

BIOS 8372 Final Project: Bayesian spatial models with Asthma ED visits in
California counties

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Introduction

Asthma is a persevering and chronic disease. In California, approximately 13.8% of adults reported that they had ever been diagnosed with asthma (lifetime asthma) and 8.1% said they still have asthma (current asthma). The prevalence of the Asthma for both groups has not changed significantly since 2001. The Asthma patients usually followed the asthma management plan following Global Initiative for Asthma (GINA) report. However, it is reported that only 38% of children with asthma have a recent asthma management plan. This will most likely lead to Asthma exacerbation. One measurement to measure asthma exacerbation is the ED visit for Asthma patients. For this study, we are interested in learning the Asthma patients ED visits rate in California counties between 2012 and 2017. To further investigate our question of interest, we conducted county-level and zipcode-level analysis. In the county-level analysis, we used the total ED visits in each county as outcome. In this level, we compared different models with and without considering spatial correlation. We assessed the convergence and conducted model selection. We then applied the selected model with the zipcode level analysis. In this level, we will consider the ED visits at the zipcode level within each county. We want to compare the results between county and zipcode-level analysis and further compared the result with frequentist approach where the incorporation of spatial information is currently not feasible for generalized linear model.

Method

Data source

The dataset was published by California Health and Human Services containing zipcodes level Asthma population information in each California county for 2012 and 2017. The number of Asthma ED visits, stratified by age (Adult and Children groups) is reported at the zipcode level. There's additional column mapping each zipcode to the county. There are 55 counties and 1030 zipcodes. In this study, we focused on the Adult population.

Proposed models

Since the ED visits are count-based data, Poisson model was fitted for both level analyses. For the spatial correlation, we implemented the power exponential covariance structure.

County level

The outcome of interest in the level analysis will be the total number of ED counts in each county. Here are some notations:

- Denote outcome as y_k where $k = 1, \dots, N$ counties
- $b1_k$ indicates the log counts for each county at baseline.
- $b3_k$ indicates the additional log counts at 2017 for each county comparing to 2012. The exponentiated values will be the rate ratio between 2017 and 2012 for county k and this is our variable of interest.

The outcome y follows Poisson distribution. We proposed to compare the models with and without spatial correlation. All the candidate models share the same likelihood:

$$y_{k,t} \sim \text{Pois}(\lambda_{k,t})$$

$$\log(\lambda_{k,t}) = b1_k I(\text{county} = k) + b3_k I(t = 2017)$$

The candidate models contains different prior assumptions on $b1_k$ and $b3_k$ and can be categorized into models with and without spatial correlation.

No spatial correlation model (No spatial):

$$\begin{aligned} b1_k &\sim N(\theta, \tau_{1,k}) \\ b3_k &\sim N(\theta_2, \tau_{2,k}) \\ \tau_{1,k} &= 1/\sigma_{\theta_{1,k}}^2 ; \tau_{2,k} = 1/\sigma_{\theta_{2,k}}^2 \\ \theta &\sim N(0, 0.000001) \\ \theta_2 &\sim N(0, 0.000001) \\ \sigma_{\theta_{1,k}}^2 &\sim \text{dunif}(0, 1000) \\ \sigma_{\theta_{2,k}}^2 &\sim \text{dunif}(0, 1000) \end{aligned}$$

Spatial correlation model 1 (Spatial 1):

$$\begin{aligned} b1_k &\sim N(\theta, \Sigma_{\phi_1, \tau_1, \kappa_1}) \\ \Sigma_{\phi_1, \tau_1} &= 1/\tau_1 \text{Exp}(-\phi_1 \kappa_1 \text{ dist}) \\ b3_k &\sim N(\theta_2, \Sigma_{\phi_2, \tau_2, \kappa_2}) \\ \Sigma_{\phi_2, \tau_2} &= 1/\tau_2 \text{Exp}(-\phi_2 \kappa_2 \text{ dist}) \\ \theta &\sim N(0, 0.000001) \\ \theta_2 &\sim N(0, 0.000001) \\ \phi_1 &\sim \text{dunif}(0.05, 50) \\ \phi_2 &\sim \text{dunif}(0.05, 50) \\ \tau_1 &\sim \text{Gamma}(0.001, 0.001) \\ \tau_2 &\sim \text{Gamma}(0.001, 0.001) \\ \kappa_1 &\sim \text{dunif}(0.05, 1.95) \\ \kappa_2 &\sim \text{dunif}(0.05, 1.95) \end{aligned}$$

Spatial correlation model 2 (Spatial 2):

$$\begin{aligned} b1_k &\sim N(\theta, \Sigma_{\phi_1, \tau, \kappa_1}) \\ \Sigma_{\phi_1, \tau_1} &= 1/\tau \text{Exp}(-\phi_1 \kappa_1 \text{ dist}) \\ b3_k &\sim N(\theta_2, \tau_{2,k}) \\ \theta &\sim N(0, 0.000001) \\ \theta_2 &\sim N(0, 0.000001) \\ \tau_{2,k} &= 1/\sigma_{\theta_{2,k}}^2 \\ \phi_1 &\sim \text{dunif}(0.05, 50) \\ \tau &\sim \text{Gamma}(0.001, 0.001) \\ \kappa_1 &\sim \text{dunif}(0.05, 1.95) \\ \sigma_{\theta_{2,k}}^2 &\sim \text{dunif}(0, 1000) \end{aligned}$$

Zipcode level

The outcome of interest in the level analysis will be the ED count in each zipcode. Each zipcode corresponds to 1 county.

- Denote county as k where $k = 1, \dots, N$ county
- Denote j as zipcode in each county where $j = 1, \dots, N_k$. N_k is the number of zipcodes in each county
- $y_{k,j,t}$ denotes the ED county at j^{th} zipcode in county k at year t
- $b1_k$ indicates the log counts for each county at baseline.
- $b3_k$ indicates the additional log counts at 2017 for each county comparing to 2012. The exponentiated values will be the rate ratio between 2017 and 2012 for county k and this is our variable of interest.

$$y_{k,j,t} \sim \text{Pois}(\lambda_{j,k,t})$$

$$\log(\lambda_{j,k,t}) = b1_k I(\text{county} = k) + b3_k I(t = 2017)$$

The priors and hyper-priors are same as Spatial 2.

Originally, the goal was to fit $b1$ and $b3$ for each zipcode and assign higher level hierarchical with region effects (the complete original model plan is summarized in the appendix.) However, The model fails to converge with more than 2000 parameters. This simplified model treats the zipcodes in each county as repeated measurements.

Analysis

County level

The priors in all models were selected to be non-informative first. All models were run with 3 chains, each with 5000 iterations (first 2500 discarded) in openbugs. The initial values are described as the following:

- θ is a random draw from $N(2,2)$
- θ_2 is a random draw from $N(0,2)$
- All σ^2 are random draws from uniform(0, 10)
- All $\phi = \kappa = \tau = 1$

Model convergence and selection

The model selection process was conducted in this level between No spatial, Spatial 1 and Spatial 2 model. The DIC criteria will be used for model selection. $b3_k$ is of interest to obtain the rate ratio between year 2012 and 2017. The convergence plots for $b3_k$ of the selected model are presented while the convergence for other 2 models were described in the main text. Our main goal is to see if implementing spatial correlation will improve the model. The posterior predictive checks for Spatial 1 and Spatial 2 were conducted.

Priors sensitivity analysis

Some sensitivity analyses of priors were carried out on θ , θ_2 and τ . For τ distribution, different priors including uniform, gamma (0.001,0.001) and gamma (1,1) were implemented to compare the influence on τ distribution. For θ distribution, we will compare the original non-informative priors with informative priors. The informative priors were selected from GLM (Generalized Linear Model) estimates (mean and variance). For θ_2 , the mean and variance of the estimates from GLM were used to approximate and construct the informative prior. For θ , the informative priors are obtained as the following: estimates from GLM were considered as random effects.

- Denote γ as the GLM estimates which γ is a $N \times 1$ vector.
- γ can be re-written as $\beta_0 + b$ where b is a $N \times 1$ vector residual
- Estimate b with empirical variogram and conducted iterative weighted least squares method to estimate β_0
- β_0 and its variance will be incorporated into as mean and variance for θ priors

Frequentist approach

GLM was run with `glm` function in R 3.5.2.

Zipcode level

The computation, priors and initial values are identical to county level analysis.

Result

Exploratory Analysis

Table 1 summarizes the number of zipcodes, baseline total counts of ED visits and the rate ratio of ED visits between 2012 and 2017 in each county. The information can also be visualized with Figure 1. From Figure 1, left and Table 1, Los Angeles has the highest number of zipcodes within the county and the most total ED counts while Mono has only 1 zipcode within the county and 14 ED visits at 2012. In Figure 1, right, We see that Mono has the highest rate ratio of 2.071 while the rate ratio for Los Angeles is around 1. The lowest rate ratio was observed in Colusa county where the total ED count is only 27 in 2012. Most of the extreme rate ratios happen in the county where the baseline total ED visits count is small. However, if we look deeper into zipcode level data within Los Angeles, the ED visit counts range from 7 to 703 and the rate ratio ranges from 0.05 to 31.8. In addition, we noticed that Northern part of California has fewer zipcodes in each county than Southern part. Therefore, the rate ratios are more extreme. This observation could potentially be modeled with spatial correlation.

County level

Model convergence and selection

The criteria for model selection was based on DIC. DIC for No spatial model was 1111. The DIC for Spatial 1 and 2 were 1009 and 1001, respectively. The DIC values for the models with some spatial correlation were lower comparing to model without any spatial correlation. In addition, the posterior mean for ϕ_2 in Spatial 1 is around 30 with wide range. It seems to be a uniform-like distribution from 10 to 50, similar to our prior distribution. (Figure 3) The maximum distance in the dataset is around 15, indicating that ϕ_2 was largely driven by the priors. On the other hand, ϕ_1 is a sharp peak at around 0.8 despite our wide range uniform prior, indicating the present of correlation in b1 parameters and low correlation between the b3 parameters. Therefore, Spatial 2 was selected as our main model to proceed for priors sensitivity analysis. Since the ϕ_2 for spatial indicates that there's no correlation between b3 parameters, we still assumed they share same variance in Spatial 1. Therefore, we will also include Spatial 1 inference to explore the same variance assumption. All models converged well with Rhat values for all parameters less than 1.1. The convergence plots for Spatial 2 b3 parameters are shown in Figure 2. In addition, the posterior predictive checks plots for Spatial 2 are included in the appendix Figure 22 and 23 while the plots for Spatial 1 are included in the appendix Figure 24 and 25. The predictive counts are located in the center of each of the predictive distributions. Therefore, we can conclude that both models fit well. It is worth noting that for counties with few sample sizes (ex: Inyo, Mono or Colusa), the observed ED visits values are more towards the right or left of the distribution comparing to Spatial 2 where the observed visits are centered.

Prior sensitivity

We assessed the priors for Spatial 2 on θ , θ_2 , ϕ and τ . As mentioned in the Methods section, the prior distribution for θ and θ_2 were obtained from the glm estimates. The informative prior for θ is $N(5.984782, 0.01571683)$ and informative prior for θ_2 is $t(0.2050, 14.34982, 7)$. The t distribution was chosen based on the wide range of posterior distribution in Figure 4. The results for informative priors are shown in Figure 5. We do not see much shift in the center of the posterior distribution for both parameters, indicating that the posterior distribution was robust with different priors settings. However, more smoothness was observed for θ_2 with informative prior where t distribution was able to capture the variation over the original normal prior. Different priors for the precision τ give us similar results for the posterior. In Figure 6, the posterior distribution of σ^2 shows a peak around 5. The uniform prior gives the longest tail range to around 65 while the gamma(1,1) prior gives a tail to around 30. The posterior distributions of ϕ with different priors are shown in Figure 7. We observe the same sharp peak as in Figure 3. The difference in prior only results in the range of the posterior density plots. However, we do see the shape and center are similar. The density for values larger than 5 are very close to 0 regardless of the priors used. The convergence plots for b3, ϕ , τ , are presented in Appendix Figure 14. All Rhat values are less than 1.1. The b3 estimates with informative priors are highly similar to non-informative priors. We will proceed the following with results from informative priors model.

Comparison with frequentist model

The summary statistics for the Spatial 2 was summarized in Table 2. The line plots for 95% credible intervals were shown in Figure 8. The summary statistics for the Spatial 1 was summarized in Table 3. The line plots for 95% credible intervals were shown in Figure 9. The summary statistics for glm results was summarized in Table 4. The convergence and density plots for b1 were shown in Appendix Figure 16 and 17.

The visual results for all three models were summarized in Figure 10. The posterior density plots for b3 from Spatial 2 and 1 were summarized in Appendix Figure X and X. In Figure 8 and 9, we see that the counties with wide credible intervals were those with few baseline visits. These counties were usually the ones with more extreme rate values. We noticed that in general, the posterior mean estimates are higher than the glm for Spatial 2. The increase is more obvious for counties with wider intervals. For example, the log rate estimate is -0.708 for Colusa with Bayesian model and -0.81 with glm. In contrast, Spatial 1 tends to shrink the estimates toward 0. We can also observe this trend in Figure 10 where comparing to glm, Spatial 2 has larger upper and lower bound while Spatial 1 has lower upper and lower bound, indicating the shrinking toward rate 1. Therefore, we could expect that more counties will not be significant due to the shrinkage. Mono and Inyo are the the obvious counties that were not significant as the estimates and intervals were largely shrunk towards the null.

To further investigate the larger rates observation, we looked into b1 estimates which estimated the baseline ED visits count. The results were listed in Table 5. We can observe that for Spatial 2, the estimated baseline counts are smaller than estimates from the glm. In contrast, for Spatial 1, the estimates are usually larger for counties with positive b3 and lower for negative b3 parameters. When calculated rates, this difference could affect counties with small baseline counts, for example, Colusa, Inyo or Mono.

Zipcode level

For the zipcode level analysis, we directly adapt the settings in county level but treated the zipcode data as repeated measurements. The glm results for zipcode level is the same as county level data as shown in Table 4. The summary statistics for Spatial 2 and Spatial 1 were summarized in Table 6 and Table 7. The line plots for 95% credible intervals for Spatial 2 and Spatial 1 were shown in Figure 11 and Figure 12. The visual results for all models were summarized in Figure 13. The posterior convergence and density plots for b3 from the proposed model was summarized in Appendix Figure 18 and 19. The convergence and density plots for b1 were shown in Appendix Figure 20 and 21.

From Table 6, 7 and Figure 11, 12, we can notice that the posterior mean for each county becomes larger comparing to county level data for both Spatial 1 and 2 models. Counties with less average sample/zipcode are more sensitive to the change. Similar to County level analysis, Spatial 1 still shrinks the estimates towards the null comparing to Spatial 2 and glm, the estimates are larger for those counties that are sensitive to change. For example, the estimates for Inyo and Mono were 0.2558 and 0.1899 for Spatial 1 in county level while the estimates were 0.4372 and 0.3435 for zipcode level. The estimates for Inyo and Mono were 0.7537 and 0.8346 for Spatial 1 in county level while the estimates were 0.9889 and 1.1869 for zipcode level. In figure 13, we also notice that the upper bound for Spatial 2 becomes more than 3 and more than 1.5 for Spatial 1.

Similar to county level analysis, the baseline ED visits estimates were similar for counties with larger visits (Table 8). For counties like Colusa, we notice the decrease for both Spatial 2 and 1 comparing to county level data (23.6, 18.93 vs 15.34, 13.13). For Mono, the estimates for Spatial 2 was 12 and Spatial 1 was 18 comparing to 14 from glm for county level analysis. The estimates for Spatial 2 is 8 and Spatial was 14 comparing to 14 from glm for zipcode level analysis. The baseline estimates from zipcode level are smaller than from county level and the decrease is more obvious in counties with smaller sample size.

Discussion

The goal of the study was to evaluate the implementation of spatial correlation structure when modeling the ED visits in the California counties between the year of 2012 and 2017. We included the results for two types of models where spatial correlation was incorporated differently. The convergence of the models and priors sensitivity analyses were assessed as well. The results were then compared with frequentist method where the incorporation of spatial correlation is not feasible in GLM. The DIC selection indicates that the incorporation of spatial correlation is needed with the difference of around 100 with DIC criteria. Among the two spatial models proposed, we found that parameter ϕ and ϕ_2 behaves differently in Spatial 1 where ϕ is sharp around 3 while ϕ_2 is uniform-like distribution with large numbers. This indicates that b_3 parameters are mostly uncorrelated. Then, the difference between Spatial 1 and 2 will be the assumption of parameters b_3 sharing same variance or not. For priors sensitivity analysis, the different priors do not affect most of the parameters in the models. The original Normal flat priors of θ_2 might not be capturing the correct variation as seen in Figure 4. Therefore, distribution that can have heavier tails, like the t-distribution could better capture the variation. Finally, different types of priors for τ results in same shape of the posterior distribution but with different ranges. However, the posterior densities become 0 after the values of 15 for all different priors used.

The behavior of the parameters of interest, b_{3k} were heavily influenced by the models we assumed when the sample size is small. When sample size is large, Spatial 1, 2 and GLM behaves similarly. In counties like Colusa, Mono or Inyo, with sample size less than 50, the posterior means of the log rates shifted more towards positive monotonically in Spatial 2 while in Spatial 1, the estimates shifted toward 0 comparing to GLM. The difference between these two models could lead to difference inference drawn. We can infer that by assuming both parameters sharing same variance, shrinkage effects toward null was observed. In these case, the wide credible intervals for counties with few sample sizes will most likely not be significant. The behavior observed in Spatial 2 is more obvious with zipcode-level analysis where the interval shifts more towards positive comparing to county-level analysis. For Spatial 1, the shrinkage effect towards null still exists while the interval shifts toward positive monotonically comparing to county-level analysis. The GLM results remain the same for both level analysis.

The reason for the behaviors observed in the two spatial models is still not clear. One possible hypothesis is that with the implementation of spatial correlation, the estimates shifts toward null. For example, in Spatial 2, the spatial correlation was implemented on only b_1 . Therefore, the baseline counts estimates are smaller than GLM. No spatial correlation was implemented on b_3 . Therefore, the counts estimates for year of 2017 are similar to GLM, resulting in monotone increase in b_3 . In contrast, spatial correlation was implemented on both b_1 and b_3 in Spatial 1 leading to shrinkage for counts estimates for both baseline and year of 2017 and further results in the shrinkage behavior towards null.

There are some limitations in the study. We assumed the spatial covariance structure followed the power exponential distribution. In reality, this assumption might not be correct. However, the DIC and posterior distribution of b_1 indicates that the neighboring areas are correlated and the current assumption of correlation might be better than no correlation assumption. For the ED visit counts distribution, we assumed the counts followed Poisson distribution and did not take into account of the dispersion. We have tried to incorporate the dispersion parameters but the estimation was not valid. Therefore, it is possible that other distribution like negative binomial could be used to compare the result with Poisson distribution. In summary, we have observed different behaviors by incorporating spatial correlation differently. Moreover, these different behaviors affect the counties with few visits more profoundly than counties with larger number of visits.

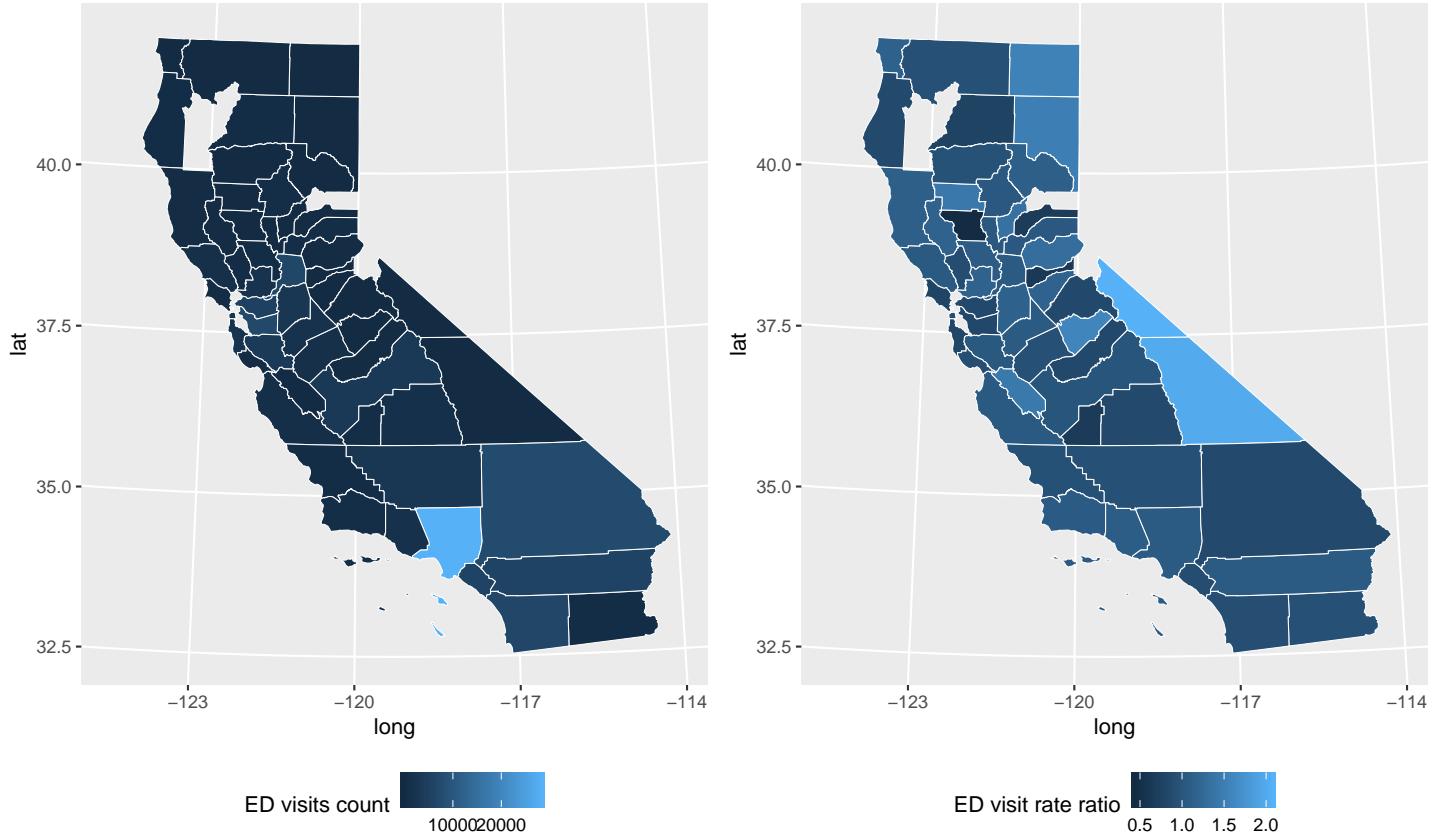


Figure 1: The left plot shows the number of ED visits in each county in 2012. The lighter colors indicate larger number of ED visits. The right plots show the ratio of ED visit between 2012 and 2017 for each county in California. The lighter colors indicate the ratio between 2017 and 2012 is larger.

Table 1: Number of zipcodes, total ED visits at 2012 and the ED visit rate ratio between 2012 and 2017 in each county

	Number of zipcodes	Total.vistis	Rate.ratio
Alameda	41	6788	0.828
Amador	4	172	0.640
Butte	8	646	1.037
Calaveras	2	67	1.164
Colusa	1	27	0.444
Contra Costa	32	5209	0.849
Del Norte	1	78	1.141
El Dorado	5	273	1.300
Fresno	34	3309	0.996
Glenn	2	61	1.426
Humboldt	6	588	0.862
Imperial	7	601	0.935
Inyo	1	27	2.000
Kern	24	2670	0.937
Kings	5	842	0.662
Lake	7	281	1.160
Lassen	1	47	1.511
Los Angeles	249	28265	1.059
Madera	4	434	0.848
Marin	7	391	0.777
Mariposa	1	26	1.577
Mendocino	3	266	1.120
Merced	12	1214	0.942
Modoc	1	28	1.536
Mono	1	14	2.071
Monterey	13	1011	1.046
Napa	3	369	0.894
Nevada	4	270	0.681
Orange	74	5662	0.903
Placer	10	700	1.037
Plumas	2	32	1.125
Riverside	59	5679	1.056
Sacramento	42	6428	1.063
San Benito	1	123	1.439
San Bernardino	51	7376	0.859
San Diego	70	6342	0.909
San Francisco	21	2348	0.897
San Joaquin	23	2682	1.153
San Luis Obispo	11	478	0.948
San Mateo	18	1887	0.814

	Number of zipcodes	Total.vistis	Rate.ratio
Santa Barbara	13	742	1.078
Santa Clara	44	3575	1.044
Santa Cruz	8	441	0.907
Shasta	6	581	0.764
Siskiyou	2	64	0.938
Solano	10	1982	1.173
Sonoma	16	1232	1.050
Stanislaus	18	1786	1.058
Sutter	3	167	1.042
Tehama	3	198	0.955
Tulare	15	1179	0.858
Tuolumne	2	141	0.851
Ventura	20	1504	1.104
Yolo	7	506	1.087
Yuba	2	163	1.337

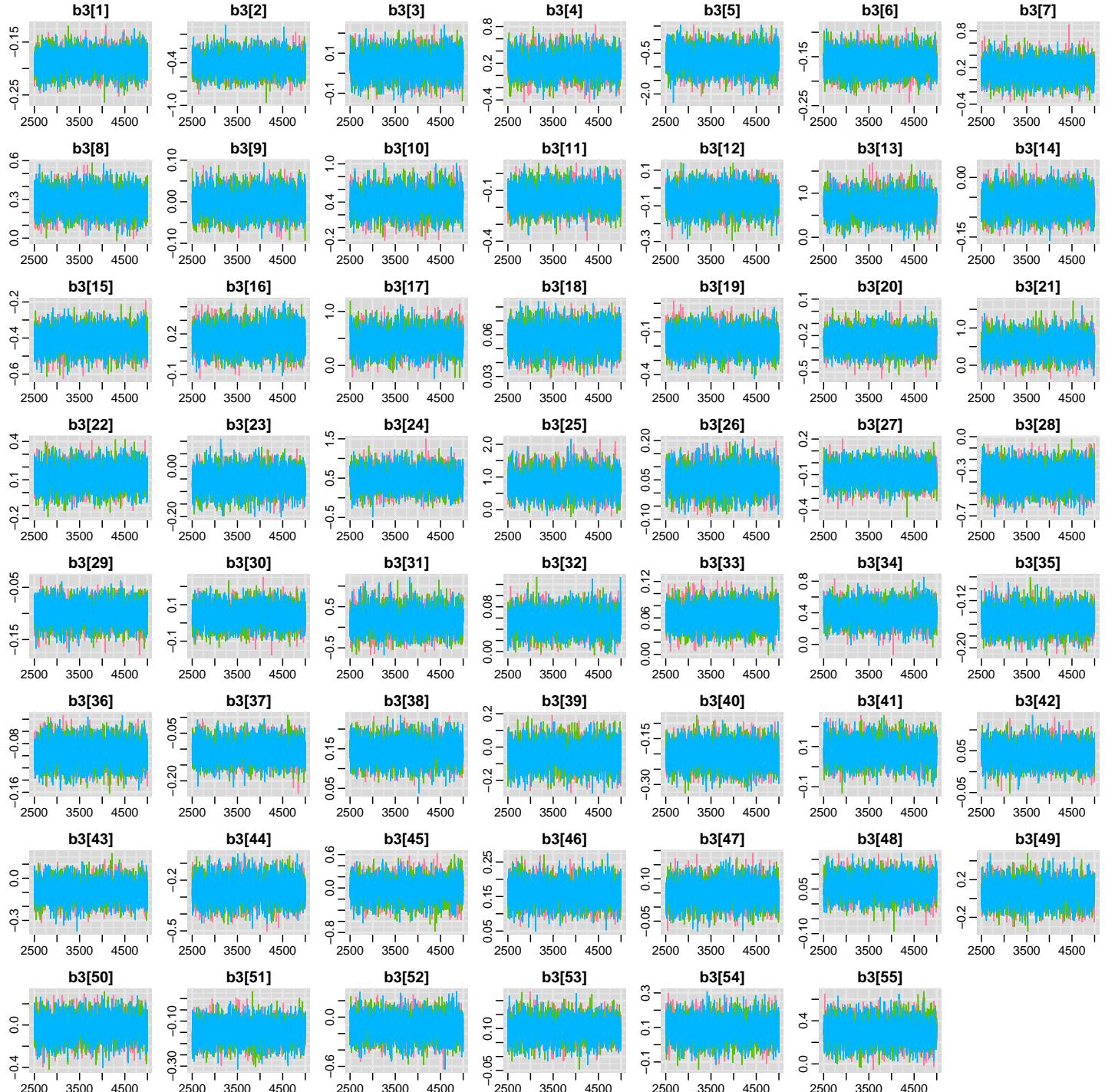


Figure 2: Convergence plots for b_3 for county level analysis with non-informative priors. The numbers in the bracket indicate the order of the counties. All counties were ordered alphabetically as in Table 1

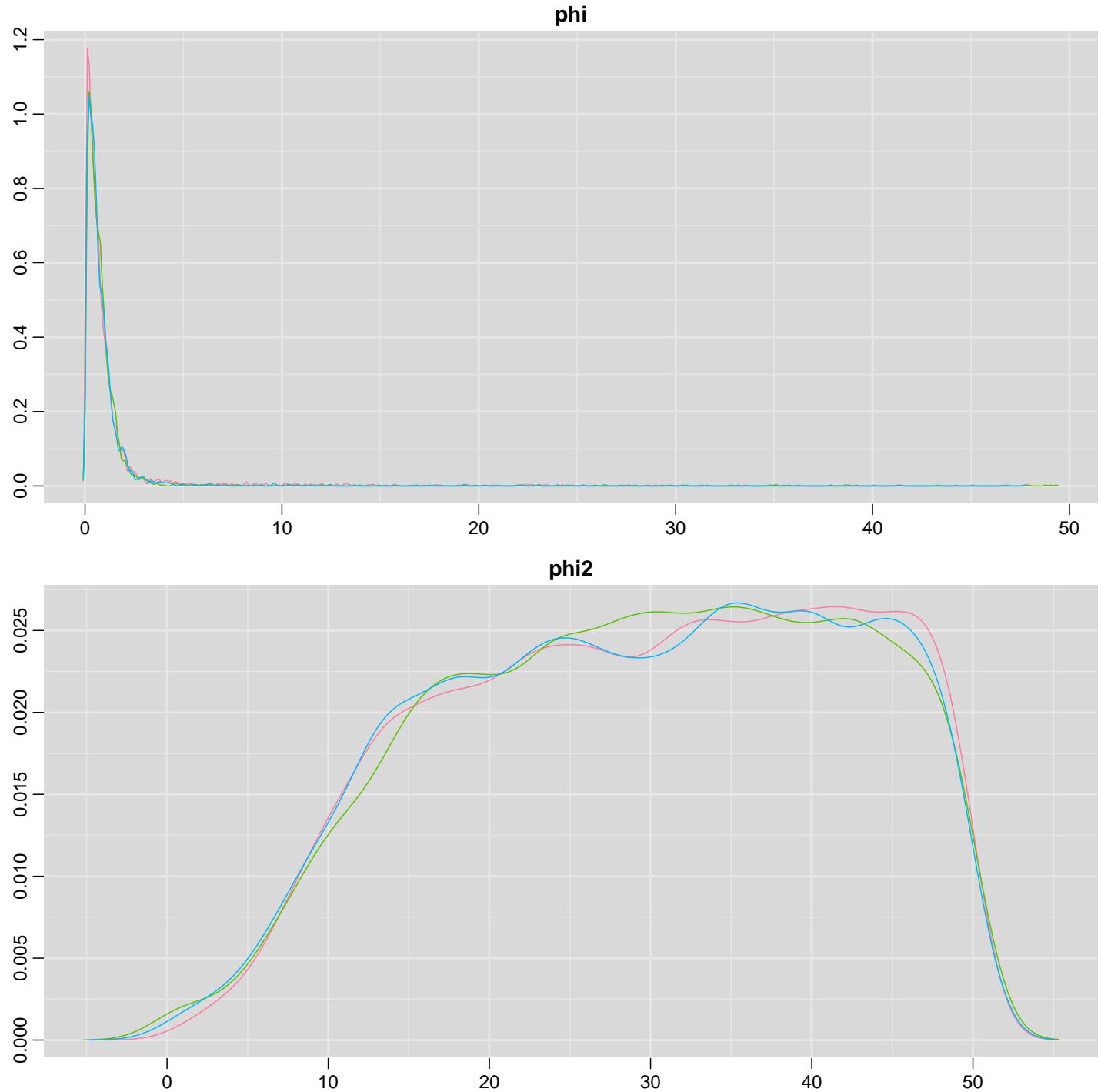


Figure 3: Density plots for both decaying parameters in Spatial 1

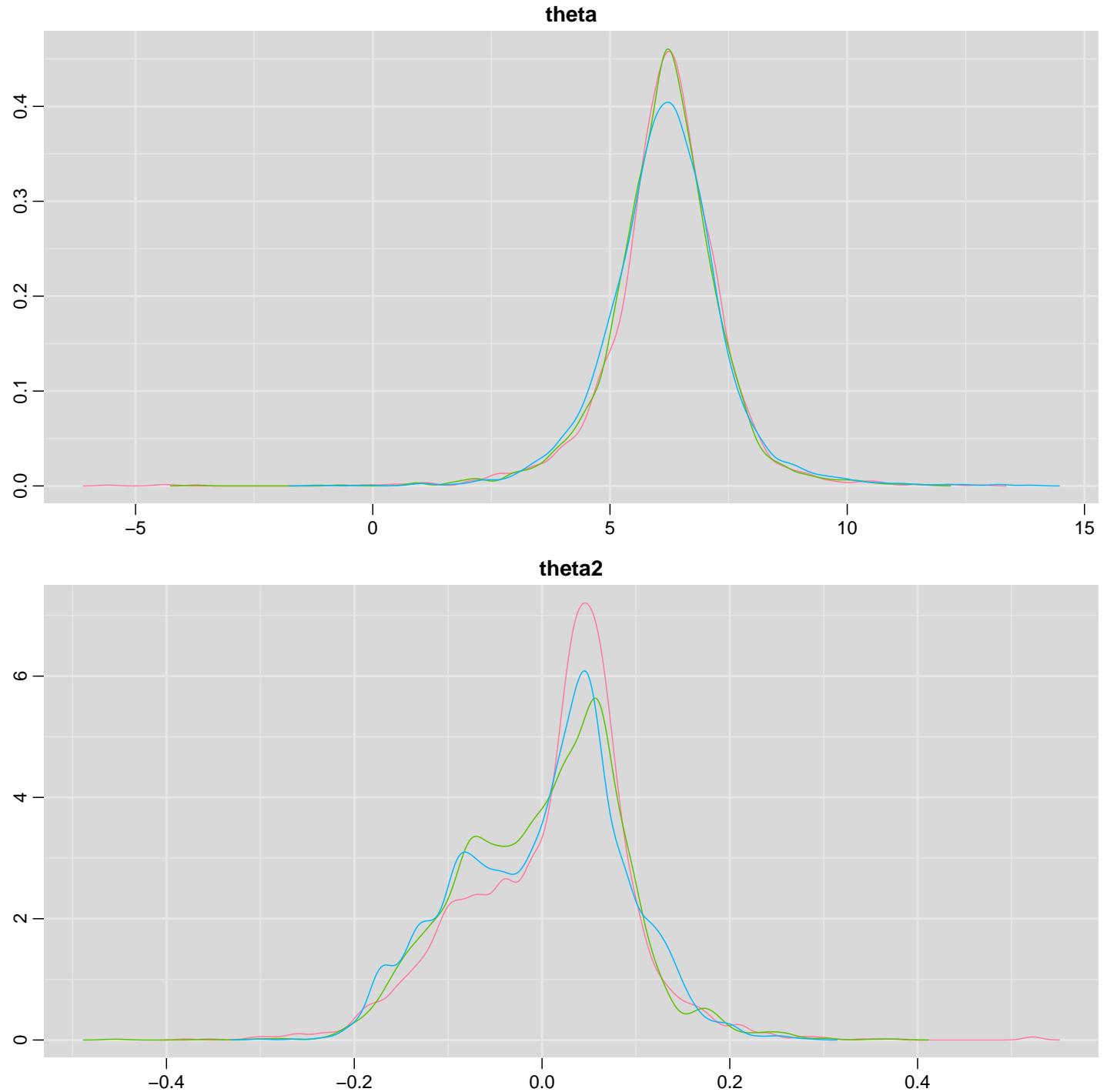


Figure 4: Density plots for theta distribution with non-informative priors in Spatial 2

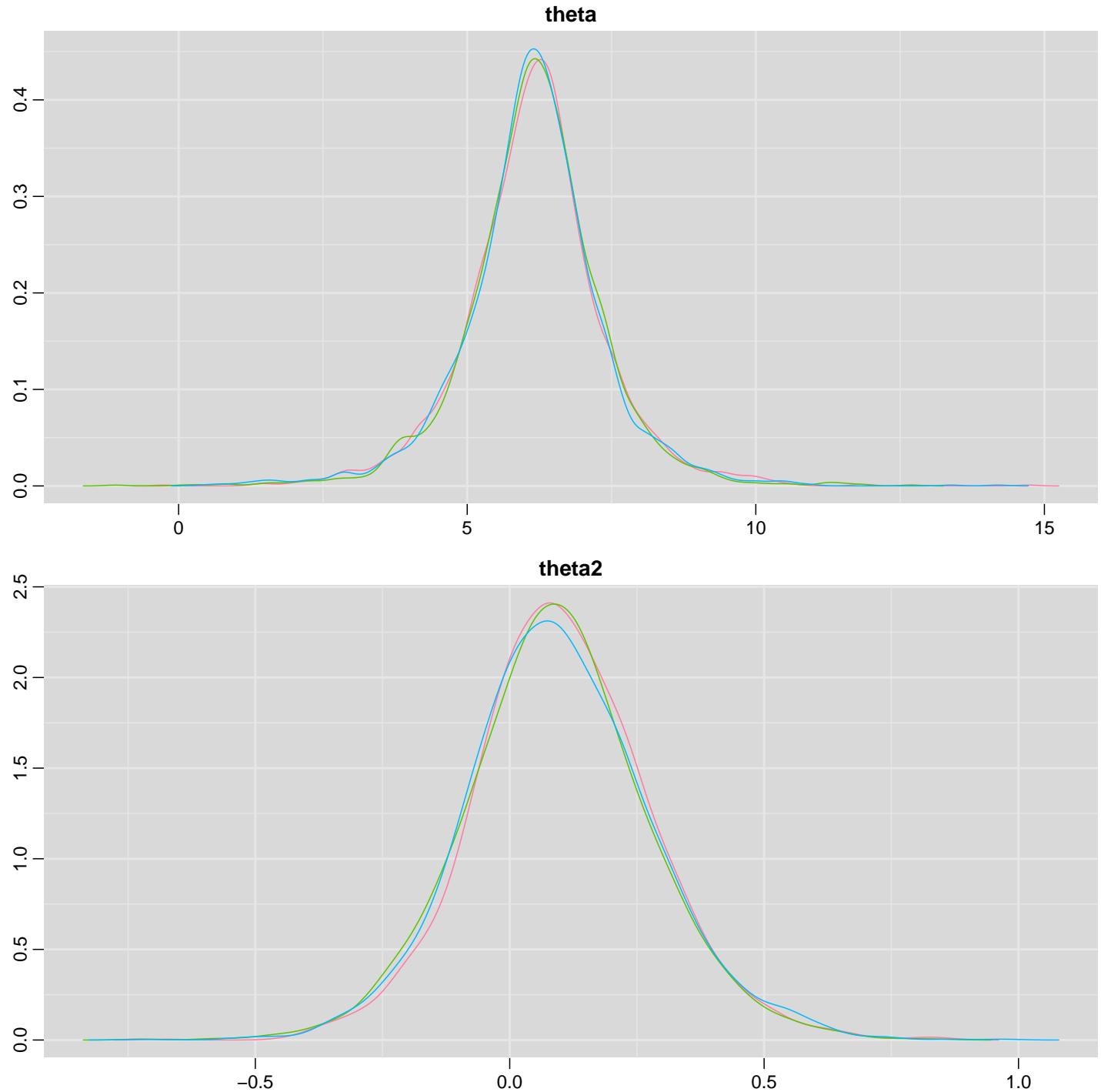


Figure 5: Density plots for theta distribution with informative priors in Spatial 2

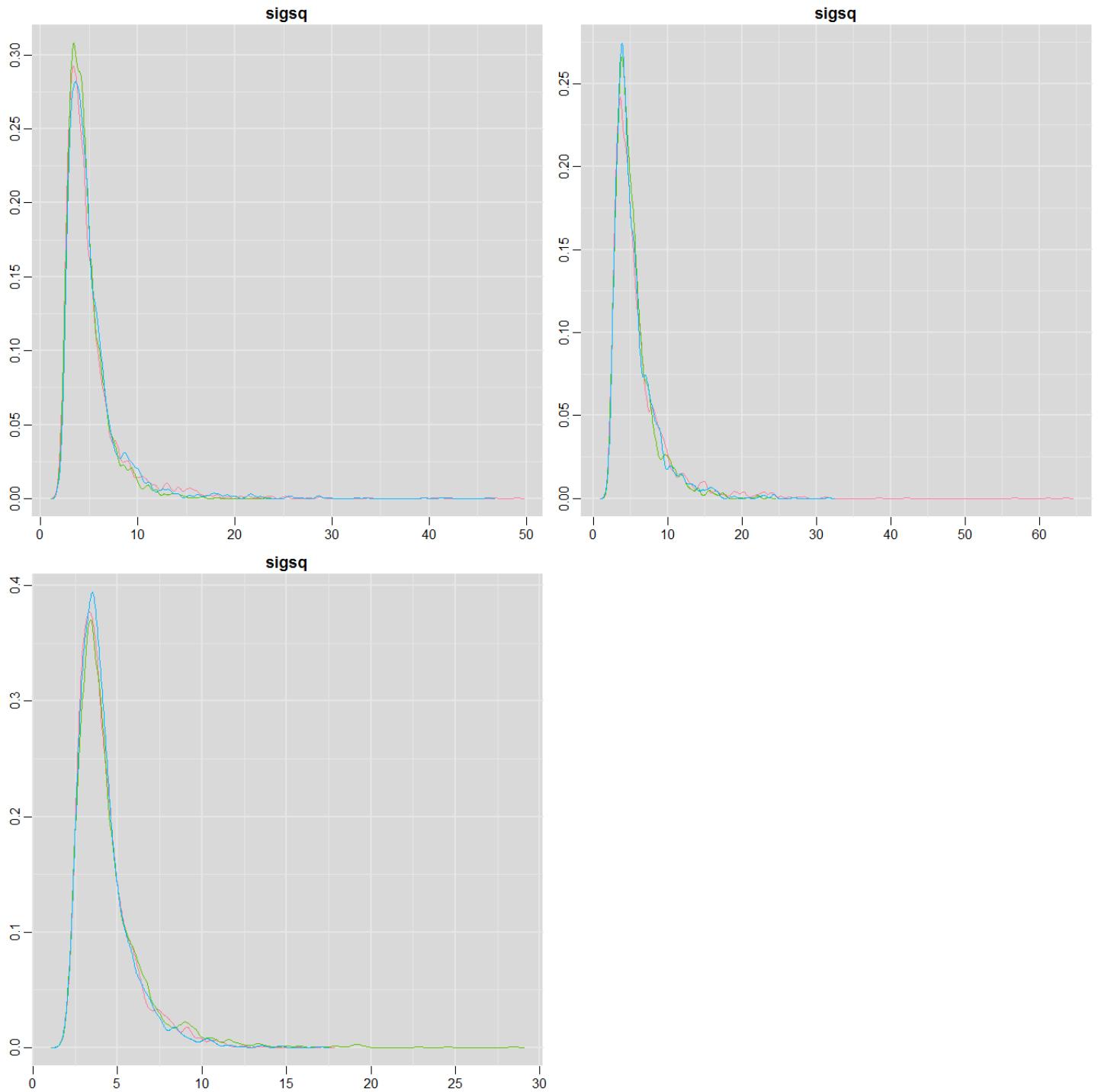


Figure 6: Posterior density plots for σ^2 ($1/\tau$). The top left figure corresponds to τ prior with $\text{gamma}(0.001, 0.001)$. The top right figure corresponds to τ prior with $\text{uniform}(0, 1000)$. The bottom left figures corresponds to τ prior with $\text{gamma}(1, 1)$.

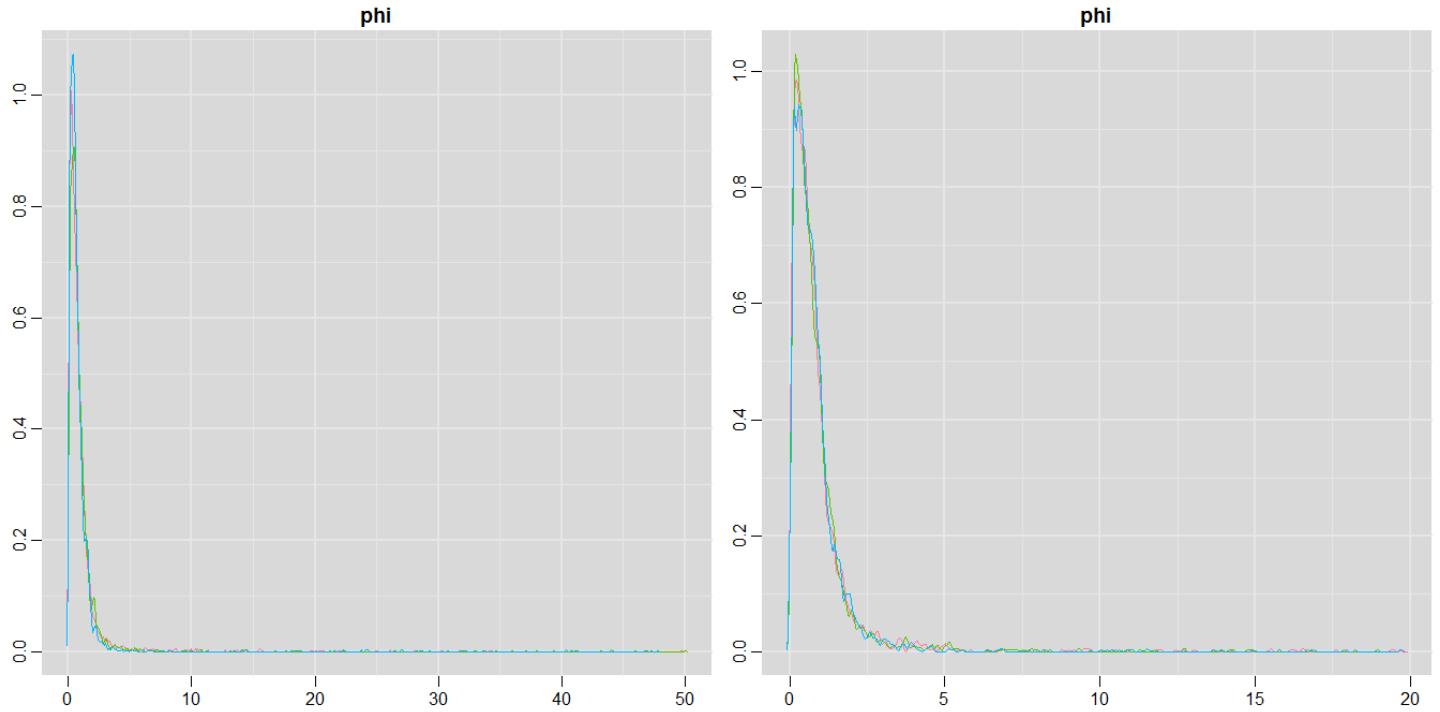


Figure 7: Posterior density plots for ϕ . The left figure corresponds to wider uniform prior $(0.05, 50)$. The right figure corresponds to narrower uniform prior $(0.05, 20)$.

Table 2: Summary statistics table for Spatial 2 with informative priors including posterior mean, 95 percent credible intervals and if b3 (log rate) intervals contain 0 for county level analysis.

	Mean	2.5%	97.5%	Contain.zero
Alameda	-0.1879	-0.2237	-0.1524	TRUE
Amador	-0.4162	-0.6566	-0.1756	TRUE
Butte	0.0427	-0.0689	0.1521	FALSE
Calaveras	0.1896	-0.1406	0.5311	FALSE
Colusa	-0.7083	-1.4290	-0.0122	TRUE
Contra Costa	-0.1629	-0.2032	-0.1228	TRUE
Del Norte	0.1551	-0.1489	0.4681	FALSE
El Dorado	0.2836	0.1245	0.4431	TRUE
Fresno	-0.0032	-0.0508	0.0443	FALSE
Glenn	0.4111	0.0880	0.7387	TRUE
Humboldt	-0.1429	-0.2607	-0.0264	TRUE
Imperial	-0.0657	-0.1795	0.0487	FALSE
Inyo	0.7537	0.2848	1.2420	TRUE
Kern	-0.0637	-0.1185	-0.0088	TRUE
Kings	-0.4091	-0.5168	-0.3021	TRUE
Lake	0.1664	-0.0001	0.3273	FALSE
Lassen	0.4683	0.0945	0.8481	TRUE
Los Angeles	0.0579	0.0413	0.0743	TRUE
Madera	-0.1563	-0.2979	-0.0153	TRUE
Marin	-0.2439	-0.3963	-0.0986	TRUE
Mariposa	0.5687	0.0817	1.0820	TRUE
Mendocino	0.1205	-0.0432	0.2810	FALSE
Merced	-0.0574	-0.1386	0.0233	FALSE
Modoc	0.4734	0.0153	0.9643	TRUE
Mono	0.8346	0.2131	1.4980	TRUE
Monterey	0.0519	-0.0354	0.1381	FALSE
Napa	-0.0992	-0.2493	0.0532	FALSE
Nevada	-0.3655	-0.5563	-0.1751	TRUE
Orange	-0.1021	-0.1397	-0.0643	TRUE
Placer	0.0433	-0.0583	0.1441	FALSE
Plumas	0.1997	-0.2783	0.6888	FALSE
Riverside	0.0550	0.0189	0.0910	TRUE
Sacramento	0.0619	0.0284	0.0960	TRUE
San Benito	0.3951	0.1580	0.6305	TRUE
San Bernardino	-0.1513	-0.1846	-0.1189	TRUE
San Diego	-0.0956	-0.1306	-0.0600	TRUE
San Francisco	-0.1070	-0.1640	-0.0467	TRUE
San Joaquin	0.1442	0.0923	0.1960	TRUE
San Luis Obispo	-0.0497	-0.1809	0.0815	FALSE
San Mateo	-0.2039	-0.2725	-0.1361	TRUE

	Mean	2.5%	97.5%	Contain.zero
Santa Barbara	0.0799	-0.0209	0.1790	FALSE
Santa Clara	0.0440	-0.0010	0.0897	FALSE
Santa Cruz	-0.0927	-0.2279	0.0450	FALSE
Shasta	-0.2603	-0.3838	-0.1390	TRUE
Siskiyou	-0.0289	-0.3833	0.3185	FALSE
Solano	0.1614	0.1019	0.2223	TRUE
Sonoma	0.0524	-0.0263	0.1304	FALSE
Stanislaus	0.0583	-0.0059	0.1230	FALSE
Sutter	0.0632	-0.1482	0.2793	FALSE
Tehama	-0.0248	-0.2234	0.1734	FALSE
Tulare	-0.1499	-0.2356	-0.0638	TRUE
Tuolumne	-0.1239	-0.3738	0.1204	FALSE
Ventura	0.0999	0.0311	0.1710	TRUE
Yolo	0.0923	-0.0256	0.2122	FALSE
Yuba	0.3106	0.1079	0.5168	TRUE

Table 3: Summary statistics table for Spatial 1 with informative priors including posterior mean, 95 percent credible intervals and if b3 (log rate) intervals contain 0 for county level analysis.

	Mean	2.5%	97.5%	Contain.zero
Alameda	-0.1863	-0.2214	-0.1518	TRUE
Amador	-0.2466	-0.4484	-0.0410	TRUE
Butte	0.0387	-0.0656	0.1421	FALSE
Calaveras	0.0966	-0.1354	0.3326	FALSE
Colusa	-0.1229	-0.4361	0.1715	FALSE
Contra Costa	-0.1606	-0.2008	-0.1203	TRUE
Del Norte	0.0836	-0.1433	0.3203	FALSE
El Dorado	0.2170	0.0720	0.3630	TRUE
Fresno	-0.0025	-0.0495	0.0442	FALSE
Glenn	0.2033	-0.0330	0.4516	FALSE
Humboldt	-0.1265	-0.2419	-0.0144	TRUE
Imperial	-0.0581	-0.1696	0.0515	FALSE
Inyo	0.2558	-0.0214	0.5641	FALSE
Kern	-0.0626	-0.1179	-0.0077	TRUE
Kings	-0.3709	-0.4739	-0.2673	TRUE
Lake	0.1349	-0.0101	0.2836	FALSE
Lassen	0.2131	-0.0428	0.4815	FALSE
Los Angeles	0.0576	0.0412	0.0742	TRUE
Madera	-0.1303	-0.2623	-0.0032	TRUE
Marin	-0.2022	-0.3426	-0.0660	TRUE
Mariposa	0.1728	-0.1014	0.4691	FALSE
Mendocino	0.1001	-0.0480	0.2495	FALSE
Merced	-0.0558	-0.1358	0.0228	FALSE
Modoc	0.1605	-0.1206	0.4408	FALSE
Mono	0.1899	-0.1071	0.5243	FALSE
Monterey	0.0532	-0.0302	0.1374	FALSE
Napa	-0.0835	-0.2215	0.0536	FALSE
Nevada	-0.2705	-0.4441	-0.1070	TRUE
Orange	-0.1011	-0.1392	-0.0625	TRUE
Placer	0.0385	-0.0595	0.1357	FALSE
Plumas	0.0688	-0.2166	0.3528	FALSE
Riverside	0.0541	0.0167	0.0906	TRUE
Sacramento	0.0609	0.0273	0.0954	TRUE
San Benito	0.2613	0.0707	0.4573	TRUE
San Bernardino	-0.1504	-0.1842	-0.1161	TRUE
San Diego	-0.0946	-0.1303	-0.0588	TRUE
San Francisco	-0.1052	-0.1642	-0.0464	TRUE
San Joaquin	0.1406	0.0898	0.1929	TRUE
San Luis Obispo	-0.0444	-0.1629	0.0745	FALSE
San Mateo	-0.1959	-0.2612	-0.1298	TRUE

	Mean	2.5%	97.5%	Contain.zero
Santa Barbara	0.0725	-0.0210	0.1697	FALSE
Santa Clara	0.0433	-0.0019	0.0889	FALSE
Santa Cruz	-0.0808	-0.2057	0.0464	FALSE
Shasta	-0.2276	-0.3459	-0.1144	TRUE
Siskiyou	-0.0147	-0.2595	0.2273	FALSE
Solano	0.1556	0.0950	0.2160	TRUE
Sonoma	0.0481	-0.0289	0.1236	FALSE
Stanislaus	0.0577	-0.0053	0.1199	FALSE
Sutter	0.0470	-0.1349	0.2236	FALSE
Tehama	-0.0262	-0.1962	0.1527	FALSE
Tulare	-0.1405	-0.2221	-0.0567	TRUE
Tuolumne	-0.0694	-0.2720	0.1304	FALSE
Ventura	0.0969	0.0291	0.1672	TRUE
Yolo	0.0809	-0.0318	0.1934	FALSE
Yuba	0.2295	0.0541	0.4156	TRUE

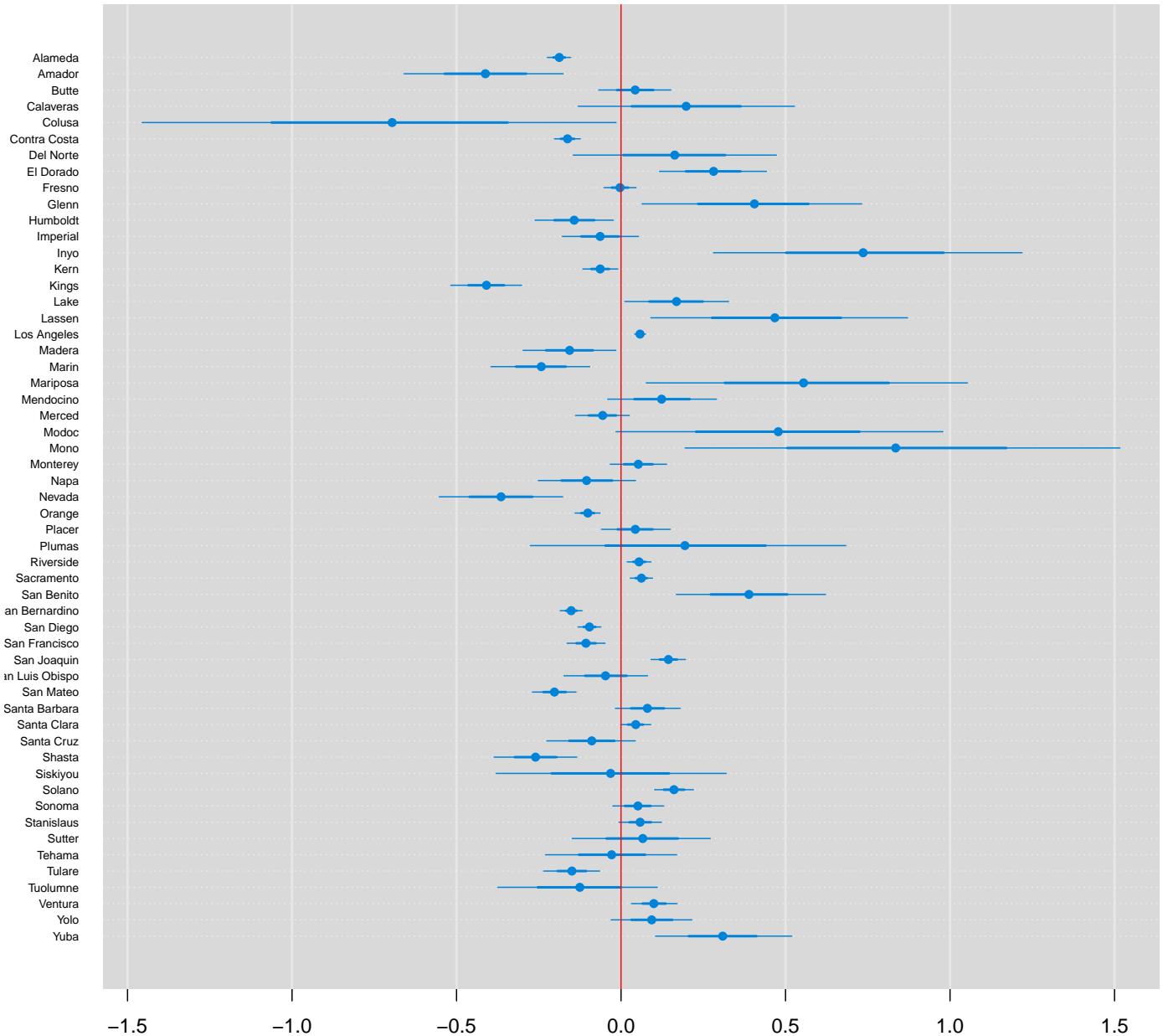


Figure 8: Line plots for Spatial 2 model with informative priors, 95 percent credible intervals in each county for county level analysis

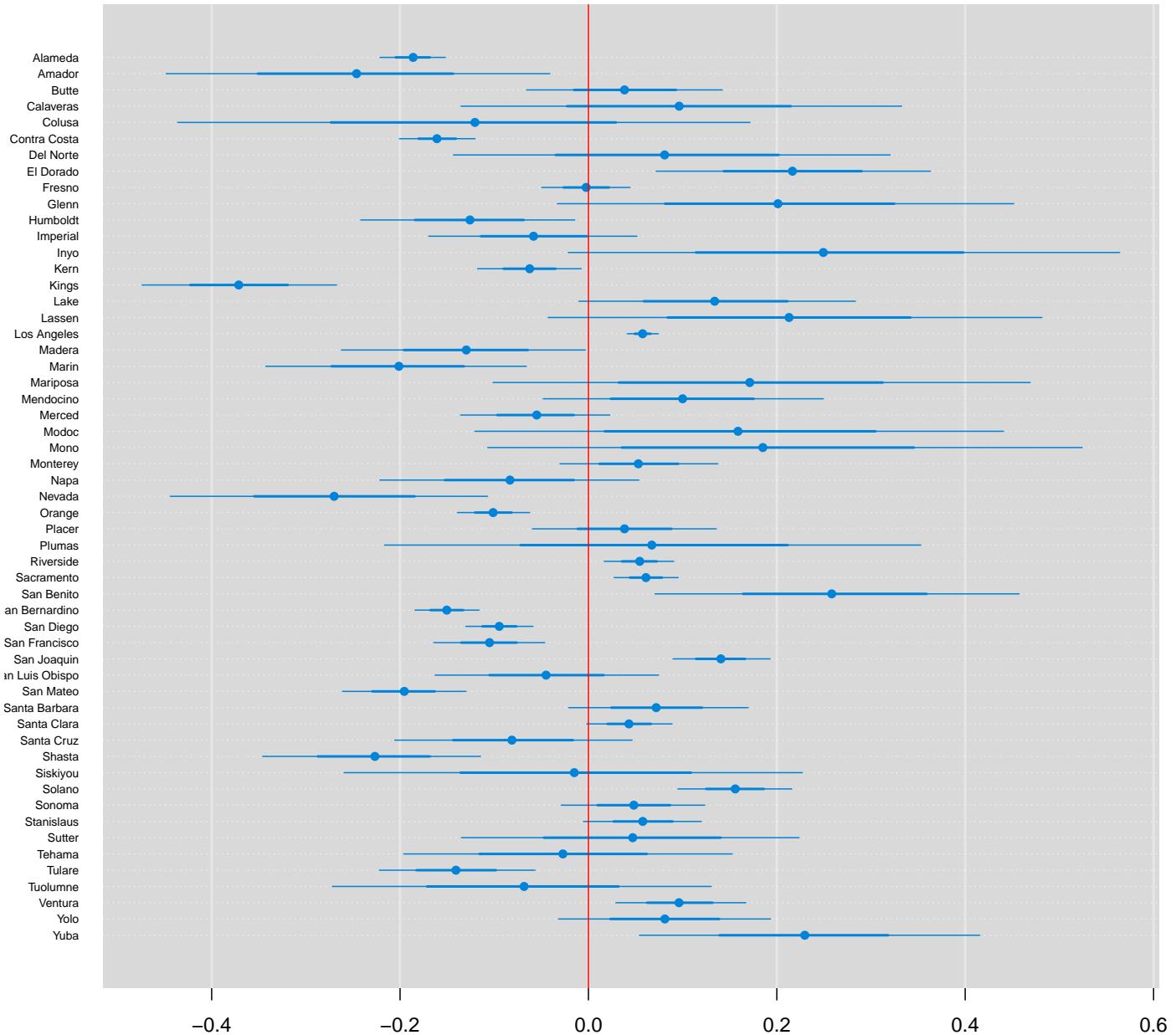


Figure 9: Line plots for Spatial 1 model with informative priors, 95 percent credible intervals in each county for county level analysis

Table 4: Summary statistics table for b3 with glm result. The table includes the glm estimate, lower and upper bound of 95 percent confidence intervals and if the analysis survive FDR correction at 0.1. The analysis used county level data

	Estimate	lowerCI	upperCI	sig
Alameda	-0.1886	-0.2240	-0.1533	TRUE
Amador	-0.4470	-0.6889	-0.2051	TRUE
Butte	0.0365	-0.0772	0.1502	FALSE
Calaveras	0.1520	-0.1764	0.4804	FALSE
Colusa	-0.8109	-1.4919	-0.1300	TRUE
Contra Costa	-0.1638	-0.2172	-0.1104	TRUE
Del Norte	0.1319	-0.1741	0.4380	FALSE
El Dorado	0.2626	0.1010	0.4243	TRUE
Fresno	-0.0039	-0.0637	0.0559	FALSE
Glenn	0.3550	0.0258	0.6842	TRUE
Humboldt	-0.1482	-0.2722	-0.0243	TRUE
Imperial	-0.0671	-0.1874	0.0532	FALSE
Inyo	0.6931	0.2298	1.1565	TRUE
Kern	-0.0650	-0.1300	0.0000	TRUE
Kings	-0.4132	-0.5259	-0.3005	TRUE
Lake	0.1485	-0.0149	0.3120	FALSE
Lassen	0.4125	0.0423	0.7828	TRUE
Los Angeles	0.0574	0.0185	0.0963	TRUE
Madera	-0.1650	-0.3083	-0.0216	TRUE
Marin	-0.2517	-0.4057	-0.0977	TRUE
Mariposa	0.4555	-0.0372	0.9481	FALSE
Mendocino	0.1136	-0.0555	0.2827	FALSE
Merced	-0.0603	-0.1484	0.0279	FALSE
Modoc	0.4290	-0.0483	0.9063	FALSE
Mono	0.7282	0.0894	1.3671	TRUE
Monterey	0.0454	-0.0477	0.1386	FALSE
Napa	-0.1117	-0.2644	0.0409	FALSE
Nevada	-0.3835	-0.5742	-0.1928	TRUE
Orange	-0.1022	-0.1539	-0.0504	TRUE
Placer	0.0365	-0.0732	0.1461	FALSE
Plumas	0.1178	-0.3597	0.5953	FALSE
Riverside	0.0548	0.0042	0.1055	TRUE
Sacramento	0.0611	0.0120	0.1102	TRUE
San Benito	0.3640	0.1312	0.5967	TRUE
San Bernardino	-0.1518	-0.2006	-0.1031	TRUE
San Diego	-0.0959	-0.1461	-0.0457	TRUE
San Francisco	-0.1088	-0.1774	-0.0401	TRUE
San Joaquin	0.1426	0.0799	0.2052	TRUE
San Luis Obispo	-0.0537	-0.1870	0.0796	FALSE
San Mateo	-0.2058	-0.2819	-0.1297	TRUE

	Estimate	lowerCI	upperCI	sig
Santa Barbara	0.0753	-0.0307	0.1812	FALSE
Santa Clara	0.0427	-0.0152	0.1006	FALSE
Santa Cruz	-0.0976	-0.2375	0.0423	FALSE
Shasta	-0.2689	-0.3974	-0.1404	TRUE
Siskiyou	-0.0645	-0.4185	0.2894	FALSE
Solano	0.1592	0.0896	0.2288	TRUE
Sonoma	0.0483	-0.0373	0.1340	FALSE
Stanislaus	0.0566	-0.0171	0.1303	FALSE
Sutter	0.0411	-0.1742	0.2563	FALSE
Tehama	-0.0465	-0.2489	0.1559	FALSE
Tulare	-0.1527	-0.2439	-0.0616	TRUE
Tuolumne	-0.1613	-0.4073	0.0847	FALSE
Ventura	0.0987	0.0205	0.1769	TRUE
Yolo	0.0834	-0.0424	0.2092	FALSE
Yuba	0.2907	0.0847	0.4968	TRUE

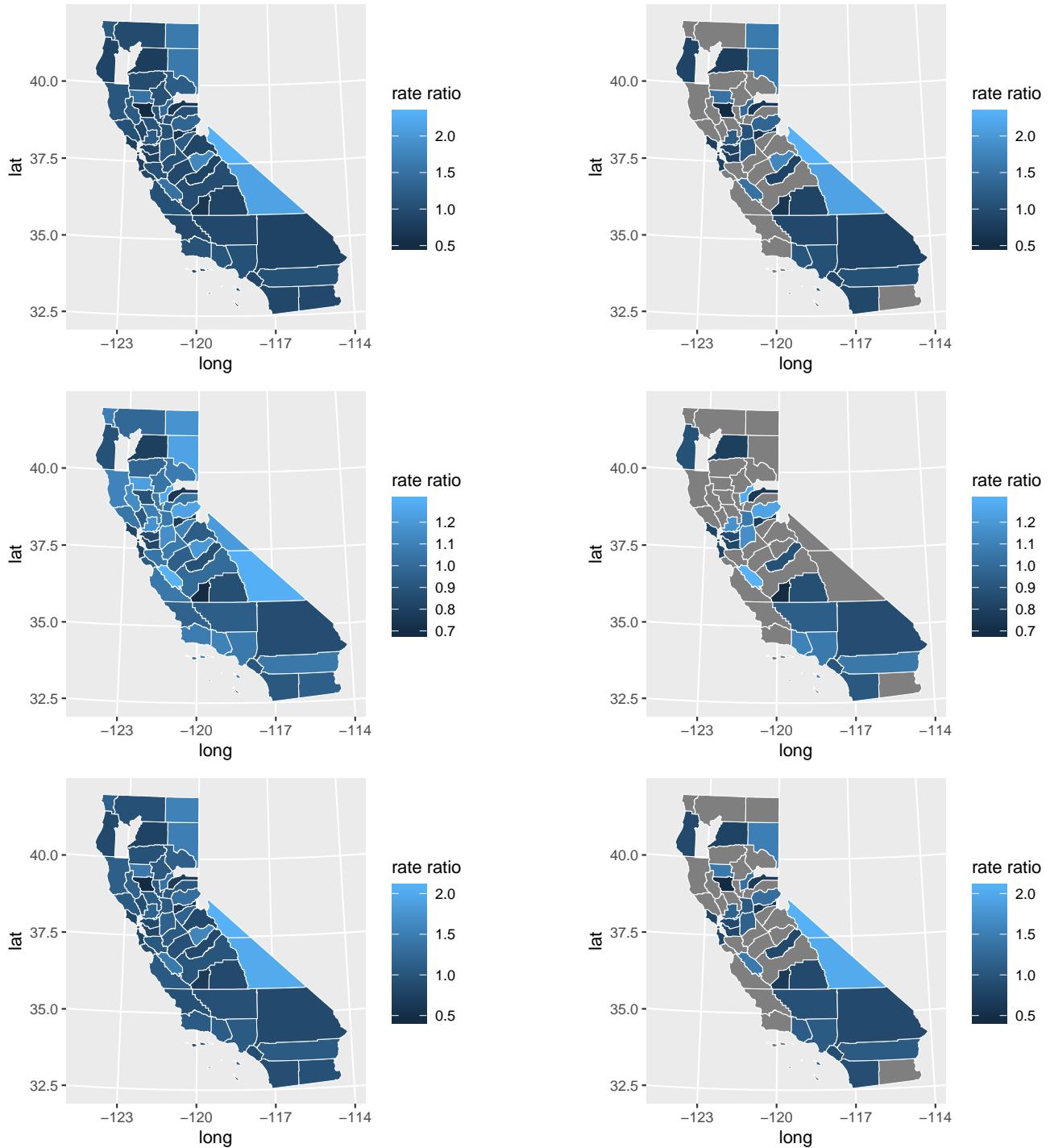


Figure 10: The plots in the first, second and third rows corresponding to Spatial 2, Spatial 1 and GLM. The left column denote the posterior mean or glm estimates of rate ($\exp(b_3)$). The right column denotes the significance of the estimated rates. The gray shaded areas were not significant. The results are shown for county level analysis

Table 5: Estimated baseline ED visits with GLM, Spatial 2 and Spatial 1 models in county level analysis.

	GLM	Spatial.2	Spatial.1
Alameda	6788	6783.2445	6777.2254
Amador	172	166.3100	154.5984
Butte	646	641.1760	642.8571
Calaveras	67	63.9486	67.1125
Colusa	27	23.5591	18.9316
Contra Costa	5209	5203.3844	5197.9840
Del Norte	78	75.6149	78.5514
El Dorado	273	267.0410	277.0292
Fresno	3309	3304.5540	3303.2774
Glenn	61	57.3898	64.8496
Humboldt	588	584.7102	580.0870
Imperial	601	599.2747	597.2179
Inyo	27	25.1766	34.3873
Kern	2670	2666.6706	2664.8682
Kings	842	838.1612	825.7262
Lake	281	275.4661	280.0228
Lassen	47	44.1345	51.1524
Los Angeles	28265	28255.8558	28258.2294
Madera	434	429.6604	424.2506
Marin	391	387.3610	380.2269
Mariposa	26	22.8949	28.8791
Mendocino	266	263.5740	266.3529
Merced	1214	1210.0413	1209.1471
Modoc	28	26.4108	31.5938
Mono	14	12.2595	18.4850
Monterey	1011	1004.2092	1002.8524
Napa	369	364.3103	361.5351
Nevada	270	264.7842	254.2583
Orange	5662	5660.2945	5656.7032
Placer	700	694.6489	696.4275
Plumas	32	29.0938	31.2650
Riverside	5679	5676.4077	5679.6078
Sacramento	6428	6422.0261	6426.0287
San Benito	123	118.8550	128.2800
San Bernardino	7376	7371.8355	7369.7009
San Diego	6342	6338.8037	6336.6193
San Francisco	2348	2343.4547	2341.1639
San Joaquin	2682	2676.9856	2682.7480
San Luis Obispo	478	475.5451	474.2697
San Mateo	1887	1882.7749	1875.1959

	GLM	Spatial.2	Spatial.1
Santa Barbara	742	738.1798	740.9617
Santa Clara	3575	3569.9893	3570.9042
Santa Cruz	441	438.1232	435.5890
Shasta	581	575.5496	566.9544
Siskiyou	64	61.3901	60.9119
Solano	1982	1977.1688	1982.9426
Sonoma	1232	1227.0229	1229.5288
Stanislaus	1786	1782.2276	1781.8170
Sutter	167	162.8440	164.3944
Tehama	198	193.3671	193.3971
Tulare	1179	1175.1975	1169.4648
Tuolumne	141	135.3925	131.8087
Ventura	1504	1501.4349	1503.3632
Yolo	506	501.2066	504.3098
Yuba	163	159.2520	166.5654

Table 6: Summary statistics table for Spatial 2 including posterior mean, 95 percent credible intervals and if b3 (log rate) intervals contain 0 for zipcode level analysis.

	Mean	2.5%	97.5%	Contain.zero
Alameda	-0.1858	-0.2215	-0.1507	TRUE
Amador	-0.3165	-0.5793	-0.0310	TRUE
Butte	0.0549	-0.0531	0.1661	FALSE
Calaveras	0.3162	-0.0266	0.6652	FALSE
Colusa	-0.2794	-1.0535	0.4875	FALSE
Contra Costa	-0.1610	-0.2015	-0.1214	TRUE
Del Norte	0.2623	-0.0494	0.5752	FALSE
El Dorado	0.3404	0.1718	0.5132	TRUE
Fresno	0.0001	-0.0489	0.0476	FALSE
Glenn	0.5174	0.1890	0.8554	TRUE
Humboldt	-0.1327	-0.2536	-0.0138	TRUE
Imperial	-0.0547	-0.1668	0.0583	FALSE
Inyo	0.9889	0.5067	1.5055	TRUE
Kern	-0.0607	-0.1160	-0.0051	TRUE
Kings	-0.4003	-0.5101	-0.2912	TRUE
Lake	0.2025	0.0416	0.3673	TRUE
Lassen	0.6358	0.2400	1.0360	TRUE
Los Angeles	0.0577	0.0413	0.0740	TRUE
Madera	-0.1305	-0.2712	0.0106	FALSE
Marin	-0.2267	-0.3720	-0.0765	TRUE
Mariposa	0.9038	0.3632	1.4620	TRUE
Mendocino	0.1512	-0.0176	0.3243	FALSE
Merced	-0.0507	-0.1322	0.0301	FALSE
Modoc	0.6790	0.1767	1.1925	TRUE
Mono	1.1869	0.5278	1.9040	TRUE
Monterey	0.0672	-0.0231	0.1554	FALSE
Napa	-0.0746	-0.2246	0.0773	FALSE
Nevada	-0.3271	-0.5222	-0.1316	TRUE
Orange	-0.1006	-0.1388	-0.0620	TRUE
Placer	0.0560	-0.0497	0.1617	FALSE
Plumas	0.3597	-0.1413	0.8624	FALSE
Riverside	0.0566	0.0213	0.0925	TRUE
Sacramento	0.0630	0.0287	0.0963	TRUE
San Benito	0.5809	0.3042	0.8949	TRUE
San Bernardino	-0.1501	-0.1839	-0.1170	TRUE
San Diego	-0.0949	-0.1312	-0.0592	TRUE
San Francisco	-0.1022	-0.1619	-0.0431	TRUE
San Joaquin	0.1473	0.0944	0.1999	TRUE
San Luis Obispo	-0.0363	-0.1620	0.0894	FALSE
San Mateo	-0.1997	-0.2681	-0.1336	TRUE

	Mean	2.5%	97.5%	Contain.zero
Santa Barbara	0.0878	-0.0114	0.1894	FALSE
Santa Clara	0.0462	0.0001	0.0927	TRUE
Santa Cruz	-0.0728	-0.2074	0.0632	FALSE
Shasta	-0.2396	-0.3645	-0.1190	TRUE
Siskiyou	0.0575	-0.3027	0.4178	FALSE
Solano	0.1674	0.1065	0.2290	TRUE
Sonoma	0.0563	-0.0222	0.1353	FALSE
Stanislaus	0.0632	-0.0012	0.1296	FALSE
Sutter	0.1110	-0.1052	0.3275	FALSE
Tehama	0.0309	-0.1728	0.2309	FALSE
Tulare	-0.1426	-0.2271	-0.0598	TRUE
Tuolumne	-0.0336	-0.2913	0.2301	FALSE
Ventura	0.1034	0.0355	0.1736	TRUE
Yolo	0.1064	-0.0130	0.2255	FALSE
Yuba	0.3777	0.1703	0.5837	TRUE

Table 7: Summary statistics table for Spatial 1 including posterior mean, 95 percent credible intervals and if b3 (log rate) intervals contain 0 for zipcode level analysis.

	Mean	2.5%	97.5%	Contain.zero
Alameda	-0.1850	-0.2205	-0.1497	TRUE
Amador	-0.1841	-0.4236	0.0739	FALSE
Butte	0.0558	-0.0478	0.1617	FALSE
Calaveras	0.2083	-0.0563	0.4829	FALSE
Colusa	-0.0289	-0.4039	0.3424	FALSE
Contra Costa	-0.1587	-0.1985	-0.1187	TRUE
Del Norte	0.1801	-0.0854	0.4351	FALSE
El Dorado	0.3049	0.1415	0.4813	TRUE
Fresno	0.0009	-0.0462	0.0480	FALSE
Glenn	0.3201	0.0552	0.5955	TRUE
Humboldt	-0.1180	-0.2361	-0.0044	TRUE
Imperial	-0.0469	-0.1597	0.0662	FALSE
Inyo	0.4372	0.1161	0.7947	TRUE
Kern	-0.0595	-0.1133	-0.0062	TRUE
Kings	-0.3702	-0.4715	-0.2656	TRUE
Lake	0.1828	0.0293	0.3392	TRUE
Lassen	0.3639	0.0751	0.6719	TRUE
Los Angeles	0.0576	0.0416	0.0738	TRUE
Madera	-0.1100	-0.2404	0.0234	FALSE
Marin	-0.1961	-0.3346	-0.0558	TRUE
Mariposa	0.3716	0.0308	0.7344	TRUE
Mendocino	0.1392	-0.0160	0.2959	FALSE
Merced	-0.0481	-0.1285	0.0307	FALSE
Modoc	0.3043	-0.0224	0.6475	FALSE
Mono	0.3435	-0.0140	0.7417	FALSE
Monterey	0.0729	-0.0125	0.1584	FALSE
Napa	-0.0610	-0.2013	0.0778	FALSE
Nevada	-0.2509	-0.4284	-0.0740	TRUE
Orange	-0.0992	-0.1374	-0.0615	TRUE
Placer	0.0578	-0.0433	0.1591	FALSE
Plumas	0.1682	-0.1505	0.4947	FALSE
Riverside	0.0568	0.0209	0.0933	TRUE
Sacramento	0.0634	0.0294	0.0979	TRUE
San Benito	0.4475	0.1986	0.7354	TRUE
San Bernardino	-0.1495	-0.1831	-0.1163	TRUE
San Diego	-0.0934	-0.1290	-0.0562	TRUE
San Francisco	-0.0997	-0.1588	-0.0407	TRUE
San Joaquin	0.1458	0.0946	0.1987	TRUE
San Luis Obispo	-0.0299	-0.1512	0.0939	FALSE
San Mateo	-0.1930	-0.2579	-0.1260	TRUE

	Mean	2.5%	97.5%	Contain.zero
Santa Barbara	0.0830	-0.0156	0.1827	FALSE
Santa Clara	0.0461	0.0011	0.0912	TRUE
Santa Cruz	-0.0631	-0.1929	0.0662	FALSE
Shasta	-0.2125	-0.3309	-0.0922	TRUE
Siskiyou	0.0420	-0.2362	0.3177	FALSE
Solano	0.1648	0.1043	0.2256	TRUE
Sonoma	0.0552	-0.0212	0.1301	FALSE
Stanislaus	0.0629	0.0000	0.1260	TRUE
Sutter	0.1037	-0.0904	0.2959	FALSE
Tehama	0.0281	-0.1529	0.2107	FALSE
Tulare	-0.1348	-0.2176	-0.0507	TRUE
Tuolumne	0.0052	-0.2235	0.2349	FALSE
Ventura	0.1017	0.0337	0.1686	TRUE
Yolo	0.1049	-0.0117	0.2230	FALSE
Yuba	0.3045	0.1183	0.4964	TRUE

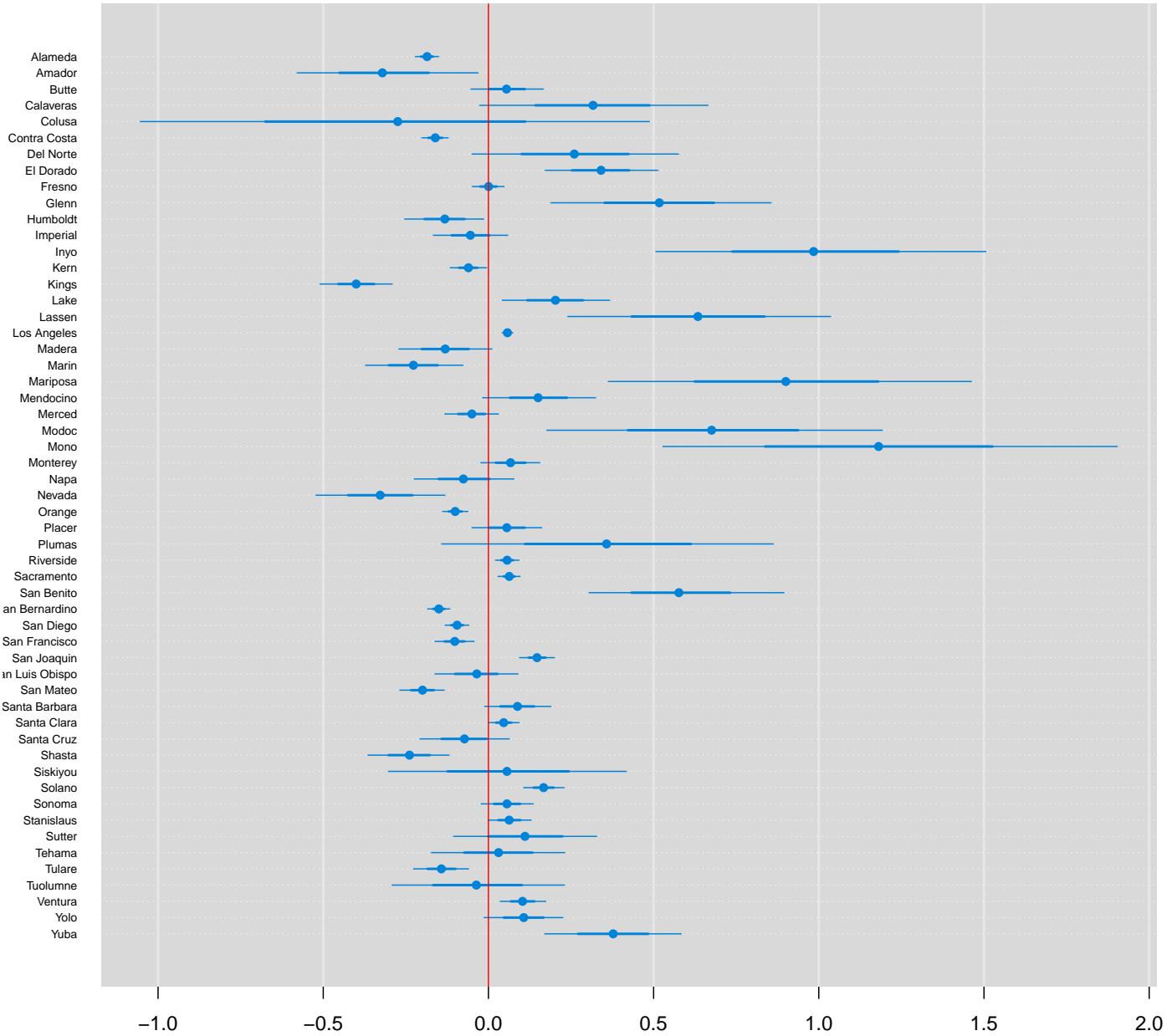


Figure 11: Line plots for Spatial 2 model, 95 percent credible intervals in each county for zipcode level analysis

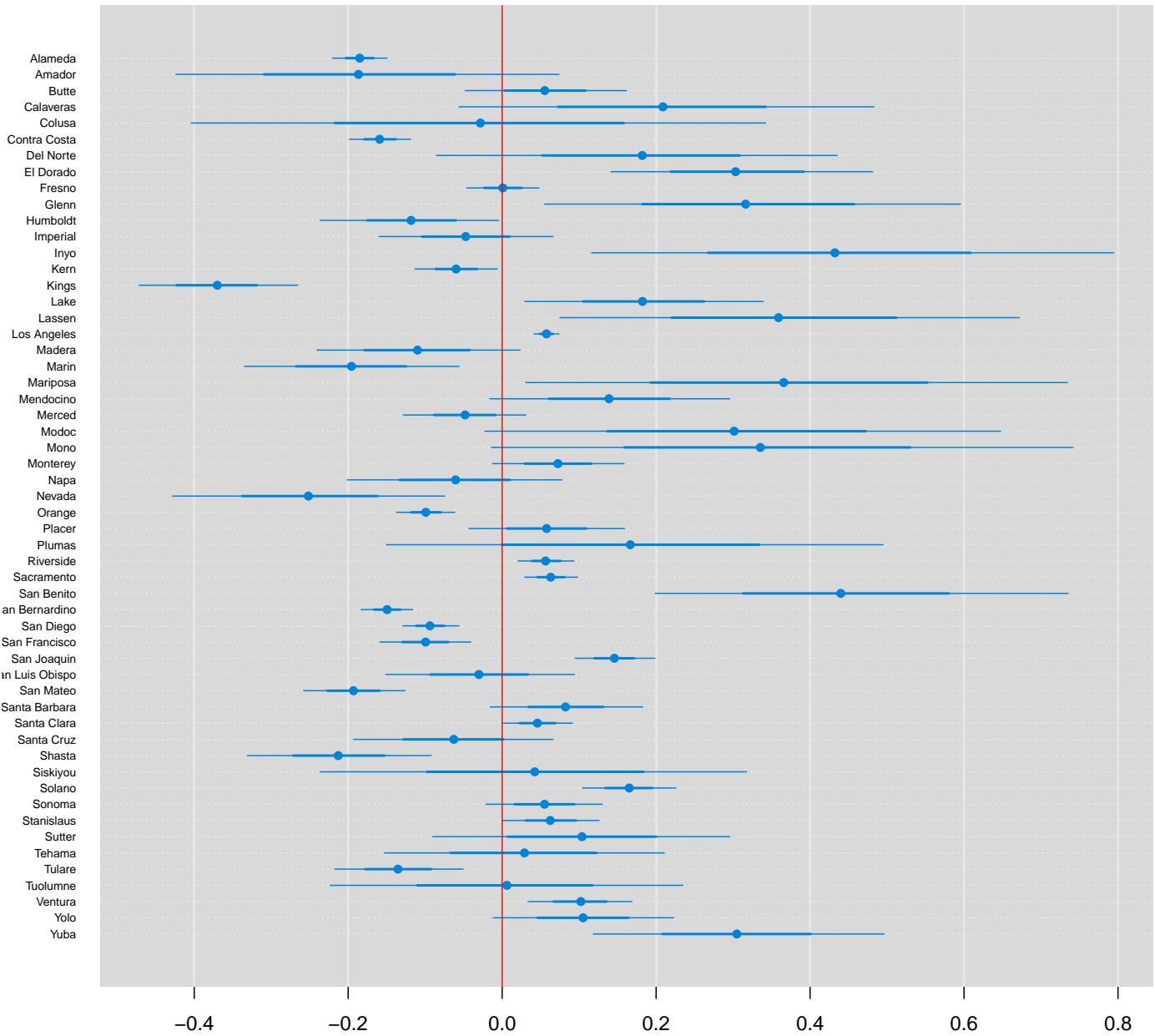


Figure 12: Line plots for Spatial 2 model, 95 percent credible intervals in each county for zipcode level analysis

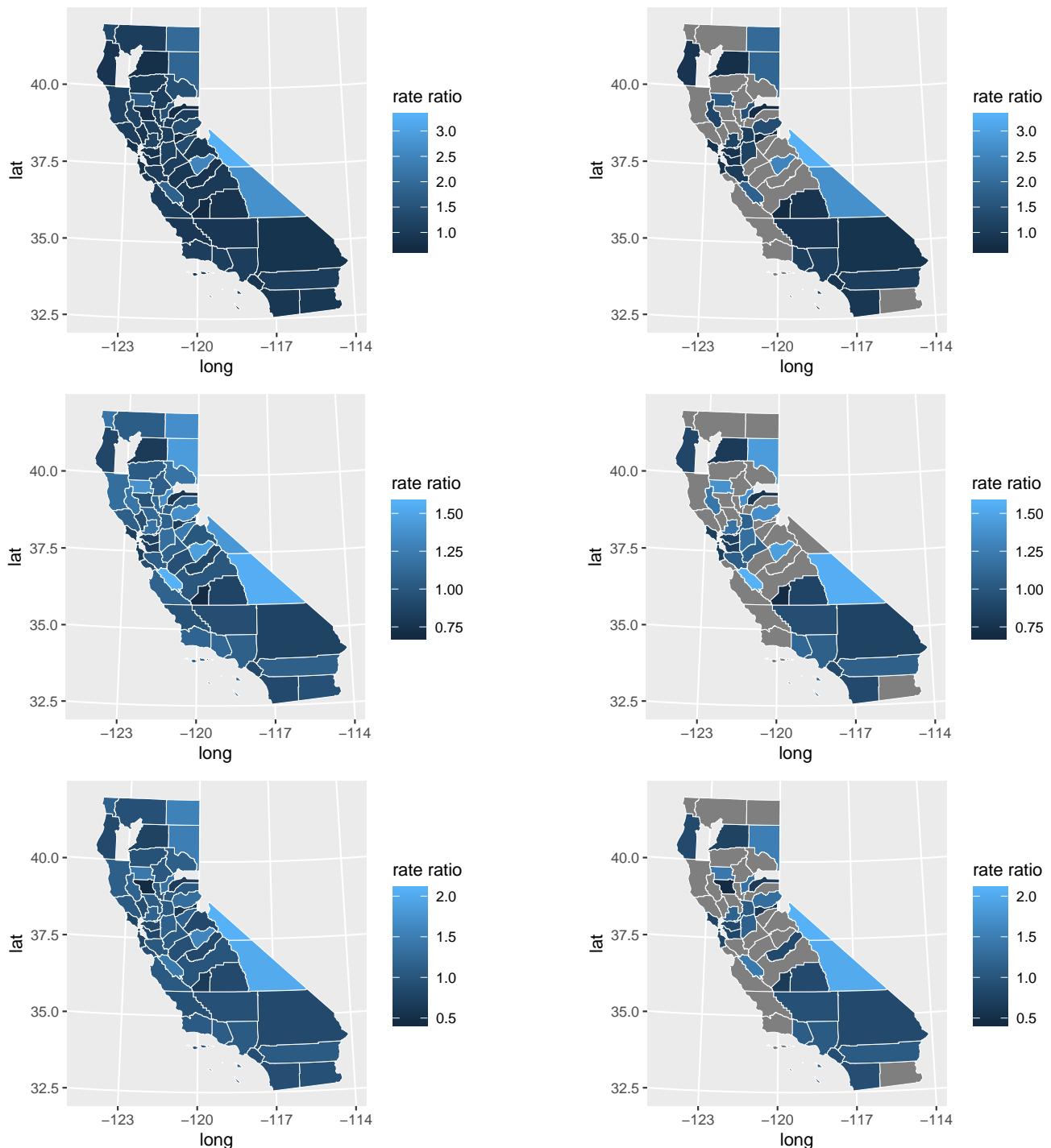


Figure 13: The plots in the first, second and third rows corresponding to Spatial 2, Spatial 1 and GLM. The left column denote the posterior mean or glm estimates of rate ($\exp(b_3)$). The right column denotes the significance of the estimated rates. The gray shaded areas were not significant. The results are shown for zipcode level analysis

Table 8: Estimated baseline ED visits with GLM, Spatial 2 and Spatial 1 models in zipcode level analysis

	GLM	Spatial.2	Spatial.1
Alameda	165.5610	165.1140	165.0296
Amador	43.0000	37.5679	34.8907
Butte	80.7500	79.2250	79.0344
Calaveras	33.5000	28.1742	29.5002
Colusa	27.0000	15.3461	13.1366
Contra Costa	162.7813	162.2823	162.0873
Del Norte	78.0000	67.9821	70.3823
El Dorado	54.6000	50.3922	50.8811
Fresno	97.3235	96.9086	96.8410
Glenn	30.5000	25.7270	28.5744
Humboldt	98.0000	96.3812	95.5408
Imperial	85.8571	84.6476	84.1370
Inyo	27.0000	19.8024	27.7977
Kern	111.2500	110.7742	110.6720
Kings	168.4000	166.0890	163.7971
Lake	40.1429	37.9801	38.1905
Lassen	47.0000	37.2311	43.3830
Los Angeles	113.5141	113.4812	113.4743
Madera	108.5000	104.6843	103.3096
Marin	55.8571	54.3346	53.4282
Mariposa	26.0000	16.3304	21.9019
Mendocino	88.6667	85.2430	85.4122
Merced	101.1667	100.1759	99.9741
Modoc	28.0000	21.4687	26.4190
Mono	14.0000	8.6808	14.7243
Monterey	77.7692	76.0842	75.6917
Napa	123.0000	118.3820	117.1909
Nevada	67.5000	63.6787	61.1578
Orange	76.5135	76.3848	76.3104
Placer	70.0000	68.5063	68.3217
Plumas	16.0000	12.4173	13.5770
Riverside	96.2542	96.0779	96.0467
Sacramento	153.0476	152.7338	152.6548
San Benito	123.0000	98.6943	105.1177
San Bernardino	144.6275	144.3952	144.3516
San Diego	90.6000	90.4814	90.4022
San Francisco	111.8095	111.0602	110.8751
San Joaquin	116.6087	116.0465	116.0964
San Luis Obispo	43.4545	42.6602	42.4246
San Mateo	104.8333	104.1615	103.7327

	GLM	Spatial.2	Spatial.1
Santa Barbara	57.0769	56.3315	56.3767
Santa Clara	81.2500	80.9686	80.9396
Santa Cruz	55.1250	53.7319	53.3580
Shasta	96.8333	93.9623	92.5660
Siskiyou	32.0000	28.1064	28.0214
Solano	198.2000	196.5272	196.6831
Sonoma	77.0000	76.3212	76.3129
Stanislaus	99.2222	98.5459	98.4954
Sutter	55.6667	51.7188	51.5292
Tehama	66.0000	60.9535	60.6089
Tulare	78.6000	77.7985	77.4156
Tuolumne	70.5000	61.6727	59.9248
Ventura	75.2000	74.8119	74.8252
Yolo	72.2857	70.5530	70.3850
Yuba	81.5000	74.5691	77.4863

Appendix

Original Zipcode model

$$y_{k,j,t} \sim \text{Pois}(\lambda_{j,k,t})$$

$$\log(\lambda_{j,k,t}) = b1_{j,k}I(\text{county} = k) + b3_{j,k}I(t = 2017)$$

$$\begin{aligned} b1_{j,k} &\sim N(\theta_{1,k}, \tau_{1,k}) \\ b3_{j,k} &\sim N(\theta_{2,k}, \tau_{2,k}) \\ \theta_{1,k} &\sim N(\theta_{o,1}, \Sigma_{\phi,\tau,\kappa}) \\ \theta_{2,k} &\sim N(\theta_{o,2}, \tau_3) \\ \tau_{1,k} &= 1/\sigma_{\theta_{1,k}}^2 \\ \sigma_{\theta_{1,k}}^2 &\sim \text{dunif}(0,1000) \\ \tau_{2,k} &= 1/\sigma_{\theta_{2,k}}^2 \\ \sigma_{\theta_{2,k}}^2 &\sim \text{dunif}(0,1000) \\ \tau_3 &= 1/\sigma_{\theta_3}^2 \\ \sigma_{\theta_3}^2 &\sim \text{dunif}(0,1000) \\ \phi &\sim \text{dunif}(0.05,50) \\ \tau &\sim \text{Gamma}(0.001,0.001) \\ \kappa &\sim \text{dunif}(0.05,1.95) \end{aligned}$$

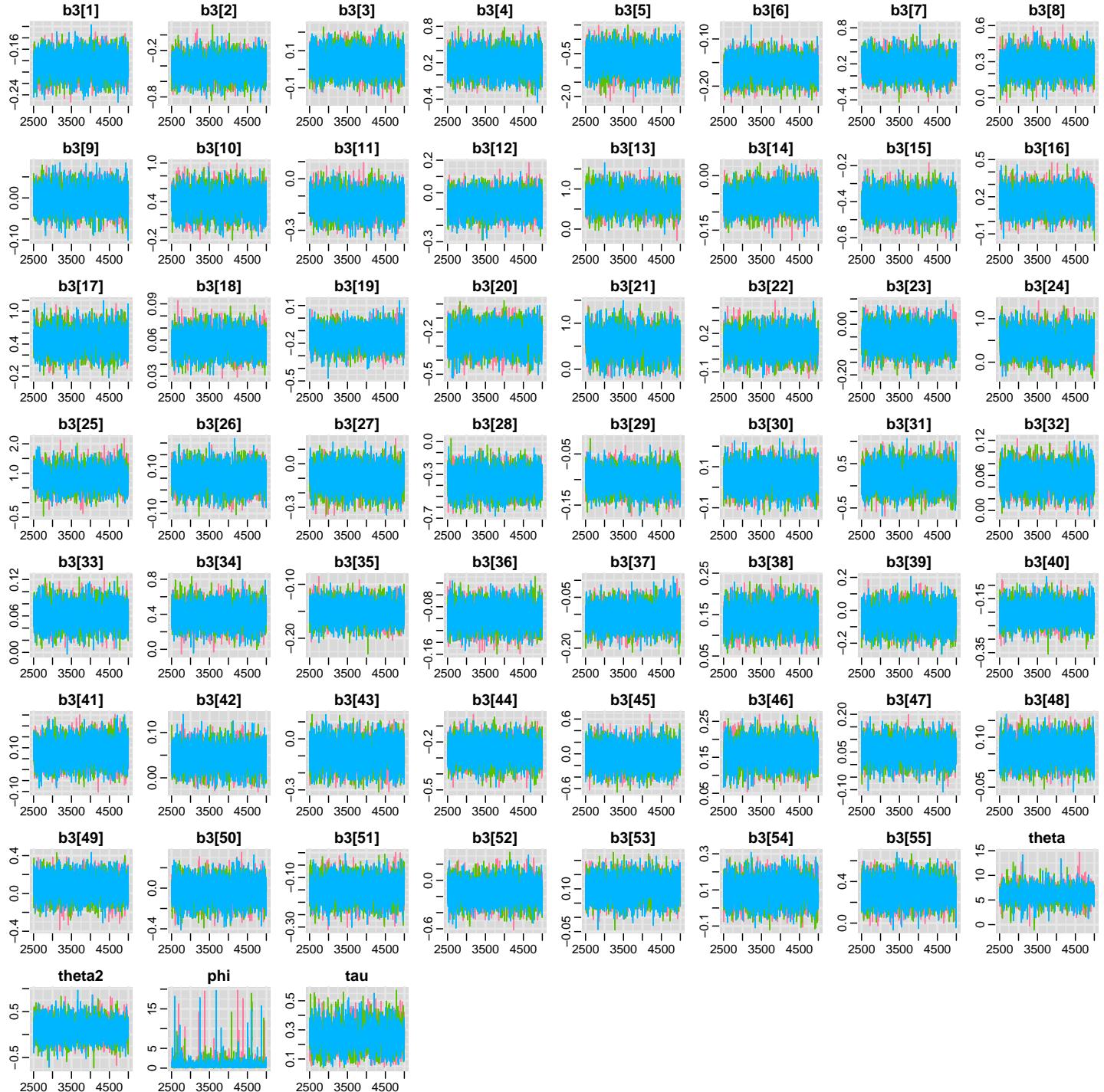


Figure 14: Convergence plots for $b3$, θ , θ_2 , ϕ and τ for Spatial 2 with informative priors at county level analysis



Figure 15: Density plots for Spatial 2, b3 in county level analysis with informative priors

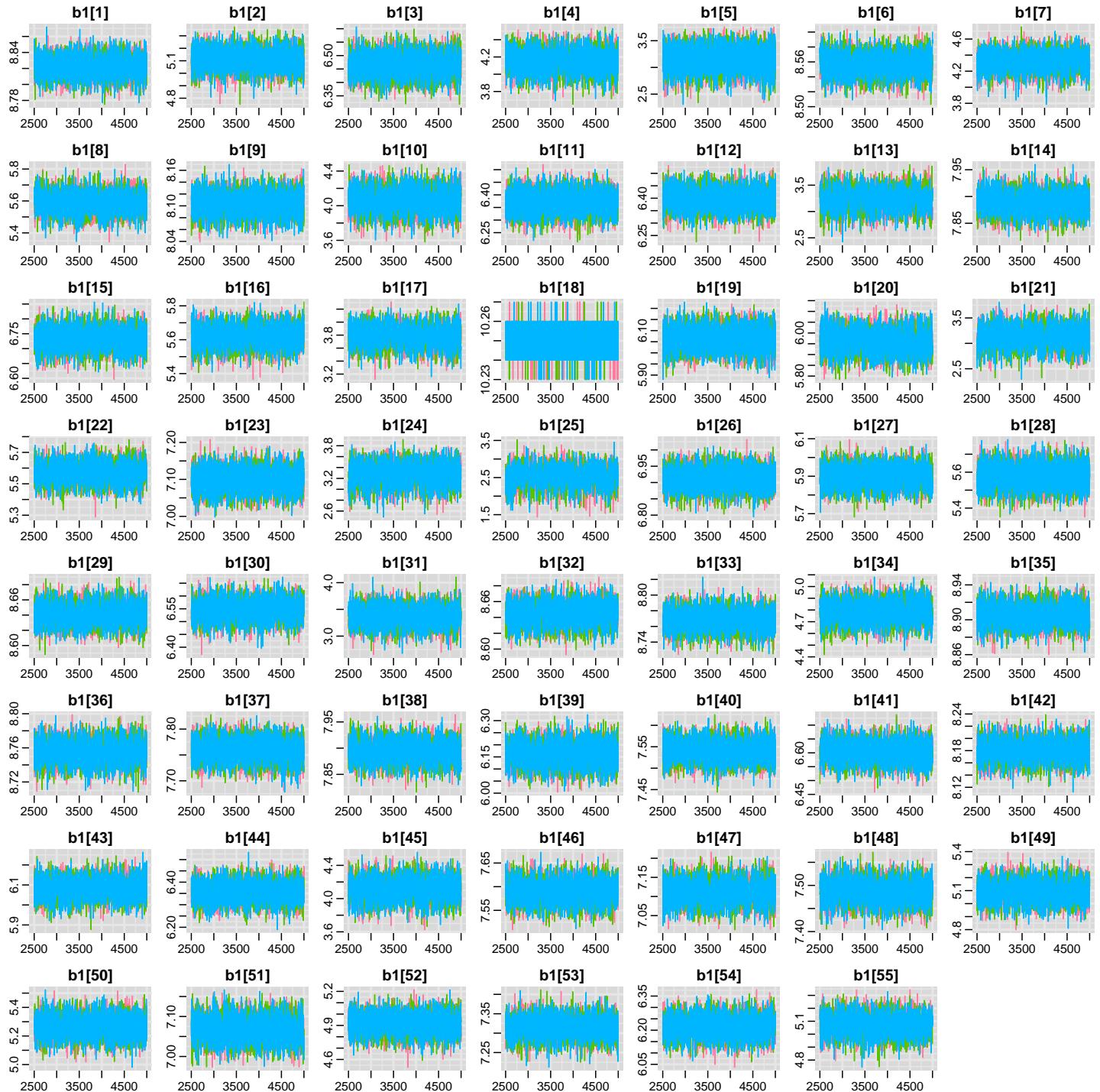


Figure 16: Convergence plots for b1 for Spatial 2 with informative priors at county level analysis

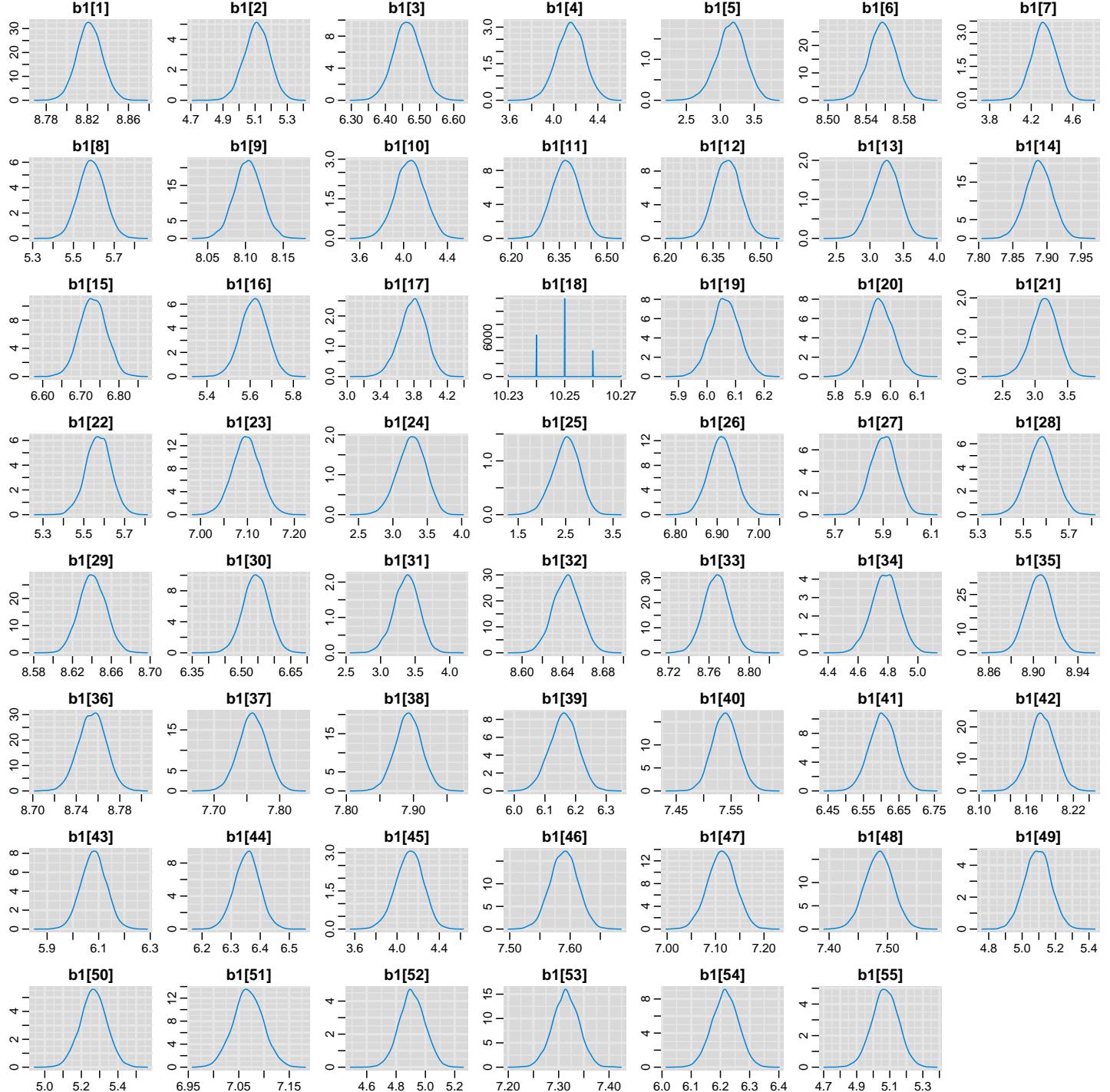


Figure 17: Density plots for Spatial 2, b1 in county level analysis with informative priors



Figure 18: Convergence plots for $b3$, θ , θ_2 and ϕ for zipcode level Spatial 2 with informative priors at zipcode level analysis



Figure 19: Density plots for Spatial 2, b3 in zipcode level analysis with informative priors

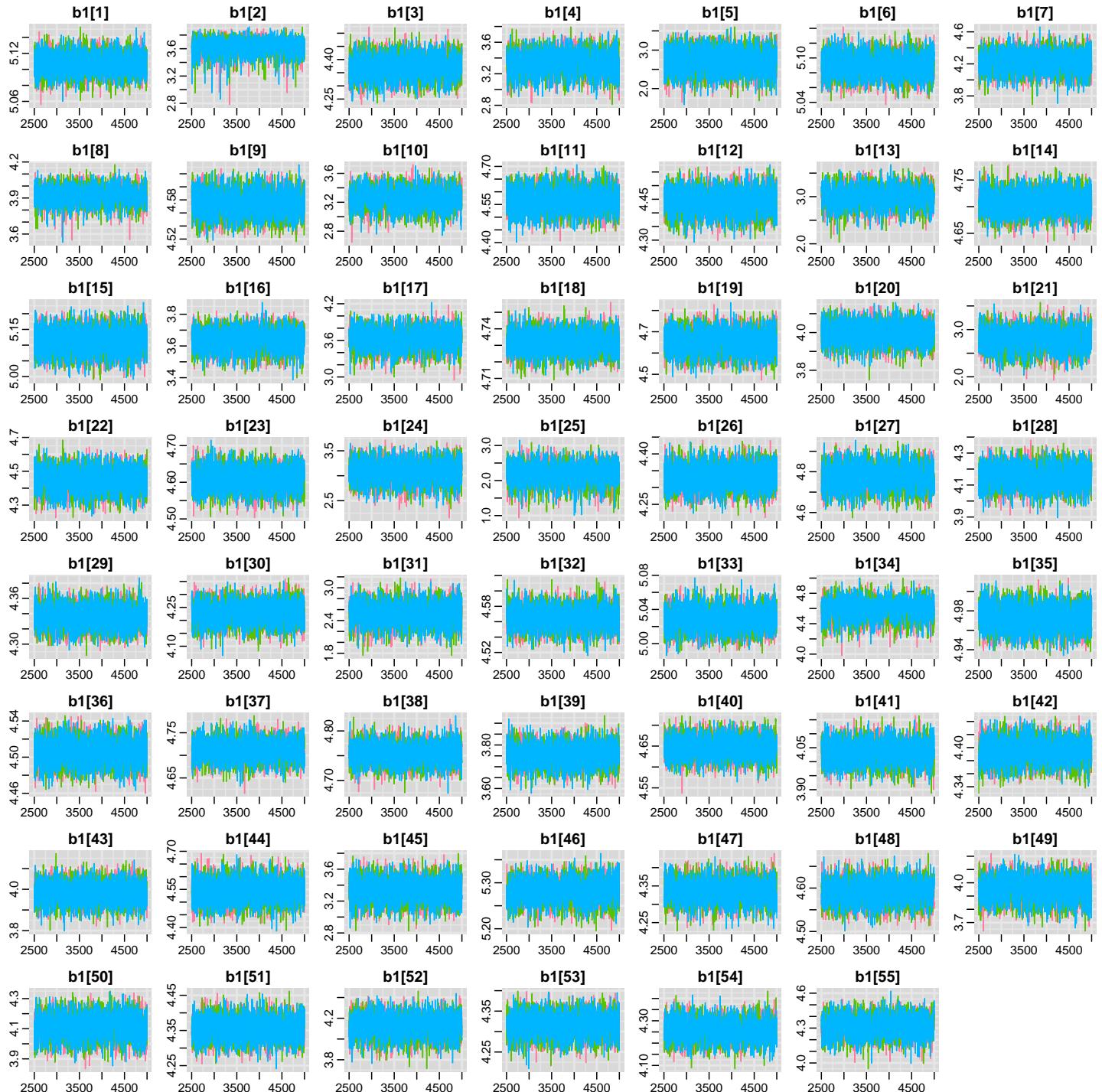


Figure 20: Convergence plots for b1 for zipcode level Spatial 2 with informative priors at zipcode level analysis

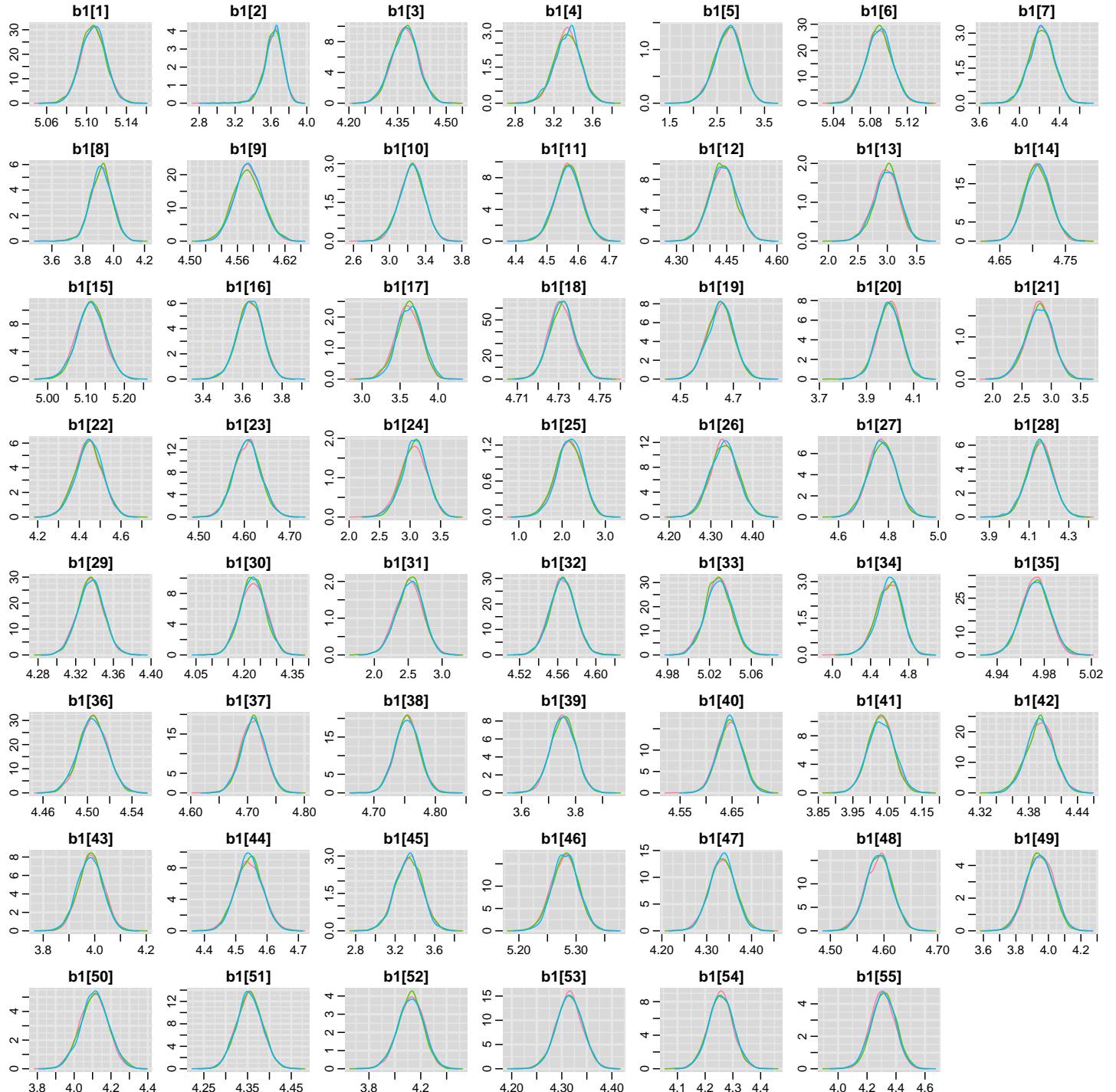


Figure 21: Density plots for Spatial 2, b1 in county level analysis with informative priors

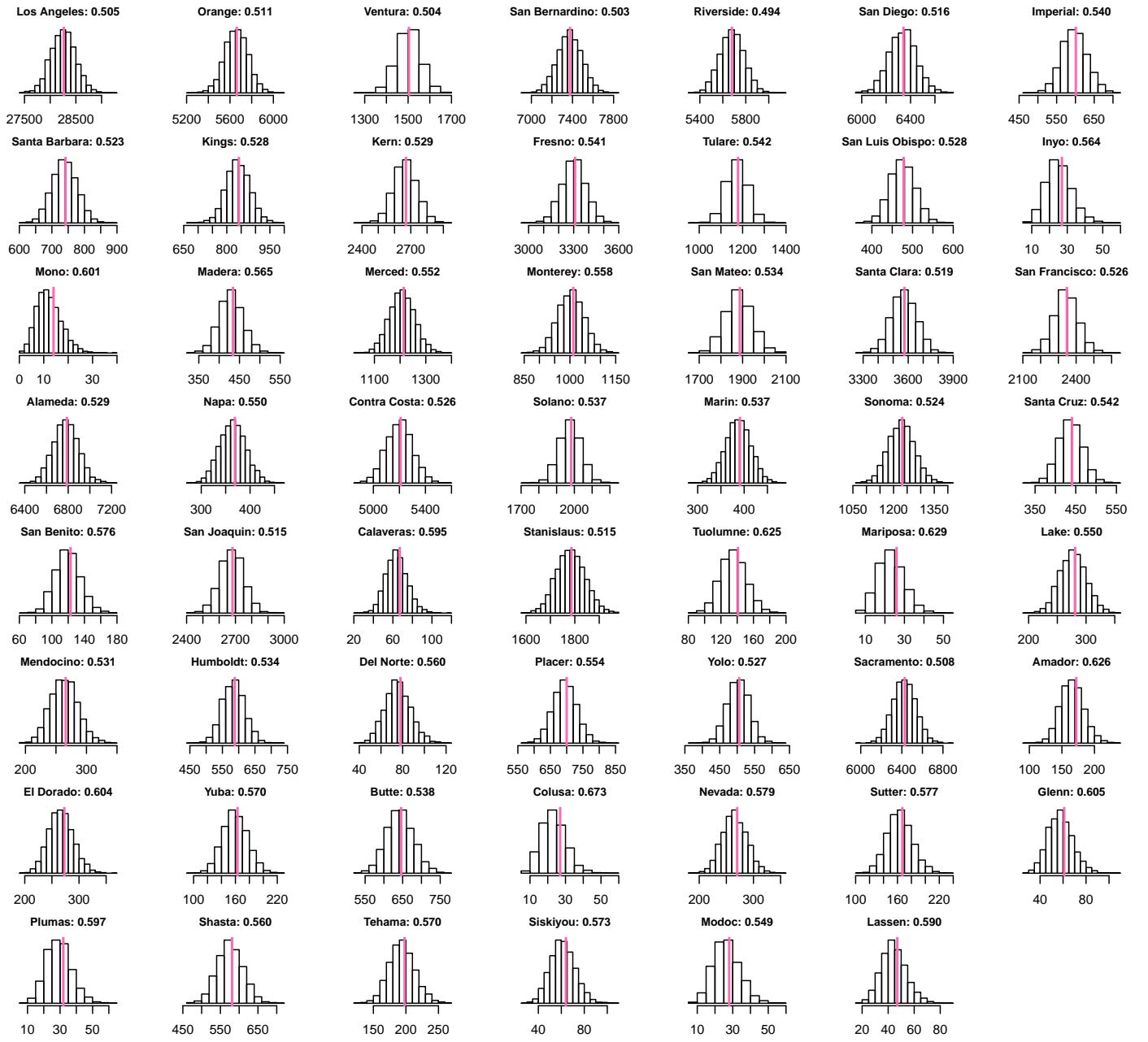


Figure 22: Distribution of the predicted number of ED visits at baseline for Spatial 2, county level analysis were plotted along with each of the observed values (pink vertical line) and the corresponding posterior p-value. Since the observed number of ED visit counts are located in the center of each of the predictive distributions (larger posterior p-values), we can conclude that the model fits these data quite well.



Figure 23: Distribution of the predicted number of ED visits at year 2017 for Spatial 2, county level analysis were plotted along with each of the observed values (pink vertical line) and the corresponding posterior p-value. Since the observed number of ED visit counts are located in the center of each of the predictive distributions (larger posterior p-values), we can conclude that the model fits these data quite well.



Figure 24: Distribution of the predicted number of ED visits at baseline for Spatial 1, county level analysis were plotted along with each of the observed values (pink vertical line) and the corresponding posterior p-value. Since the observed number of ED visit counts are located in the center of each of the predictive distributions (larger posterior p-values), we can conclude that the model fits these data quite well.



Figure 25: Distribution of the predicted number of ED visits at year 2017 for Spatial 1, county level analysis were plotted along with each of the observed values (pink vertical line) and the corresponding posterior p-value. Since the observed number of ED visit counts are located in the center of each of the predictive distributions (larger posterior p-values), we can conclude that the model fits these data quite well.

Supplemental documents

The R scripts and bug model scripts are saved in the Bayesian_final_report folder. There are 4 sub folders under the main folder. In the Datasets folder, the original dataset is asthma-ed-visit-rates-by-zip-code.csv. Other files were the cleaned dataset obtained with Data_cleaning.R under R_script folder. The R script folder contains the R scripts to run the bugs model in R2openbugs. The R scripts were separated into county-level and zipcode level. Each folder was then further separated into No spatial and Spatial analysis. The Model script folder contains the .txt files corresponding to each bugs R scripts in the R script folder. Lastly, the Models_saved folder contains the bugs models that were saved for convenience in reports generating.

Reference

1. Asthma Prevalence in California, A Surveillance Report, January 2017
2. Asthma: Findings from the 2011q2012 California Health Interview Survey, Ulfat Shaikh and Robert S. Byrd, Population Health Management, 19, 2, 145-151, 2016
3. Spatial Data Analysis, Sudipto Banerjee, Annual Review of Public Health 2016 37:1, 47-60