          4.000000e-01 1.015867e+06     2
b[CENSUS2010POP STNAME:Massachusetts]                          3.000000e-01 3.778038e+05     2
b[CULT_LAND STNAME:Massachusetts]                              0.000000e+00 2.284370e+04     2
b[FOR_LAND STNAME:Massachusetts]                               3.000000e-01 1.379005e+05     2
b[mean_QV2M STNAME:Massachusetts]                              3.000000e-01 3.610387e+05     2
b[mean_WS10M STNAME:Massachusetts]                             0.000000e+00 1.739000e+04     2
b[mean_WS50M STNAME:Massachusetts]                             1.000000e-01 1.815540e+05     2
b[mean_PRECTOT STNAME:Massachusetts]                           3.000000e-01 2.970100e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Massachusetts]                1.000000e-01 1.342916e+05     2
b[(Intercept) STNAME:Michigan]                                 1.000000e-01 1.206698e+05     2
b[drought_value STNAME:Michigan]                               5.000000e-01 2.143384e+06     2
b[CENSUS2010POP STNAME:Michigan]                               3.000000e-01 6.355040e+05     2
b[CULT_LAND STNAME:Michigan]                                   1.000000e-01 7.906250e+04     2
b[FOR_LAND STNAME:Michigan]                                    1.000000e-01 9.717600e+04     2
b[mean_QV2M STNAME:Michigan]                                   1.000000e-01 3.622100e+04     2
b[mean_WS10M STNAME:Michigan]                                  1.000000e-01 3.438086e+05     2
b[mean_WS50M STNAME:Michigan]                                  1.000000e-01 1.118463e+05     2
b[mean_PRECTOT STNAME:Michigan]                                2.000000e-01 3.008757e+05     2
b[CENSUS2010POP:CULT_LAND STNAME:Michigan]                     0.000000e+00 5.835140e+04     2
```

b[(Intercept) STNAME:Minnesota]	0.000000e+00	6.869290e+04	2
b[drought_value STNAME:Minnesota]	3.000000e-01	5.493908e+05	2
b[CENSUS2010POP STNAME:Minnesota]	3.000000e-01	1.042680e+06	2
b[CULT_LAND STNAME:Minnesota]	2.000000e-01	3.296770e+05	2
b[FOR_LAND STNAME:Minnesota]	2.000000e-01	1.096109e+05	2
b[mean_QV2M STNAME:Minnesota]	5.000000e-01	2.006044e+06	2
b[mean_WS10M STNAME:Minnesota]	2.000000e-01	9.801864e+05	2
b[mean_WS50M STNAME:Minnesota]	4.000000e-01	3.828615e+05	2
b[mean_PRECTOT STNAME:Minnesota]	0.000000e+00	4.117830e+04	2
b[CENSUS2010POP:CULT_LAND STNAME:Minnesota]	1.000000e-01	1.015923e+05	2
b[(Intercept) STNAME:Mississippi]	1.000000e-01	7.382170e+04	2
b[drought_value STNAME:Mississippi]	2.000000e-01	6.086277e+05	2
b[CENSUS2010POP STNAME:Mississippi]	1.000000e-01	1.618045e+05	2
b[CULT_LAND STNAME:Mississippi]	1.000000e-01	1.819200e+05	2
b[FOR_LAND STNAME:Mississippi]	2.000000e-01	1.628556e+05	2
b[mean_QV2M STNAME:Mississippi]	0.000000e+00	1.684645e+05	2
b[mean_WS10M STNAME:Mississippi]	3.000000e-01	3.797444e+05	2
b[mean_WS50M STNAME:Mississippi]	1.000000e-01	7.606330e+04	2
b[mean_PRECTOT STNAME:Mississippi]	2.000000e-01	4.526081e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Mississippi]	1.000000e-01	1.851128e+05	2
b[(Intercept) STNAME:Missouri]	1.000000e-01	1.475815e+05	2
b[drought_value STNAME:Missouri]	1.000000e-01	6.035126e+05	2
b[CENSUS2010POP STNAME:Missouri]	1.000000e-01	2.535554e+05	2
b[CULT_LAND STNAME:Missouri]	1.000000e-01	2.638686e+05	2
b[FOR_LAND STNAME:Missouri]	1.000000e-01	1.110153e+05	2
b[mean_QV2M STNAME:Missouri]	2.000000e-01	2.292882e+06	2
b[mean_WS10M STNAME:Missouri]	1.000000e-01	1.481695e+05	2
b[mean_WS50M STNAME:Missouri]	2.000000e-01	5.448021e+05	2
b[mean_PRECTOT STNAME:Missouri]	1.000000e-01	7.345120e+04	2
b[CENSUS2010POP:CULT_LAND STNAME:Missouri]	0.000000e+00	7.869150e+04	2
b[(Intercept) STNAME:Montana]	1.000000e-01	4.423120e+04	2
b[drought_value STNAME:Montana]	0.000000e+00	9.514200e+04	2
b[CENSUS2010POP STNAME:Montana]	1.000000e-01	4.015586e+05	2
b[CULT_LAND STNAME:Montana]	1.000000e-01	1.278431e+05	2
b[FOR_LAND STNAME:Montana]	3.000000e-01	3.242649e+05	2
b[mean_QV2M STNAME:Montana]	1.000000e-01	8.663680e+04	2
b[mean_WS10M STNAME:Montana]	2.000000e-01	2.768019e+05	2
b[mean_WS50M STNAME:Montana]	3.000000e-01	4.867751e+05	2
b[mean_PRECTOT STNAME:Montana]	1.000000e-01	5.115080e+04	2
b[CENSUS2010POP:CULT_LAND STNAME:Montana]	2.000000e-01	3.291160e+05	2
b[(Intercept) STNAME:Nebraska]	1.000000e-01	7.273250e+04	2
b[drought_value STNAME:Nebraska]	4.000000e-01	1.694563e+06	2
b[CENSUS2010POP STNAME:Nebraska]	3.000000e-01	3.221883e+05	2
b[CULT_LAND STNAME:Nebraska]	0.000000e+00	1.049078e+05	2
b[FOR_LAND STNAME:Nebraska]	2.000000e-01	9.825240e+04	2
b[mean_QV2M STNAME:Nebraska]	1.000000e-01	3.922040e+04	2
b[mean_WS10M STNAME:Nebraska]	1.000000e-01	1.943472e+05	2
b[mean_WS50M STNAME:Nebraska]	0.000000e+00	1.439670e+04	2
b[mean_PRECTOT STNAME:Nebraska]	3.000000e-01	4.076220e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Nebraska]	1.000000e-01	2.673365e+05	2
b[(Intercept) STNAME:Nevada]	1.000000e-01	2.191271e+05	2
b[drought_value STNAME:Nevada]	3.000000e-01	8.148433e+05	2
b[CENSUS2010POP STNAME:Nevada]	2.000000e-01	3.180521e+05	2
b[CULT_LAND STNAME:Nevada]	1.000000e-01	2.225365e+05	2
b[FOR_LAND STNAME:Nevada]	2.000000e-01	8.208490e+04	2
b[mean_QV2M STNAME:Nevada]	2.000000e-01	9.908520e+04	2
b[mean_WS10M STNAME:Nevada]	1.000000e-01	8.212650e+04	2
b[mean_WS50M STNAME:Nevada]	2.000000e-01	1.723410e+05	2
b[mean_PRECTOT STNAME:Nevada]	2.000000e-01	2.840490e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:Nevada]	0.000000e+00	8.871860e+04	2
b[(Intercept) STNAME:New_Hampshire]	0.000000e+00	1.620590e+04	2
b[drought_value STNAME:New_Hampshire]	1.000000e-01	1.355279e+06	2
b[CENSUS2010POP STNAME:New_Hampshire]	2.000000e-01	3.984203e+05	2
b[CULT_LAND STNAME:New_Hampshire]	1.000000e-01	6.329880e+04	2
b[FOR_LAND STNAME:New_Hampshire]	1.000000e-01	6.408810e+04	2
b[mean_QV2M STNAME:New_Hampshire]	3.000000e-01	4.228245e+05	2
b[mean_WS10M STNAME:New_Hampshire]	1.000000e-01	8.284390e+04	2
b[mean_WS50M STNAME:New_Hampshire]	2.000000e-01	2.721135e+05	2
b[mean_PRECTOT STNAME:New_Hampshire]	1.000000e-01	1.013542e+05	2
b[CENSUS2010POP:CULT_LAND STNAME:New_Hampshire]	1.000000e-01	1.259010e+05	2
b[(Intercept) STNAME:New_Jersey]	1.000000e-01	9.217380e+04	2
b[drought_value STNAME:New_Jersey]	1.000000e-01	3.772044e+05	2
b[CENSUS2010POP STNAME:New_Jersey]	1.000000e-01	2.693340e+05	2
b[CULT_LAND STNAME:New_Jersey]	2.000000e-01	2.764260e+05	2

```
b[FOR_LAND STNAME:New_Jersey]                          1.000000e-01 4.608890e+04    2
b[mean_QV2M STNAME:New_Jersey]                         0.000000e+00 4.778740e+04    2
b[mean_WS10M STNAME:New_Jersey]                        1.000000e-01 4.591190e+04    2
b[mean_WS50M STNAME:New_Jersey]                        0.000000e+00 6.871500e+03    2
b[mean_PRECTOT STNAME:New_Jersey]                      1.000000e-01 1.798899e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:New_Jersey]           0.000000e+00 4.835980e+04    2
b[(Intercept) STNAME:New_Mexico]                       0.000000e+00 8.686660e+04    2
b[drought_value STNAME:New_Mexico]                     3.000000e-01 8.438268e+05    2
b[CENSUS2010POP STNAME:New_Mexico]                     1.000000e-01 4.580570e+05    2
b[CULT_LAND STNAME:New_Mexico]                         2.000000e-01 3.335003e+05    2
b[FOR_LAND STNAME:New_Mexico]                          3.000000e-01 1.798517e+05    2
b[mean_QV2M STNAME:New_Mexico]                         2.000000e-01 3.566812e+05    2
b[mean_WS10M STNAME:New_Mexico]                        1.000000e-01 1.293870e+05    2
b[mean_WS50M STNAME:New_Mexico]                        3.000000e-01 3.094910e+05    2
b[mean_PRECTOT STNAME:New_Mexico]                      1.000000e-01 2.041065e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:New_Mexico]           1.000000e-01 2.092947e+05    2
b[(Intercept) STNAME:New_York]                         1.000000e-01 2.236999e+05    2
b[drought_value STNAME:New_York]                       1.000000e-01 3.199104e+05    2
b[CENSUS2010POP STNAME:New_York]                       1.000000e-01 5.209411e+05    2
b[CULT_LAND STNAME:New_York]                           1.000000e-01 2.185025e+05    2
b[FOR_LAND STNAME:New_York]                            2.000000e-01 7.476240e+04    2
b[mean_QV2M STNAME:New_York]                           1.000000e-01 1.346380e+05    2
b[mean_WS10M STNAME:New_York]                          1.000000e-01 1.565402e+05    2
b[mean_WS50M STNAME:New_York]                          0.000000e+00 5.901030e+04    2
b[mean_PRECTOT STNAME:New_York]                        1.000000e-01 1.914349e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:New_York]             1.000000e-01 1.259885e+05    2
b[(Intercept) STNAME:North_Carolina]                   0.000000e+00 4.162270e+04    2
b[drought_value STNAME:North_Carolina]                 1.000000e-01 3.568074e+05    2
b[CENSUS2010POP STNAME:North_Carolina]                 1.000000e-01 2.142538e+05    2
b[CULT_LAND STNAME:North_Carolina]                     2.000000e-01 2.882723e+05    2
b[FOR_LAND STNAME:North_Carolina]                      2.000000e-01 1.028115e+05    2
b[mean_QV2M STNAME:North_Carolina]                     2.000000e-01 1.871448e+05    2
b[mean_WS10M STNAME:North_Carolina]                    1.000000e-01 3.155930e+05    2
b[mean_WS50M STNAME:North_Carolina]                    3.000000e-01 5.333926e+05    2
b[mean_PRECTOT STNAME:North_Carolina]                  2.000000e-01 1.493643e+05    2
b[CENSUS2010POP:CULT_LAND STNAME:North_Carolina]       1.000000e-01 8.535630e+04    2
b[(Intercept) STNAME:North_Dakota]                     1.000000e-01 6.300110e+04    2
b[drought_value STNAME:North_Dakota]                   0.000000e+00 9.070920e+04    2
b[CENSUS2010POP STNAME:North_Dakota]                   1.000000e-01 2.039399e+05    2
b[CULT_LAND STNAME:North_Dakota]                       0.000000e+00 3.635220e+04    2
b[FOR_LAND STNAME:North_Dakota]                        0.000000e+00 4.789820e+04    2
b[mean_QV2M STNAME:North_Dakota]                       0.000000e+00 1.065430e+04    2
b[mean_WS10M STNAME:North_Dakota]                      1.000000e-01 5.320407e+05    2
b[mean_WS50M STNAME:North_Dakota]                      2.000000e-01 3.744994e+05    2
b[mean_PRECTOT STNAME:North_Dakota]                    1.000000e-01 5.545010e+04    2
b[CENSUS2010POP:CULT_LAND STNAME:North_Dakota]         0.000000e+00 7.151570e+04    2
b[(Intercept) STNAME:Ohio]                             1.000000e-01 2.384259e+05    2
b[drought_value STNAME:Ohio]                           3.000000e-01 1.343632e+06    2
b[CENSUS2010POP STNAME:Ohio]                           3.000000e-01 1.516546e+06    2
 [ reached getOption("max.print") -- omitted 215 rows ]

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is
the potential scale reduction factor on split chains (at convergence Rhat=1).
```

Supplement:

1.Code:

```
```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)
library(dplyr)
library(tidyverse)
```
Data preparing
Data prepare for condition——soil
```{r}
soil <- read.csv("soil_data.csv")
soil <- soil |>
```
```

````
select(c(fips,elevation,slope1,slope2,slope3,slope4,slope5,slope6,slope7,slope8,WAT_LAND,NV
G_LAND,URB_LAND,GRS_LAND,FOR_LAND,CULT_LAND))|>
  mutate(
    weighted_slope = slope1 * 0.25 +
                     slope2 * 1.25 +
                     slope3 * 3.5 +
                     slope4 * 7.5 +
                     slope5 * 12.5 +
                     slope6 * 22.5 +
                     slope7 * 37.5 +
                     slope8 * 50  #choose the last group's median point as 50
  )|>#using median point to calculate slopes
  select(-slope1, -slope2, -slope3, -slope4, -slope5, -slope6, -slope7, -slope8)
rows <- nrow(soil)
third <- rows / 3
soil <- soil %>%
  arrange(desc(weighted_slope)) %>%
  mutate(slope = ifelse(row_number() <= third, "large", ifelse(row_number() >= third*2, "small",
"medium"))) %>%
  select(-weighted_slope)

```
### Data prepare for condition——weather
```{r}
test <- read.csv("test_timeseries.csv")
test <- test |>
  select(fips, date, QV2M, WS10M, WS50M, PRECTOT)
test$year <- sapply(strsplit(test$date, "-"), `[`, 1) #select year
test <- test |>
  select(-date)
# since train_timeseries.csv is too big, I use Sqlite to deal with it
library(DBI)
library(RSQLite)
con <- dbConnect(RSQLite::SQLite(),"my_database.sqlite")
dbWriteTable(con, "train", "train_timeseries.csv", row.names = FALSE)
dbSendQuery(con, "
  CREATE TABLE train_processed_1 AS
  SELECT
    fips,
    QV2M,
    WS10M,
    WS50M,
    PRECTOT,
````

````
    SUBSTR(date, 1, 4) AS year
  FROM train
  WHERE SUBSTR(date, 1, 4) BETWEEN '2012' AND '2020'
")
train <- dbReadTable(con, "train_processed_1")
dbDisconnect(con)

#combine 2 dataset
weather <- rbind(test,train)
rm(test,train)# remove test and train from the environment
weather <- weather |>
  group_by(fips) |>
  summarise(
    mean_QV2M = mean(QV2M, na.rm = TRUE),
    mean_WS10M = mean(WS10M, na.rm = TRUE),
    mean_WS50M = mean(WS50M, na.rm = TRUE),
    mean_PRECTOT = mean(PRECTOT, na.rm = TRUE)
  )

#Compare which county miss between weather and soil
missing_fips <- setdiff(soil$fips, weather$fips)
#Missing Weston County, Wyoming
```
### Data prepare for drought
```{r}
drought <- read.csv("drought.csv")
drought <- drought|>
  mutate(None = as.numeric(gsub(",", "", None)),#remove ","
         D0 = as.numeric(gsub(",", "", D0)),
         D1 = as.numeric(gsub(",", "", D1)),
         D2 = as.numeric(gsub(",", "", D2)),
         D3 = as.numeric(gsub(",", "", D3)),
         D4 = as.numeric(gsub(",", "", D4)),
  )|>
  mutate(sum = None + D0)|>
  mutate(fips = FIPS,
         None = None/sum,
         D0 = D0/sum,
         D1 = D1/sum,
         D2 = D2/sum,
         D3 = D3/sum,
         D4 = D4/sum,
         .keep = "none"
  )|>
````

````
  group_by(fips) |>
  summarise(
    mean_None = mean(None, na.rm = TRUE),
    mean_D0 = mean(D0, na.rm = TRUE),
    mean_D1 = mean(D1, na.rm = TRUE),
    mean_D2 = mean(D2, na.rm = TRUE),
    mean_D3 = mean(D3, na.rm = TRUE),
    mean_D4 = mean(D4, na.rm = TRUE),
  )|>
  mutate(drought_value =
1*mean_D0+2*mean_D1+3**mean_D2+4**mean_D3+5**mean_D4)|>
  select(fips,drought_value)
drought$fips <- sprintf("%05d", as.integer(drought$fips))
```
### Data prepare for drought
```{r}
population <- read.csv("population.csv")
population$STATE <- sprintf("%02d", as.integer(population$STATE))
population$COUNTY <- sprintf("%03d", as.integer(population$COUNTY))
population <- population |>
  select(STATE,COUNTY,STNAME,CTYNAME,CENSUS2010POP)|>
  mutate(fips = paste0(STATE, COUNTY),.keep="unused",.before=1)
```
### Data prepare for fire
```{r}
fire <- read_csv("fire.csv")
fire_processed_last <- fire |>
  select(FIPS_CODE, FIRE_SIZE_CLASS, DISCOVERY_DOY, DISCOVERY_TIME, CONT_DOY,
CONT_TIME, FIRE_YEAR) |>
  rename(fips = FIPS_CODE, fire_size_class = FIRE_SIZE_CLASS) %>%
  mutate(
    fire_last = (CONT_DOY - DISCOVERY_DOY) * 2400 +
                as.numeric(substr(CONT_TIME, 1, 2)) * 60 + as.numeric(substr(CONT_TIME, 3, 4)) -
                as.numeric(substr(DISCOVERY_TIME, 1, 2)) * 60 + as.numeric(substr(DISCOVERY_TIME,
3, 4))
    ,fire_last_new = ifelse(fire_last > 0, fire_last, fire_last + 525600)
  ) |>
   filter(fire_last_new>0)|>
  filter(FIRE_YEAR >= 2012 & FIRE_YEAR <= 2020) |>
  filter(!is.na(fips)) |>
  group_by(fips) |>
  summarise(
    avg_fire_last = mean(fire_last_new, na.rm = TRUE),
    times = n()
````

````
 )
fire_processed_times <- fire |>
 select(FIPS_CODE, FIRE_SIZE_CLASS, DISCOVERY_DOY, DISCOVERY_TIME, CONT_DOY,
CONT_TIME, FIRE_YEAR) |>
 rename(fips = FIPS_CODE, fire_size_class = FIRE_SIZE_CLASS) %>%
 mutate(
  fire_last = (CONT_DOY - DISCOVERY_DOY) * 2400 +
        as.numeric(substr(CONT_TIME, 1, 2)) * 60 + as.numeric(substr(CONT_TIME, 3, 4)) -
        as.numeric(substr(DISCOVERY_TIME, 1, 2)) * 60 + as.numeric(substr(DISCOVERY_TIME,
3, 4))
  ,fire_last_new = ifelse(fire_last >= 0, fire_last, fire_last + 525600)
 ) |>
 filter(FIRE_YEAR >= 2012 & FIRE_YEAR <= 2020) |>
 filter(!is.na(fips)) |>
 group_by(fips) |>
 summarise(
  avg_fire_last = mean(fire_last_new, na.rm = TRUE),
  times = n()
 )
```
### Combine all dataset
```{r}
weather$fips <- sprintf("%05d", as.integer(weather$fips))
soil$fips <- sprintf("%05d", as.integer(soil$fips))
#find intersect of 5 dataset
common_fips <- Reduce(intersect, list(drought$fips, fire_processed_last$fips, population$fips,
soil$fips, weather$fips))
drought_filtered <- drought |> filter(fips %in% common_fips)
fire_filtered <- fire_processed_last |> filter(fips %in% common_fips)
population_filtered <- population |> filter(fips %in% common_fips)|>
 mutate(CENSUS2010POP = as.numeric(CENSUS2010POP))
soil_filtered <- soil |> filter(fips %in% common_fips)
weather_filtered <- weather |> filter(fips %in% common_fips)
combined_data_last <- reduce(list(drought_filtered, fire_filtered, population_filtered,
soil_filtered, weather_filtered), full_join, by = "fips")

weather$fips <- sprintf("%05d", as.integer(weather$fips))
soil$fips <- sprintf("%05d", as.integer(soil$fips))
#find intersect of 5 dataset
common_fips_times <- Reduce(intersect, list(drought$fips, fire_processed_times$fips,
population$fips, soil$fips, weather$fips))
drought_filtered <- drought |> filter(fips %in% common_fips)
fire_filtered <- fire_processed_times |> filter(fips %in% common_fips)
population_filtered <- population |> filter(fips %in% common_fips)|>
````

````
  mutate(CENSUS2010POP = as.numeric(CENSUS2010POP))
soil_filtered <- soil |> filter(fips %in% common_fips)
weather_filtered <- weather |> filter(fips %in% common_fips)
combined_data_times <- reduce(list(drought_filtered, fire_filtered, population_filtered,
soil_filtered, weather_filtered), full_join, by = "fips")
```
##EDA
```{r}
# Check missing data
missing_counts <- colSums(is.na(combined_data_times))
missing_counts <- missing_counts[missing_counts != 0]
print(missing_counts)

library(tigris)
options(tigris_use_cache = TRUE)
counties <- tigris::counties(cb = TRUE, class = "sf")
map_data <- merge(counties, combined_data_last, by.x = "GEOID", by.y = "fips")

ggplot(map_data) +
  aes(fill = avg_fire_last) +
  geom_sf(size = 1.2) +
  scale_fill_gradient(low = "#EFEFEF", high = "#0A8BEE") +
  labs(title = "avergae fire last in US")+
  theme_minimal()

map_data_times <- merge(counties, combined_data_times, by.x = "GEOID", by.y = "fips")
ggplot(map_data_times) +
  aes(fill = times) +
  geom_sf(size = 1.2) +
  scale_fill_gradient(low = "#F8F4F5", high = "#E91245") +
  labs(title = "times of fire ") +
  theme_minimal()
#correlation matrix
cor_last <- combined_data_last[,c(3,4,2,7,8,9,10,11,12,13,14,16,17,18,19)]
cor_last_matrix <- as.data.frame(as.table(abs(cor(cor_last))))
colnames(cor_last_matrix) <- c("Variable1", "Variable2", "Correlation")
ggplot(cor_last_matrix, aes(Variable1, Variable2, fill = Correlation)) +
  geom_tile() +
  scale_fill_gradient(low = "white", high = "black") +
  theme_minimal() +
  labs(title = "Correlation Heatmap", x = "", y = "") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```
## model for fire last
````
````

~~~
### Null Model
```{r}
fit_null_last <- lm(avg_fire_last~1,data = combined_data_last)
summary(fit_null_last)
```
### choose variable
```{r}
percentile_1 <- quantile(combined_data_last$avg_fire_last, 0.01)
percentile_99 <- quantile(combined_data_last$avg_fire_last, 0.99)

# Truncate the data
truncated_data_last <- subset(combined_data_last, avg_fire_last >= percentile_1 &
avg_fire_last <= percentile_99)
#remove , overdispersion, using Gamma
fit_1 <- glm(avg_fire_last~drought_value + elevation + WAT_LAND + NVG_LAND + URB_LAND +
GRS_LAND + FOR_LAND + slope + mean_QV2M + mean_WS10M + mean_WS50M +
mean_PRECTOT,data=truncated_data_last,family=Gamma(link="log"))
summary(fit_1)
library(car)
vif(fit_1)
#remove mean_WS50M, failed
fit_2 <- glm(avg_fire_last~drought_value + elevation + WAT_LAND + NVG_LAND + URB_LAND +
GRS_LAND + FOR_LAND + slope + mean_QV2M + mean_WS10M +
mean_PRECTOT,data=truncated_data_last,family=Gamma(link="log"))
summary(fit_2)
#Model stability and data distribution: Removing certain variables may change the overall
stability of the model. For example, if mean_WS50M is correlated with other variables, its
presence may help balance the model. After removing this variable, the model may become
unstable, especially if the variability of avg_fire_last is not well explained by other variables.

#Effect of collinearity: High collinearity may lead to unstable model parameter estimates. In
some cases, including variables with high collinearity may unexpectedly increase the stability of
the model, although such a model may not have good predictive power.

#remove WAT_LAND, mean_WS10M, mean_PRECTOR, according to the actual
fit_3 <- glm(avg_fire_last~elevation + NVG_LAND + URB_LAND + GRS_LAND + FOR_LAND +
slope + mean_QV2M + mean_WS50M,data=truncated_data_last,family=Gamma(link="log"))
summary(fit_3)

#residual test
residuals <- residuals(fit_3)
plot(truncated_data_last$avg_fire_last, residuals)
abline(h=0)
~~~

~~~
qqnorm(residuals)
qqline(residuals)

#exist heteroskedasticity, using log
truncated_data_last$log_avg_fire_last=log(truncated_data_last$avg_fire_last)
fit_4 <- glm(log_avg_fire_last ~ elevation + NVG_LAND + URB_LAND + GRS_LAND + FOR_LAND +
slope + mean_QV2M + mean_WS50M,
             data = truncated_data_last,
             family = Gamma(link = "log"))
summary(fit_4)

residuals <- residuals(fit_4)
plot(truncated_data_last$log_avg_fire_last, residuals)
abline(h=0)

qqnorm(residuals)
qqline(residuals)
#The results are still not ideal, and variables that may already exist cannot accurately predict fire
duration. Maybe the duration of the fire is more related to the local fire protection situation,
etc.
```
###partial pooling
```{r}
library(lme4)
fit_5 <- glmer(log_avg_fire_last ~ elevation + NVG_LAND + URB_LAND + GRS_LAND +
FOR_LAND + slope + mean_QV2M + mean_WS50M +(1|STNAME),
             data = truncated_data_last,
             family = Gamma(link = "log"))
# Warning: Model failed to converge with max|grad| = 0.755596 (tol = 0.002, component
1)Warning: Model is nearly unidentifiable: very large eigenvalue
#  - Rescale variables?;Model is nearly unidentifiable: large eigenvalue ratio
#  - Rescale variables?
# cannot forecast the last of fire.
```
## model for fire times
### Null Model
```{r}
boxplot(combined_data_times$times)
percentile_1 <- quantile(combined_data_times$times, 0.05)
percentile_99 <- quantile(combined_data_times$times, 0.95)
# Truncate the data
truncated_data_times <- subset(combined_data_times, times >= percentile_1 & times <=
percentile_99)
time_data <- truncated_data_times
~~~

````
fit_6 <- lm(times ~ 1, data = time_data)
summary(fit_6)
```

###complete pooling
```{r}
cor_last <- time_data[,c(4,2,7,8,9,10,11,12,13,14,16,17,18,19)]
cor_last_matrix <- as.data.frame(as.table(abs(cor(cor_last))))
colnames(cor_last_matrix) <- c("Variable1", "Variable2", "Correlation")
ggplot(cor_last_matrix, aes(Variable1, Variable2, fill = Correlation)) +
  geom_tile() +
  scale_fill_gradient(low = "white", high = "black") +
  theme_minimal() +
  labs(title = "Correlation Heatmap", x = "", y = "") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplot(time_data, aes(x = slope, y = times)) +
  geom_boxplot()
hist(time_data$times)
library(MASS)
library(rstan)
library(rstanarm)
library(brms)
library(bayesplot)
fit_7<-
stan_glm(times~drought_value+CENSUS2010POP+CULT_LAND+FOR_LAND+mean_QV2M+mean
_WS10M+mean_WS50M+mean_PRECTOT,data=time_data,family=poisson(link="log"))
summary(fit_7,digits=2)
post_resid <- posterior_predict(fit_7)
ppc_dens_overlay(time_data$times,post_resid[1:100,])
#
# residuals <- residuals(fit_7)
#
# plot(time_data$times, residuals)
# abline(h=0)
#
# qqnorm(residuals)
# qqline(residuals)
#
# weights <- 1/residuals(fit_7)^2
# fit_8<-
stan_glm(times~drought_value+CENSUS2010POP+CULT_LAND+FOR_LAND+mean_QV2M+mean
_WS10M+mean_WS50M+mean_PRECTOT,data=time_data,family=poisson(link="log"),weights =
weights)
# summary(fit_8,digits=2)
````

post_resid <- posterior_predict(fit_8)
ppc_dens_overlay(time_data$times,post_resid[1:100,])

residuals <- residuals(fit_8)

plot(time_data$times, residuals)
abline(h=0)

qqnorm(residuals)
qqline(residuals)
```
### partial pooling
```{r}
fit_9<-
stan_glmer(times~drought_value+CENSUS2010POP*CULT_LAND+FOR_LAND+mean_QV2M+me
an_WS10M+mean_WS50M+mean_PRECTOT + (1|STNAME),data=time_data,
family=poisson(link="log"))
summary(fit_9,digits=3)
residuals <- residuals(fit_8)
plot(time_data$times, residuals)
abline(h=0)
post_resid <- posterior_predict(fit_9)
ppc_dens_overlay(time_data$times,post_resid[1:100,])
```
no pooling
```{r}
fit_no_pooling <- stan_glmer(times ~ drought_value + CENSUS2010POP * CULT_LAND +
FOR_LAND + mean_QV2M + mean_WS10M + mean_WS50M + mean_PRECTOT + (1 +
drought_value + CENSUS2010POP * CULT_LAND + FOR_LAND + mean_QV2M + mean_WS10M +
mean_WS50M + mean_PRECTOT | STNAME), data = time_data, family = Gamma(link =
"inverse"))
summary(fit_no_pooling)
stan_rhat(fit_no_pooling)
```
```