15TH NATIONAL CONVENTION ON STATISTICS

03-05 OCTOBER 2022

Organized by the Philippine Statistical System Spearheaded by the Philippine Statistics Authority

ON THE BAYESIAN ZERO INFLATED SPATIO-TEMPORAL MODELING OF DENGUE HEMORRHAGIC FEVER

Daniel R. Sanson

Assistant Professor IV

Mindanao State University- Marawi Campus

Session Topic

Crowne Plaza Galleria Manila

10:00 AM-12:00NN, October 4, 2022

ON THE BAYESIAN ZERO INFLATED SPATIO-TEMPORAL MODELING OF DENGUE HEMORRHAGIC FEVER

Motivation

- Dengue is one of the fastest spreading vector-borne diseases in the world. There are four serotypes: DENV-1, DENV-2, DENV-3 and DENV-4. Dengue is found in more than 150 countries where more than 40 percent of the world's population live in at-risk areas.
- According to Laflamme (2015), once one is infected with one of the viruses, he/she develops immunity to that virus for a lifetime. However, this immunity will not provide protection from the other viruses/strains. Repeated exposure to the dengue virus can make it more likely that a person will develop dengue hemorrhagic fever.

Continuation

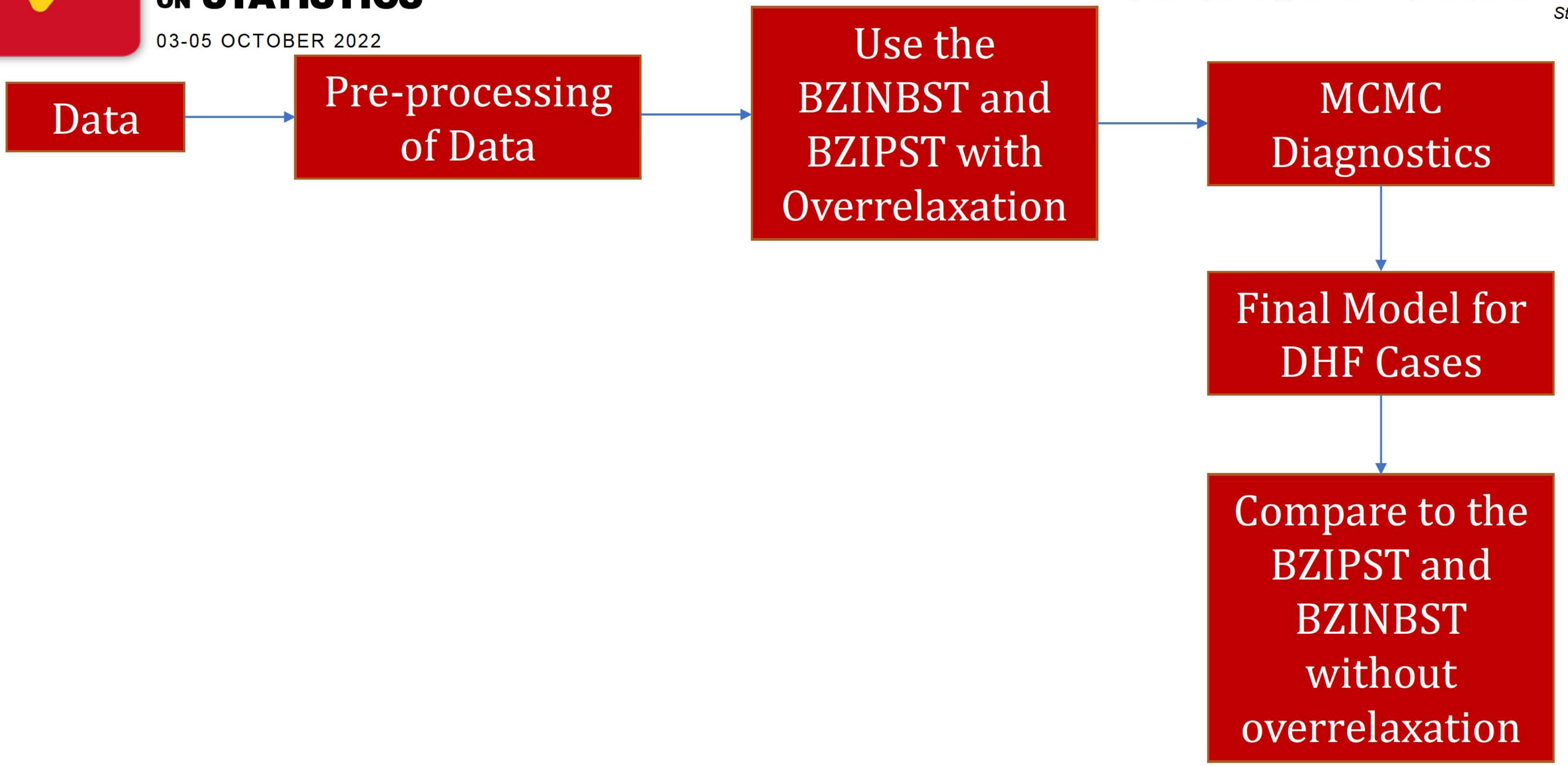
- Mukhsar 2016
- Mukhsar 2017
- Mukhsar 2018
- Overrelaxation is widely used over the decade to improve convergence rate.
- The concept of rate of convergence is of practical importance when working with a sequence of successive approximations for an iterative method, as then typically fewer iterations are needed to yield useful approximation.

Objective of the Study

This study aims to extend and improve the existing model formulated by Mukhsar (2018) in a data with an excessive number of zeros, while accounting for over-dispersion. The modification will consider methods to improve the rates of convergence in the estimation of the model parameters.

Specifically

1. Explore some MCMC convergence diagnostics tools;
2. improve the existing BZINB S-T and BZIP S-T models by Mukhsar (2018) by applying the overrelaxation algorithm on the convergence of the models' parameter estimates;
3. using the number of iteration runs, compare the rates of convergence of the BZIP S-T and BZINB S-T model parameter estimates with and without the overrelaxation algorithm; and
4. use the improved BZINB S-T model and BZIP S-T model to predict the DHF Caraga Region, Philippines;


Data
Pre-processing of Data
Use the BZINBST and BZIPST with Overrelaxation
MCMC Diagnostics
Final Model for DHF Cases
Compare to the BZIPST and BZINBST without overrelaxation

Pre-processing the DHF Data

About the data

- **DHF Kendari Data (2016-2018)**

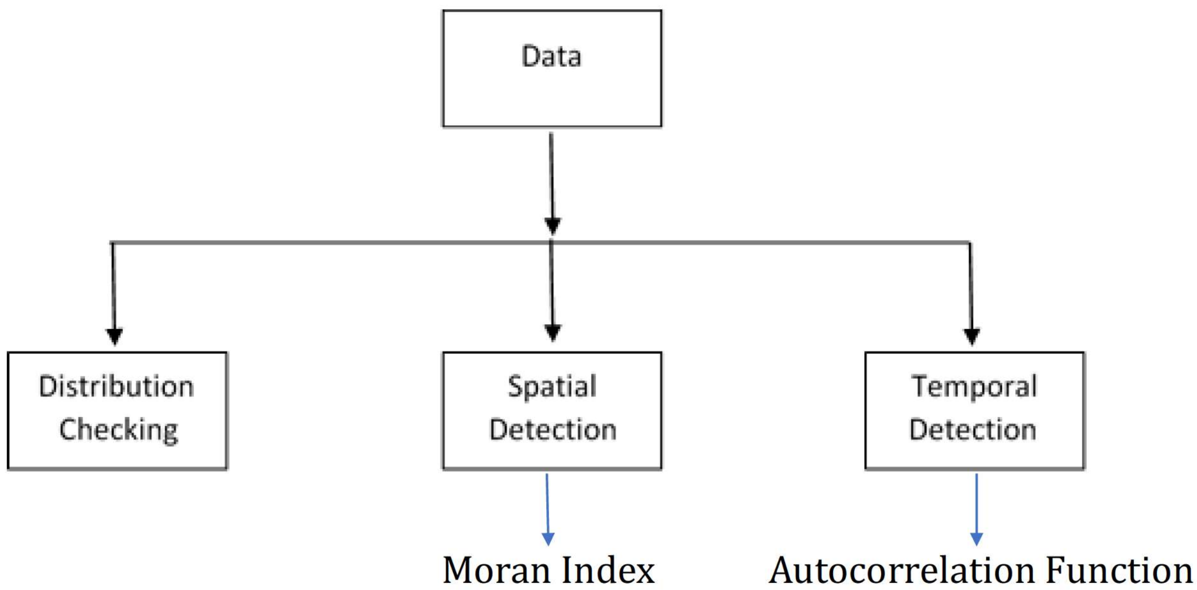
The data were obtained from the Meteorological, Climatological and Geophysics Agency (BMKG) and the Central Bureau of Statistics. It contains the DHF Cases from the Different Districts, Population Density and the Rainfall.

- **DHF Caraga Data (2015-2017)**

The DHF Dengue data were obtained from the DOH Caraga.

The Rainfall data where obtained from DOST-PAGASA and the Population Density of the different cities were obtained from PSA.

Pre-processing the Data



Schematic Diagram for the Bayesian Zero Inflated Spatio-Temporal Model for the DHF data

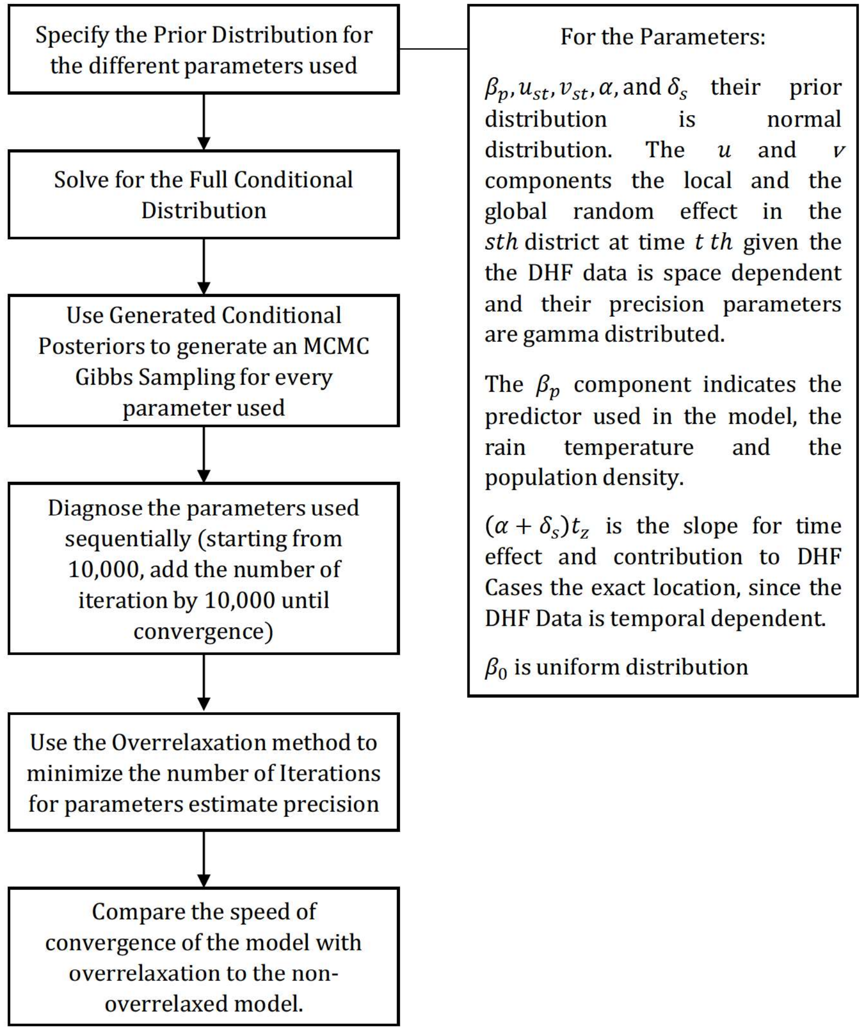


Table 1 Relationship between cities in Caraga Region, Philippines and Distribution Fitting

City	Adjacency Matrix	Kolmogorov-Smirnov	P-value	Distribution
Tandag	3,4,8,10	0.1342	0.236	Poisson
Bayugan	3,5,6,8	0.1317	0.314	Poisson
Surigao del Norte	1,2,4,5	0.0620	0.063	Poisson
Agusan del Norte	1,3,5,8	0.0800	0.059	Poisson
Agusan del Sur	2,3,4,8	0.0400	0.074	Poisson
Butuan	2,7,8	0.0047	0.541	Poisson
Surigao	6	0.0511	0.521	Poisson
Cabadbaran	1,2,4,5,6	0.1811	0.665	Poisson
Bislig	10	0.0578	0.085	Poisson
Surigao del Sur	1,9	0.0298	0.081	Poisson

Table 2 and 3 Moran Index and Correlation Matrix of the Districts in Caraga Region in terms of DHF Cases

City	TAN	CAB	BAY	SDS	ADS	SDN	BUT	BIS	ADN	SUR
Tandag	1	.695*	.267	.550*	.304	.751*	.078	.221	.625*	.213
Cabadbaran	.695*	1	.443*	.214	.460*	.171	.503*	.082	.575*	.182
Bayugan	.267	.443*	1	.113	.434*	.674*	.491*	.078	.291	.044
Surigao del Sur	.550*	.214	.113	1	.014	.284	.247	.749*	.092	.265
Agusan del Sur	.304	.460*	.443*	.014	1	.682*	.096	.013	.575*	.285
Surigao del Norte	.751*	.171	.674*	.284	.682*	1	.302	.161	.853*	.086
Butuan	.078	.503*	.491*	.247	.096	.302	1	.104	.269	.898*
Bislig	.221	.082	.078	.749*	.013	.161	.104	1	.278	.051
Agusan del Norte	.625*	.575*	.291	.092	.575*	.853*	.269	.278	1	.023
Surigao	.213	.182	.044	.265	.285	.086	.898*	.051	.023	1

Observed	Expected	Standard Deviation	P-value
.1891087	0.2185515	0.004447555	0.0002882172

Table 5. Monthly Average Rainfall (mm) in the Caraga Region, Philippines from January 2015-December 2017

Month	Rainfall (mm/hr)		
	2015	2016	2017
January	11.1	11.8	18.7
February	3	2.9	14.2
March	1.4	0.1	10.8
April	1.0	1.1	6
May	2.5	5.7	8.2
June	7.2	11.9	7.6
July	4.3	8.7	7.1
August	2	1.8	2.4
September	5.2	8	6.4
October	4.3	7	8.1
November	9.8	10.1	8.1
December	8.1	5.4	8.9
Average Yearly Rainfall	5.6	6.8	6.8

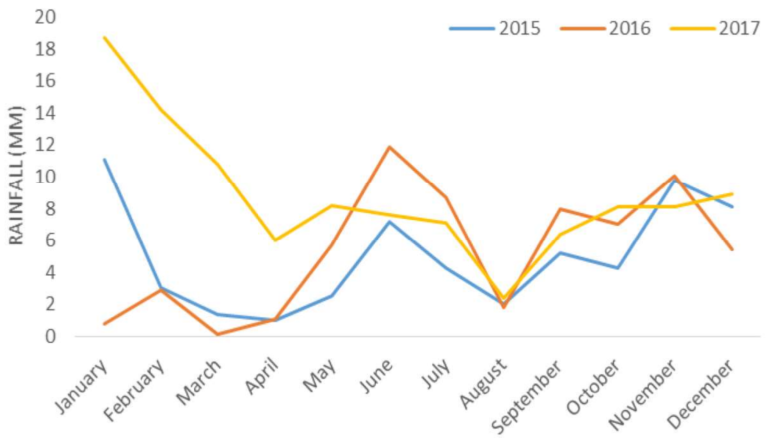


Figure 1. Monthly Average Rainfall (mm) in the Caraga Region, Philippines from January 2015-December 2017

Monthly Average Rainfall (mm) in the Caraga Region, Philippines from January 2015-December 2017

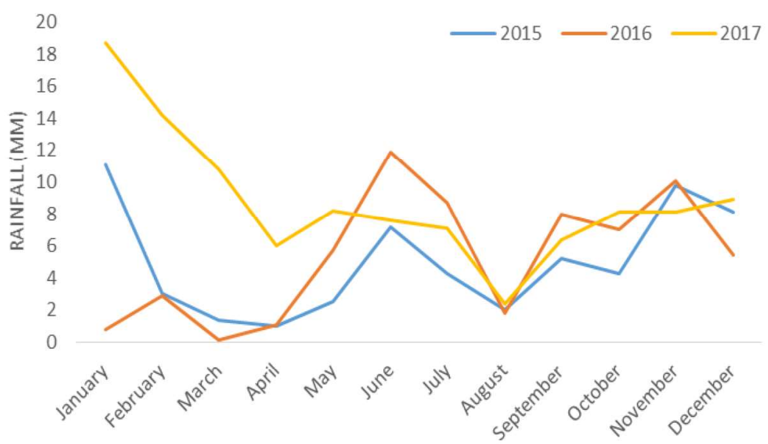


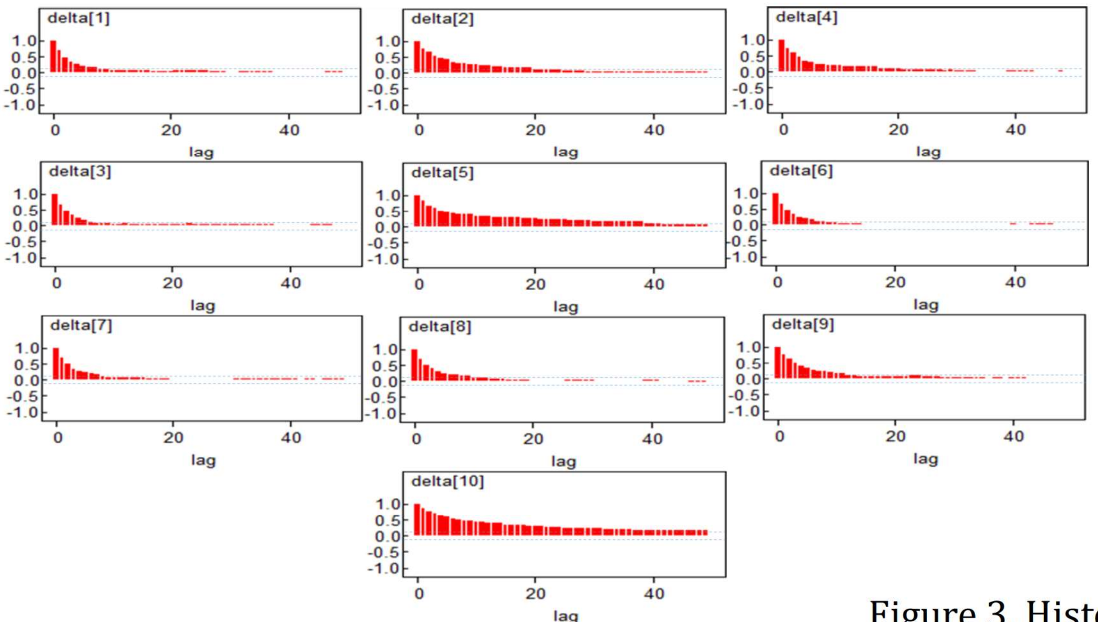
Figure 1. Monthly Average Rainfall (mm) in the Caraga Region, Philippines from January 2015-December 2017

In 2015: heavy rainfall in the months of January, November and December, moderate rains in February, May, June, July, Spetember and October and light rains in March, April, Augsut.

In 2016, the said region experienced heavy rains in the months of January, June July, September and December, moderate rains in February, May and October and light rains in March, April and August.

In 2017, the said region experienced heavy rainfall in the months of January, February, March, May, October, November and December, moderate rains in April, June, July and light rains in August.

Figure 2. Autocorrelation Function of the Monthly DHF Data in Caraga Region, Philippines



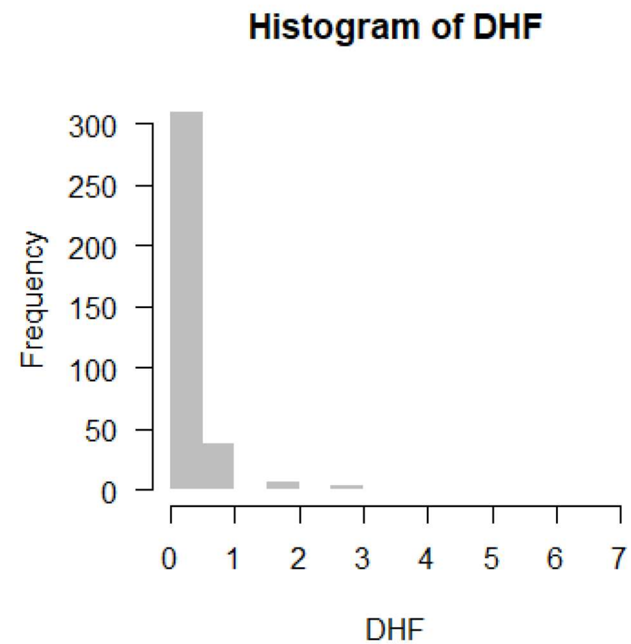


Figure 3. Histogram of DHF Cases in the Caraga Region from 2015-2017

Table 6. Summary of the Generalized Linear Model For the Zero Inflated Poisson Distribution

Deviance Residuals				
Min	Q1	Median	Q3	Max
−1.5502	−0.6528	−0.4895	−0.3574	4.7211
Coefficients	Estimate	Std. Error	Z-value	P-value
Population Density	0.002887	0.000611	4.726	2.29e-06 ***
Rainfall (mm)	0.161838	0.035506	4.558	5.16e-06 ***
AIC	378.68	Deviance	314.30	

Table 7. Over-dispersion test of the Zero Inflated Poisson Distribution

Z-value	P-value	Dispersion
1.8474	0.03234	1.360809

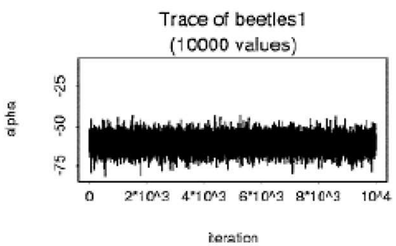
Table 8. Summary of the Generalized Linear Model For Zero Inflated Negative Binomial Distribution

Deviance Residuals				
Min	Q1	Median	Q3	Max
−1.0800	−0.5858	−0.4624	−0.3474	2.3773
Coefficients	Estimate	Std. Error	Z-value	P-value
Population Density	0.0030514	0.3585573	3.657	0.000255 ***
Rainfall (mm)	0.1512118	0.0432328	3.498	0.000469 ***
AIC	361.68	Deviance	191.61	

Convergence Diagnostics

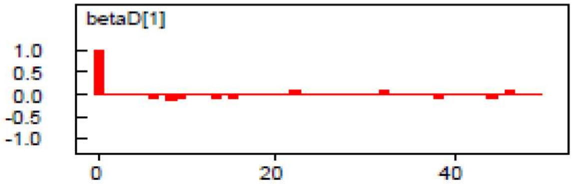
TRACE PLOTS

- No patterns or irregularities are observed, and therefore convergence can be assumed.
- If the model has converged, the trace plot will move around the mean of the distribution.
- A clear sign of non-convergence with a trace plot occurs when we observe some trending in the sample space.



AUTOCORRELATION DIAGNOSTIC

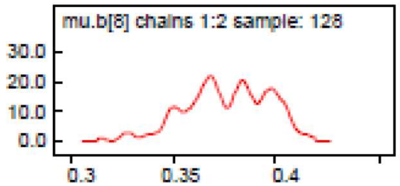
- Autocorrelation refers to a pattern of serial correlation in the chain, where sequential draws of a parameter, say β1, from the conditional distribution are correlated.
- The cause of autocorrelation is that the parameters in our model may be highly correlated, so the Gibbs Sampler will be slow to explore the entire posterior distribution..
- The reason why autocorrelation is important is that it will take a very long time to explore the entire posterior distribution.

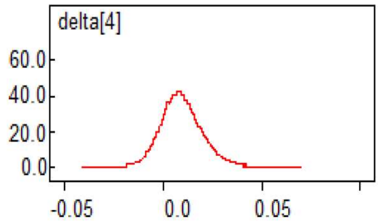


Convergence Diagnostics

DENSITY PLOTS

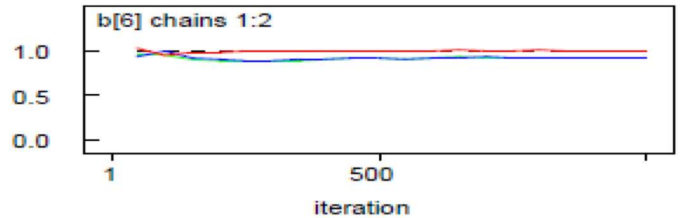
- The density plot provides a graphical representation of the posterior density estimate for each node.
- Sometimes non-convergence is reflected in multimodal distributions. This is especially true if the density plot is not just multi-modal, but lumpy.
- Often, doing this will allow you to get a much more reasonable summary of the posterior.





GELMAN-RUBIN CONVERGENCE DIAGNOSTIC

- The Gelman-Rubin convergence diagnostic or the BGR plots the evolution of the pooled posterior variance (the green color), the average within sample variance (in blue) and the their ratio (The red). The dash line denotes the reference value of one.
- If the *M* chains have converged to the target posterior distribution, then PSRF should be close to 1.
- For most, values less than 1.2 or 1.1 are acceptable, but if higher level of accuracy is required one might want values even closer to 1



BZINB S-T Model with Over Relaxation Method (Kedari's DHF Cases)

Figure 4 Trace plots for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

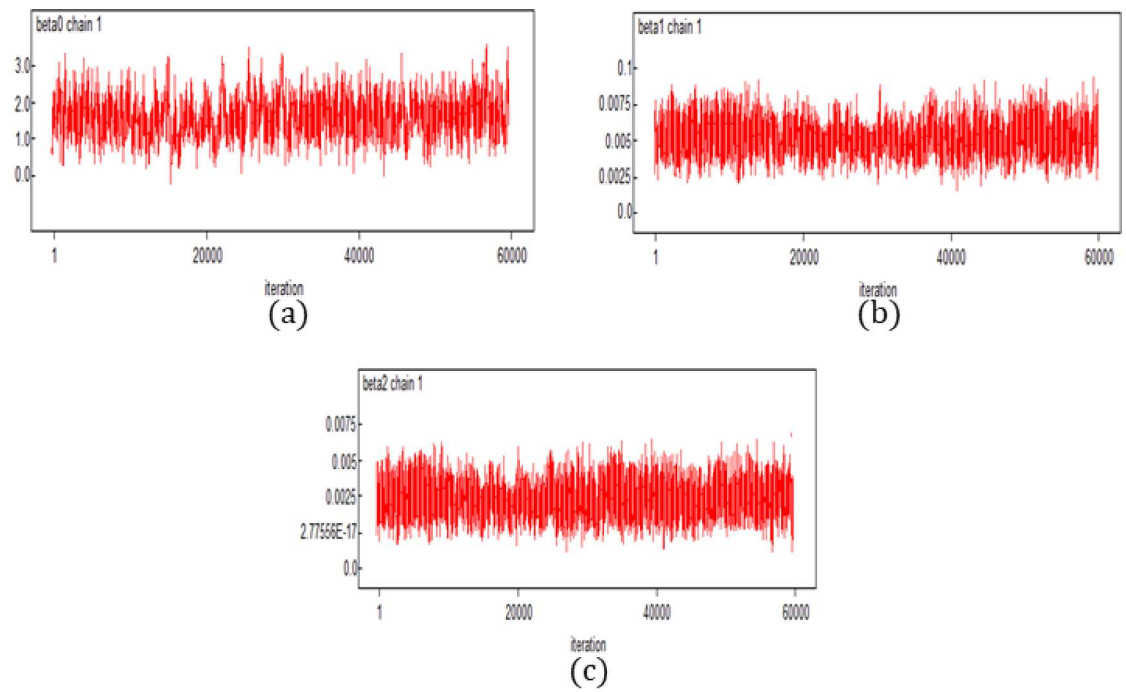


Figure 5 Density plots for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

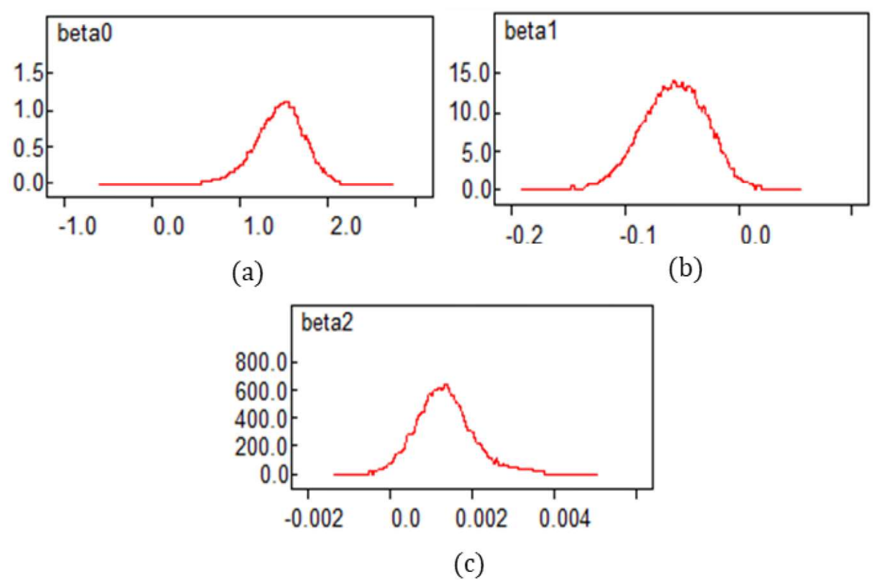


Figure 6 Trace plots (Iteration vs generated values) for (a) α, and (b-k) δ_s with 60,000 iterations

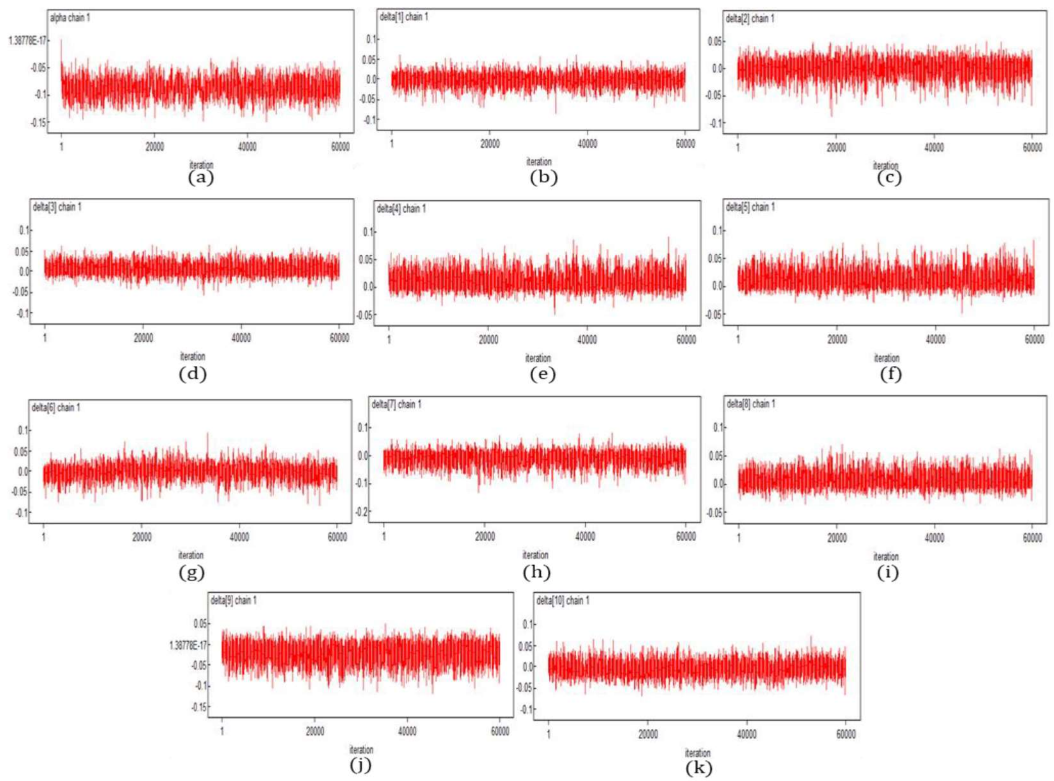


Figure 7 Density plots for (a) α, and (b-k) δ_s with 60,000 iterations

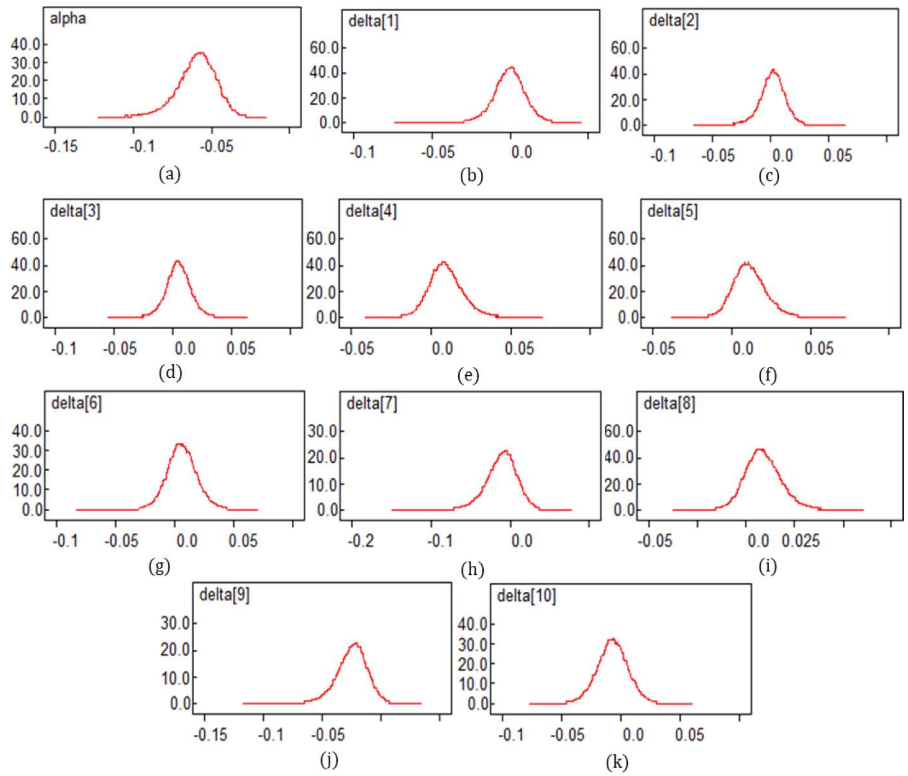


Figure 8 Autocorrelation plots for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

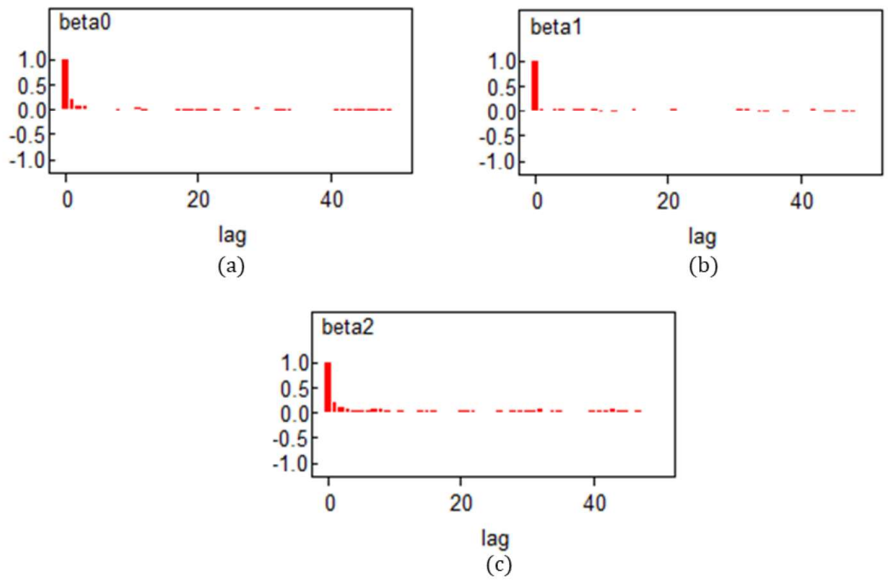


Figure 9 BGR Diagnostic Plots

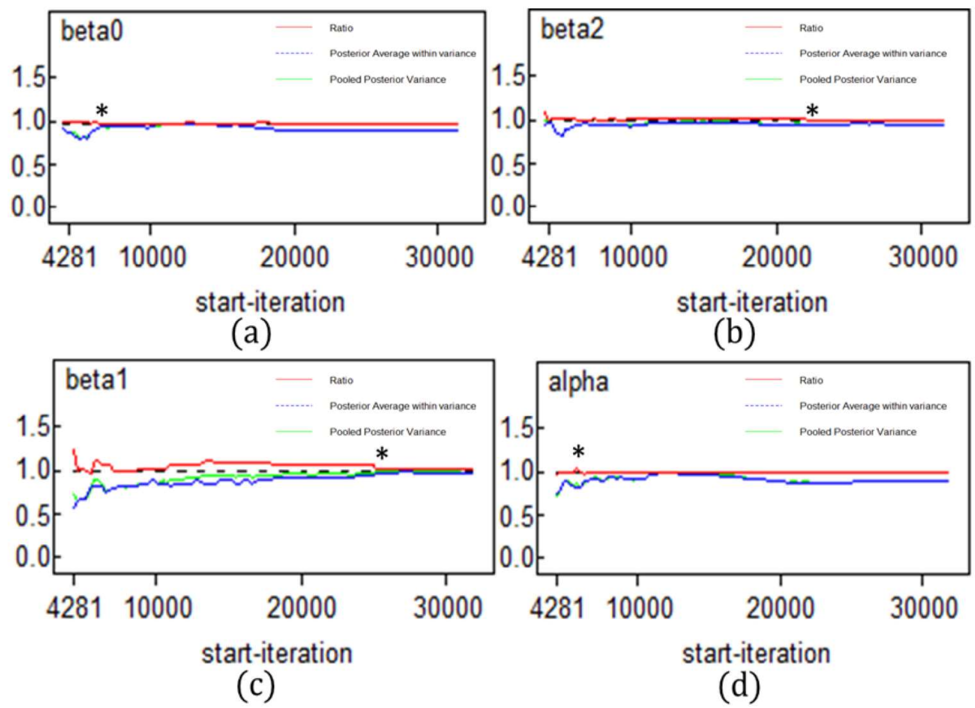


Figure 10 BGR Diagnostic Plots

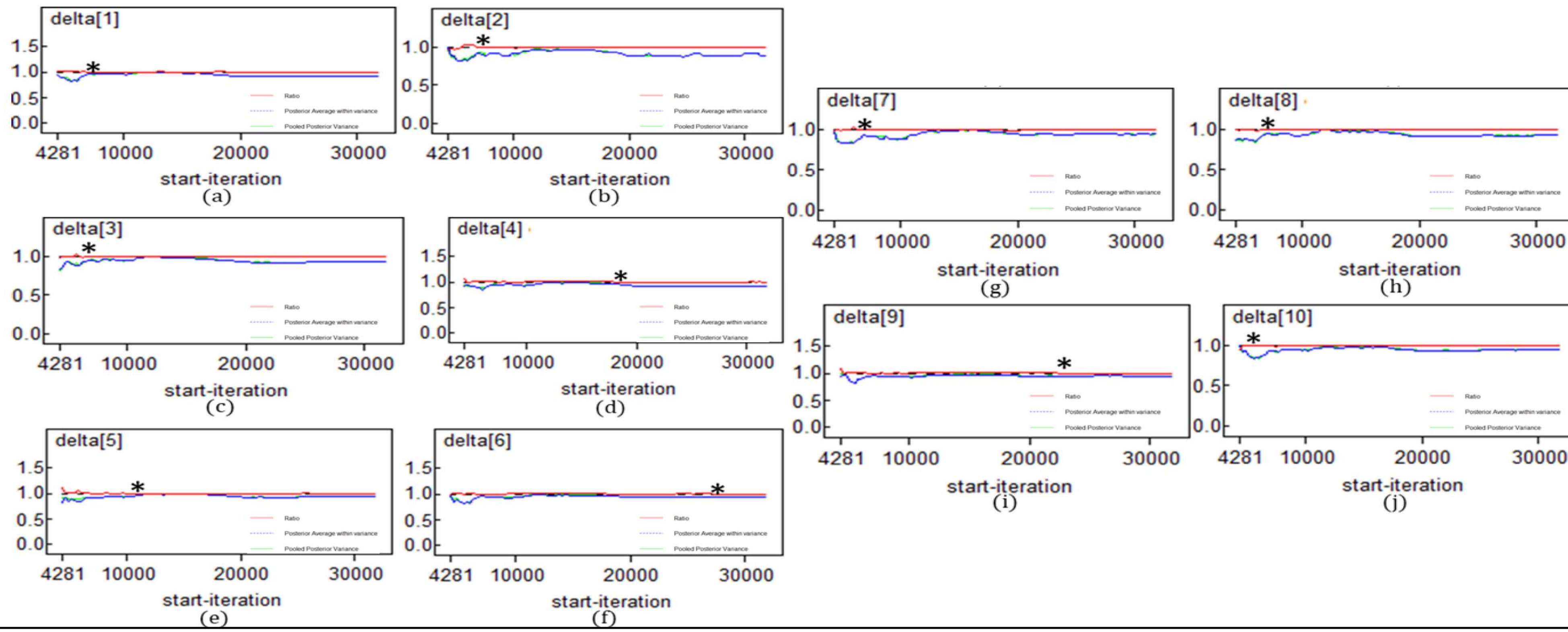
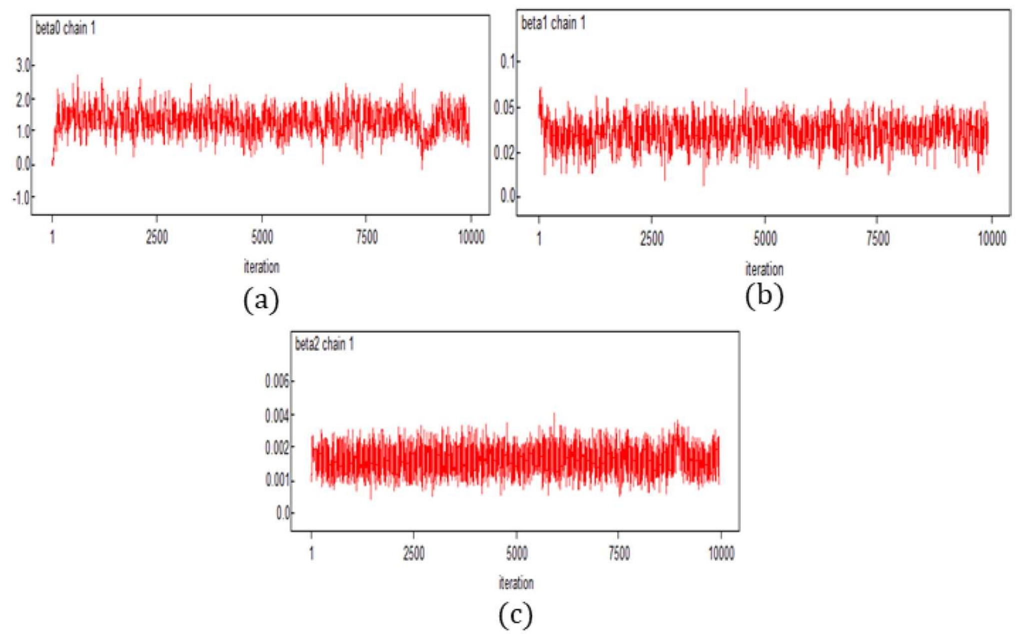


Table 9 Summary Statistics of the BZIP S-T model after the 60,000 Iterations

parameter	mean	sd	MC error	2.50%	median	97.50%
α	-0.08776	0.01562	2.22E-04	-0.1194	-0.08742	-0.05779
β_0	1.031	0.4686	0.009352	0.1582	1.012	1.989
β_1	0.03882	0.03574	8.17E-04	0.1189	0.03144	0.009181
β_2	0.002425	0.001093	1.54E-05	3.94E-04	0.002381	0.00468
δ_1	-6.50E-04	0.01031	7.18E-05	-0.02388	-1.91E-04	0.01949
δ_2	-3.74E-04	0.01076	8.39E-05	-0.02556	4.50E-04	0.01947
δ_3	0.00678	0.01037	9.28E-05	-0.01136	0.005455	0.03072
δ_4	0.009779	0.0117	1.38E-04	-0.00809	0.007604	0.0382
δ_5	0.01065	0.01187	1.40E-04	-0.00699	0.008414	0.03948
δ_6	-0.00155	0.01279	1.53E-04	-0.02941	-9.75E-04	0.02383
δ_7	-0.0096	0.01883	2.29E-04	-0.0525	-0.00745	0.02352
δ_8	0.006194	0.009508	8.89E-05	-0.00972	0.004798	0.02883
δ_9	-0.01815	0.01864	1.93E-04	-0.06006	-0.01595	0.0128
δ_{10}	-0.00309	0.01293	1.29E-04	-0.02883	-0.00313	0.02403
deviance	801.5					

BZIP S-T Model with Over Relaxation Method (Kedari's DHF Cases)

Figure 11 Trace plots for (a) β_0, (b) β_1, and (c) β_2 with 10,000 Iterations



(a) (b) (c)

15TH NATIONAL CONVENTION ON STATISTICS

03-05 OCTOBER 2022

Organized by the Philippine Statistical System Spearheaded by the Philippine Statistics Authority

Figure 12 Density plots for (a) β_0, (b) β_1, and (c) β_2 with 10,000 iterations

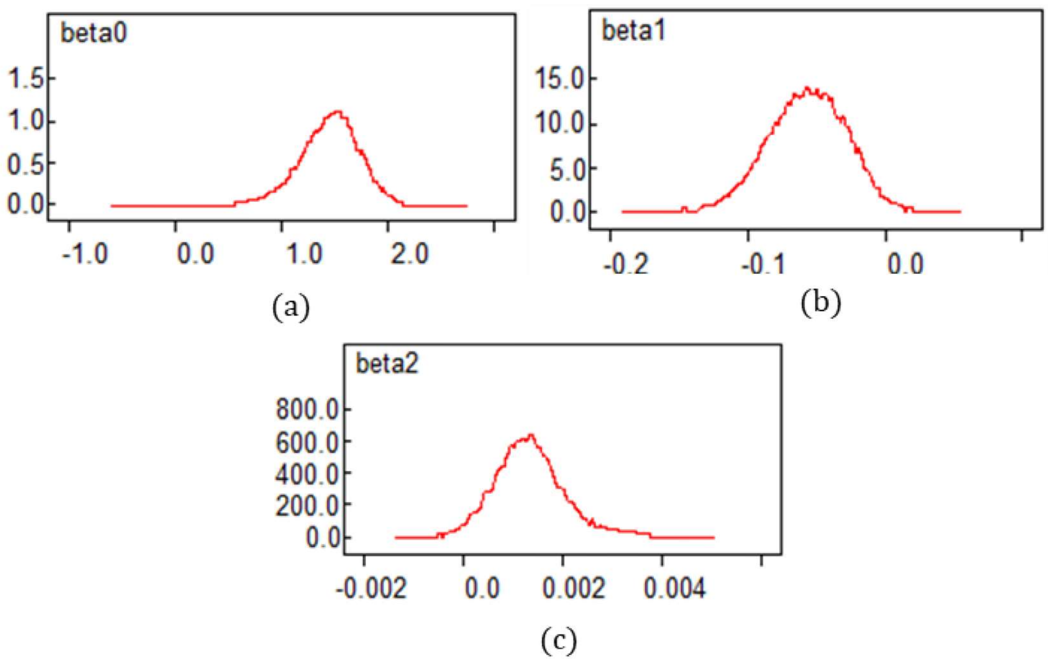


Figure 13 Trace plots (Iteration vs generated values) for (a) α, and (b-k) δ_s with 10,000 iterations

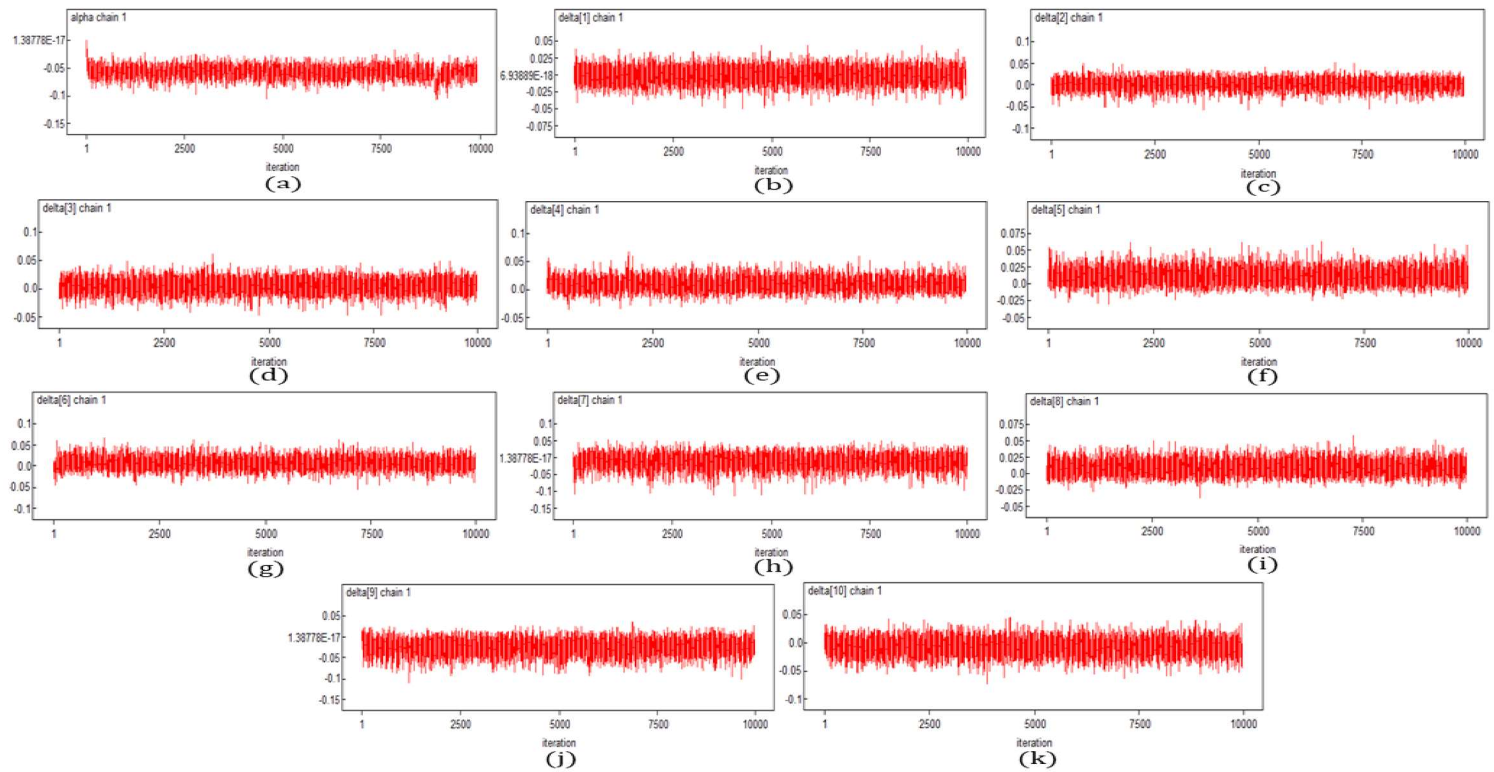


Figure 14 Density plots for (a) α, and (b-k) δ_s with 10,000 iterations

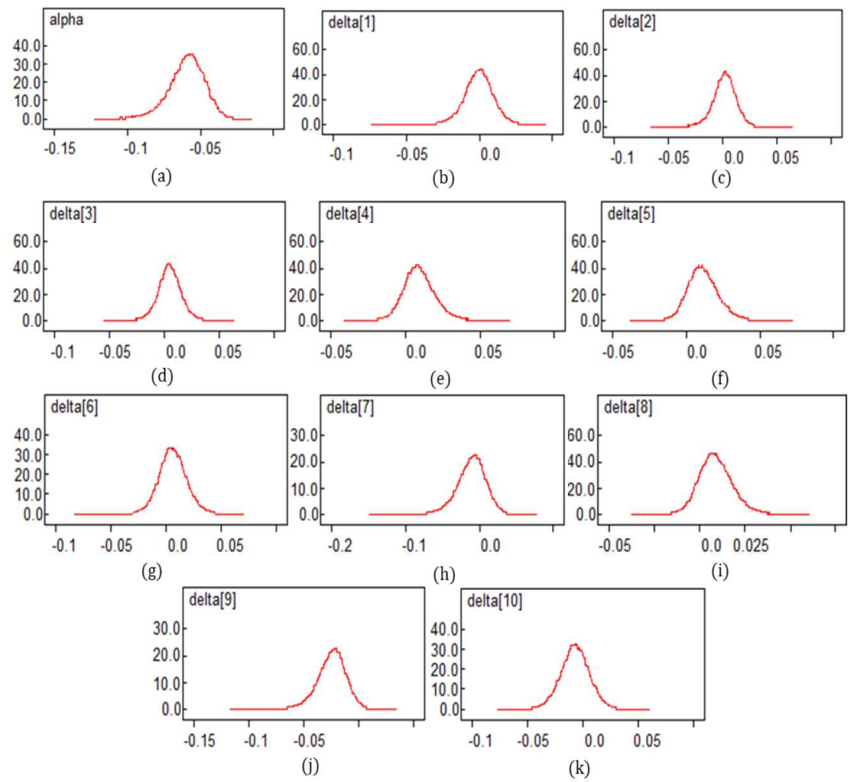


Figure 15 Autocorrelation plots for (a) β_0, (b) β_1, and (c) β_2 with 10,000 iterations

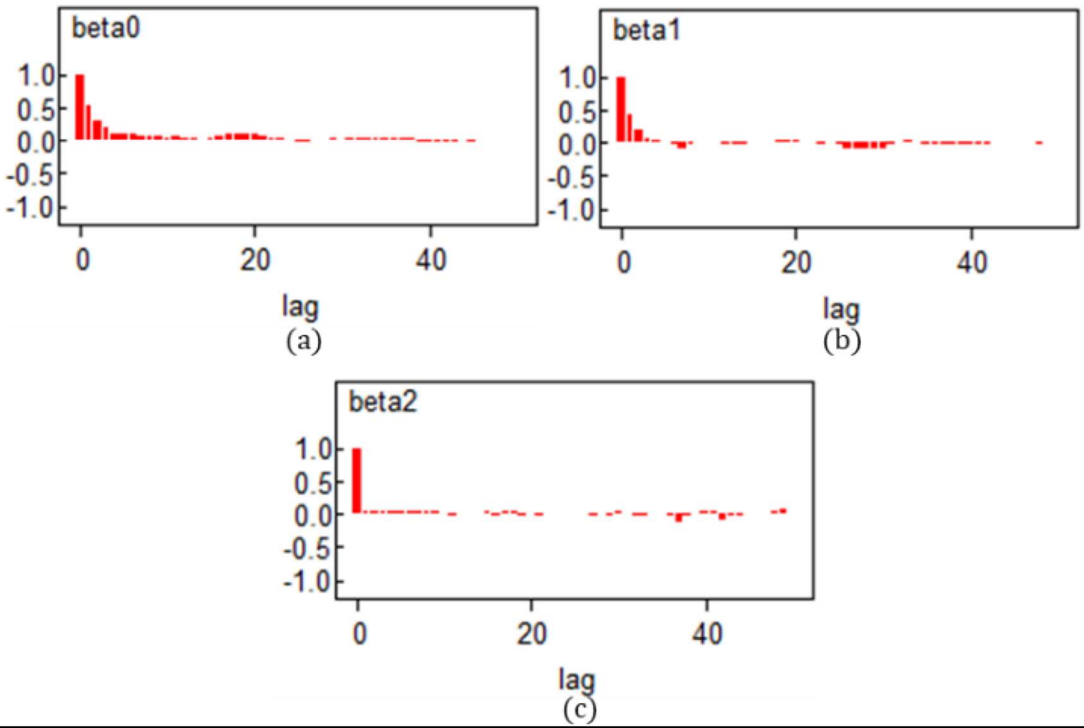
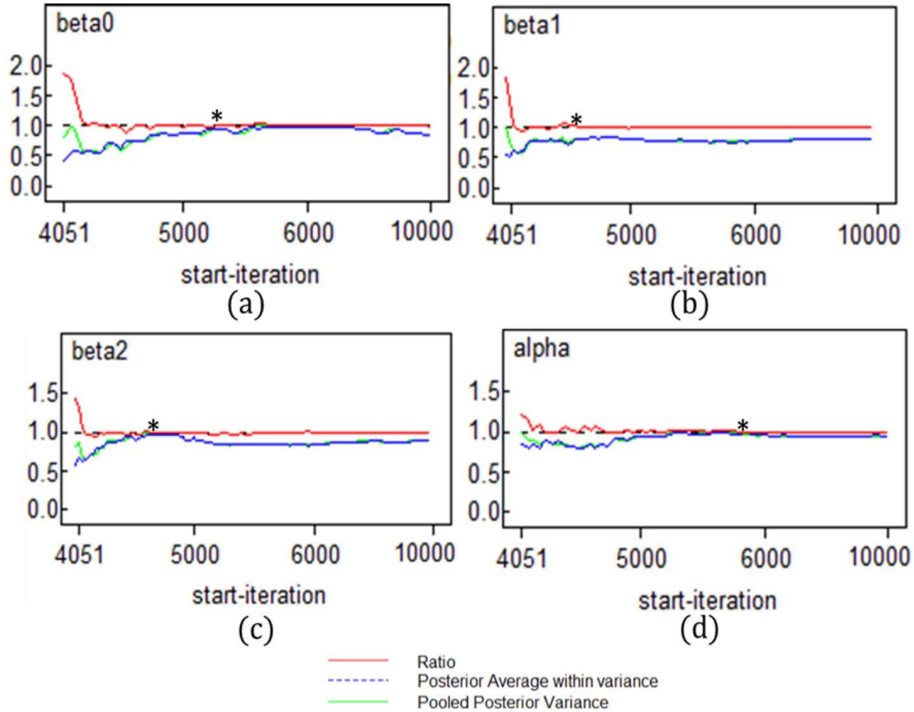


Figure 16. BGR Diagnostic Plots with 10,000 iterations



The * indicates where the posterior average within variance and the pooled variance become equal.

Figure17. BGR Diagnostic Plots with 10,000 iterations

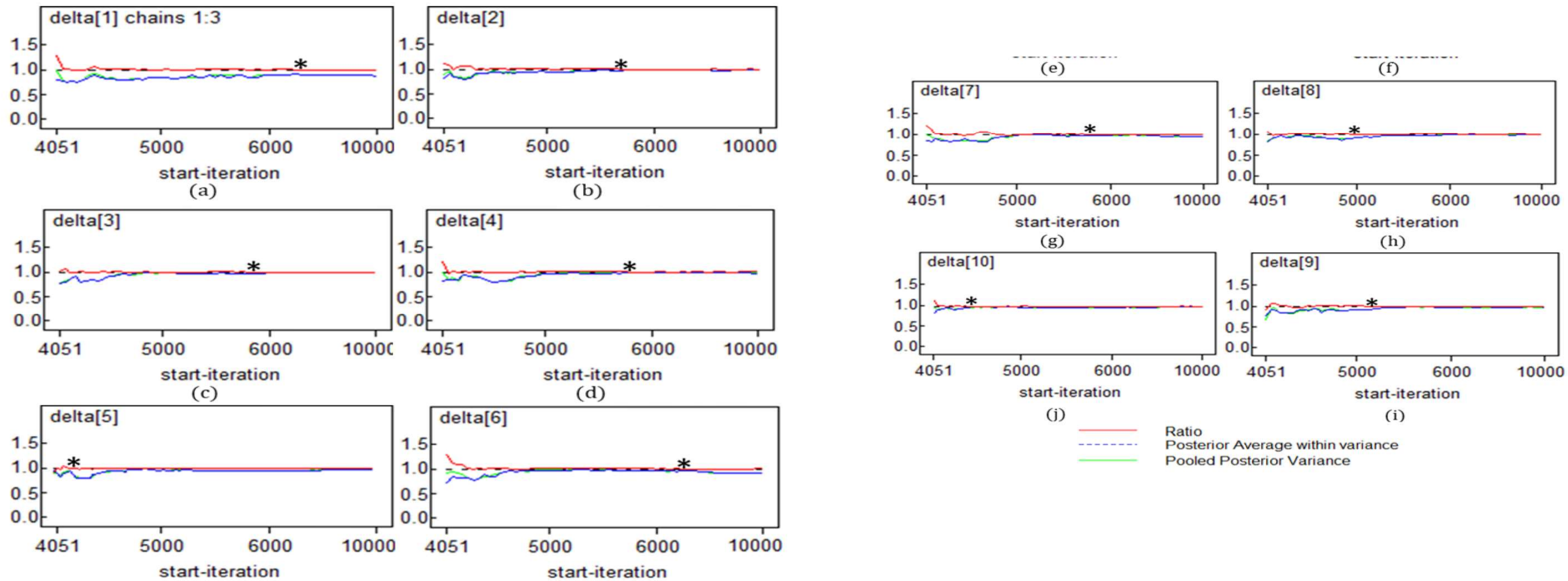


Table 10. BZIP S-T Model (With Overrelaxation Method) Summary Statistics after10,000 Iterations

parameter	mean	sd	MC error	2.50%	median	97.50%
α	-0.05736	0.01085	3.31E-04	-0.07942	-0.05696	-0.03733
β_0	1.304	0.3499	0.01636	0.6204	1.31	1.986
β_1	0.05597	0.02665	0.001084	0.01091	0.05573	0.0765
β_2	0.001255	6.33E-04	1.75E-05	4.48E-05	0.001245	0.002571
δ_1	-2.77E-04	0.009478	1.30E-04	-0.0199	-6.24E-05	0.01803
δ_2	0.001884	0.01044	1.78E-04	-0.02033	0.002302	0.02145
δ_3	0.004288	0.01019	1.37E-04	-0.01667	0.004245	0.02431
δ_4	0.009257	0.01012	2.07E-04	-0.00932	0.008594	0.03095
δ_5	0.01141	0.01006	1.89E-04	-0.00683	0.01086	0.03252
δ_6	0.006366	0.01222	2.42E-04	-0.01688	0.006031	0.03175
δ_7	-0.01055	0.01858	3.88E-04	-0.05029	-0.00932	0.02341
δ_8	0.008869	0.00903	1.23E-04	-0.00751	0.008333	0.02834
δ_9	-0.02379	0.01622	3.08E-04	-0.0583	-0.02301	0.005959
δ_{10}	-0.00746	0.01277	2.20E-04	-0.03333	-0.00731	0.0174
deviance	826.6					

Final Model with Overrelaxation

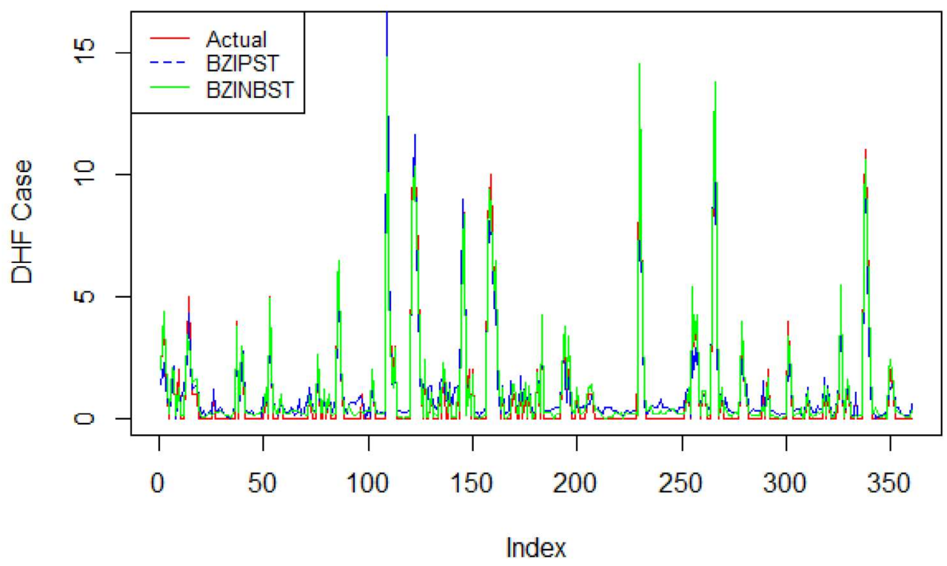
BZIP S-T Model with Overrelaxation

$$\text{DHF Cases} = \log(e_{st}) + \left(1.304 + 0.05597 \times x_{rain(st)} + 0.001255\, x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right).$$

BZINB S-T Model with Overrelaxation

$$\text{DHF Cases} = \log(e_{st}) + \left(1.357 + 0.05546 \times x_{rain(st)} + 0.001222 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$$

Figure 18 DHF Actual Values VS BZIP S-T Model VS BZINB S-T Model (Predicted Values)



Organized by the Philippine Statistical System Spearheaded by the Philippine Statistics Authority

Zero Inflated Negative Binomial Spatio-Temporal Model for DHF in Caraga Region

Figure 19 Trace plots (Iteration vs generated values) for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

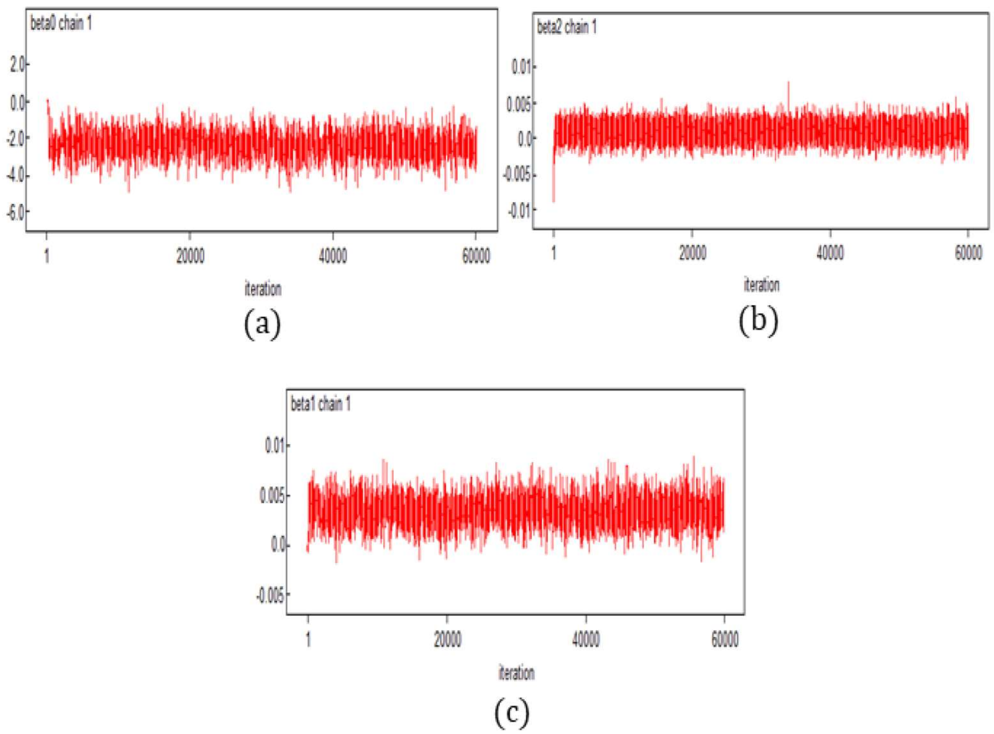


Figure 20 Density plots for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

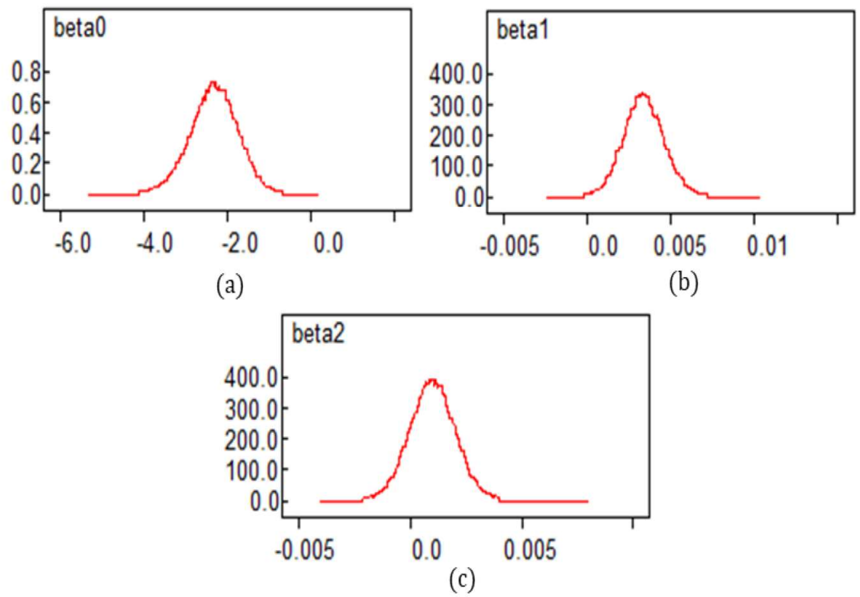


Figure 21 Trace plots (Iteration vs generated values) for (a) α, and (b-k) δ_s with 60,000 iterations

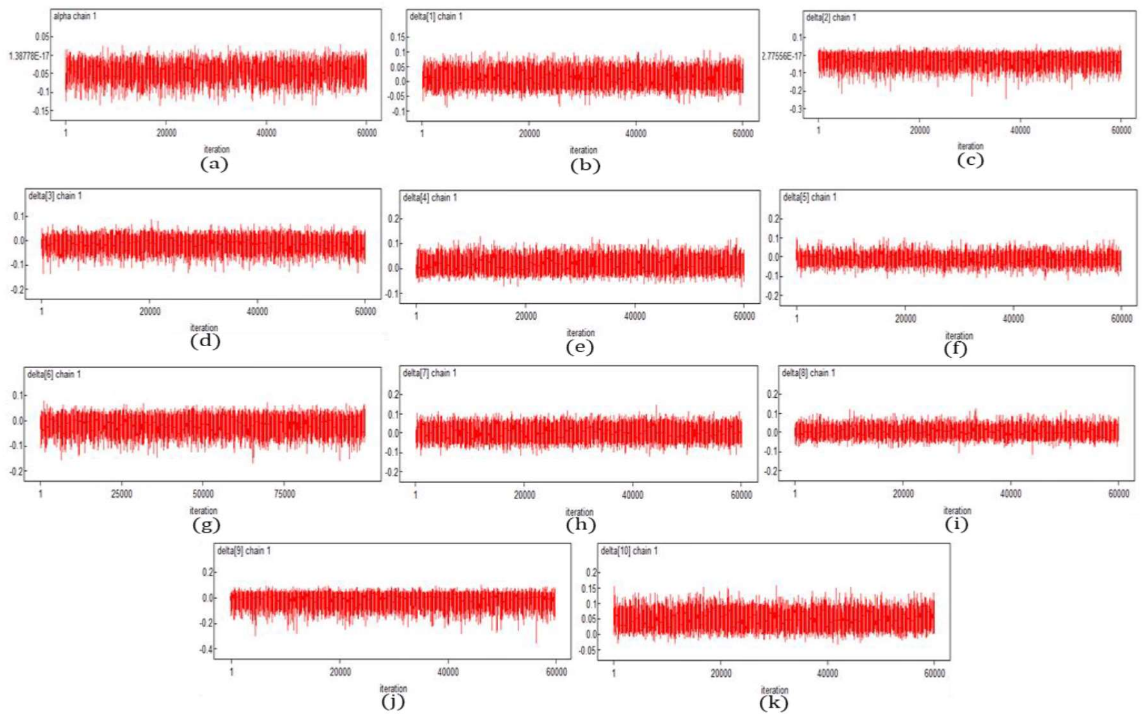


Figure 22 Density plots for (a) α, and (b-k) δ_s with 60,000 iterations

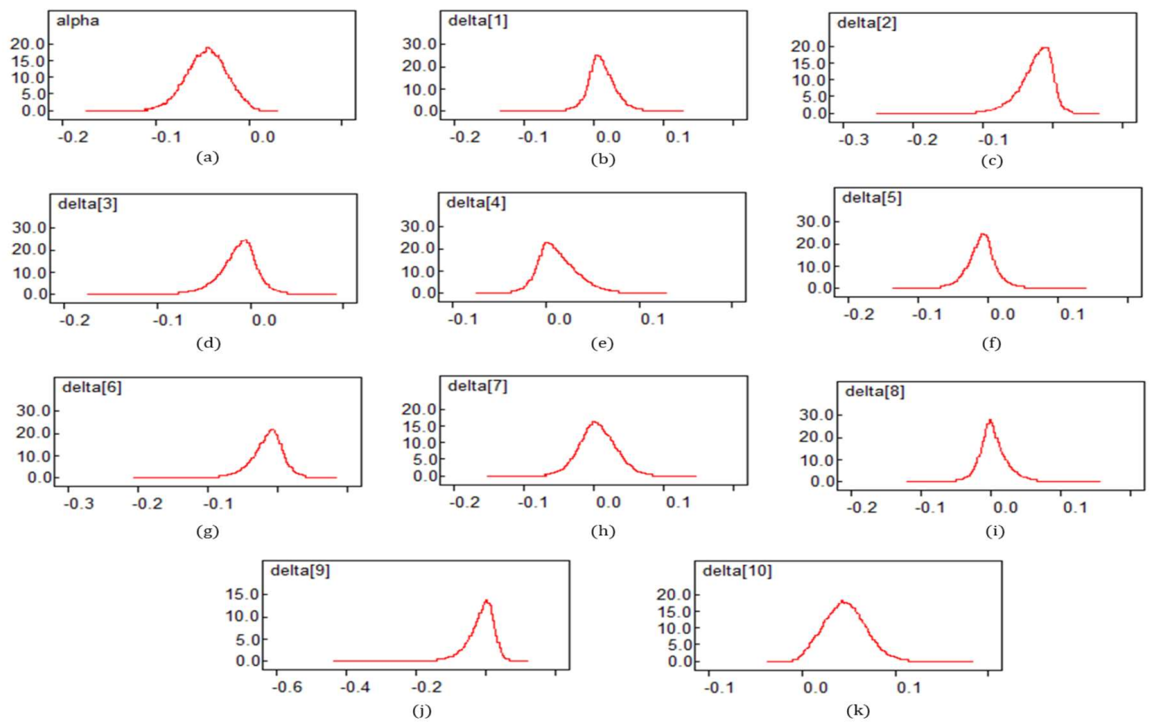


Figure 23 Autocorrelation plots for (a) β_0, (b) β_1, and (c) β_2 with 60,000 iterations

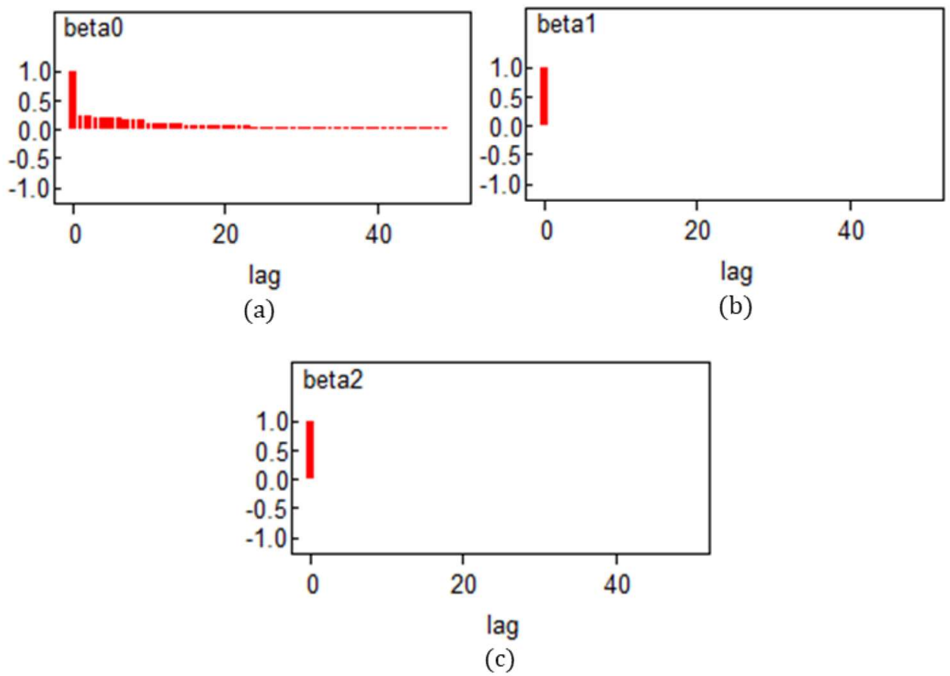


Figure 24 BGR Plots with 60,000 iterations

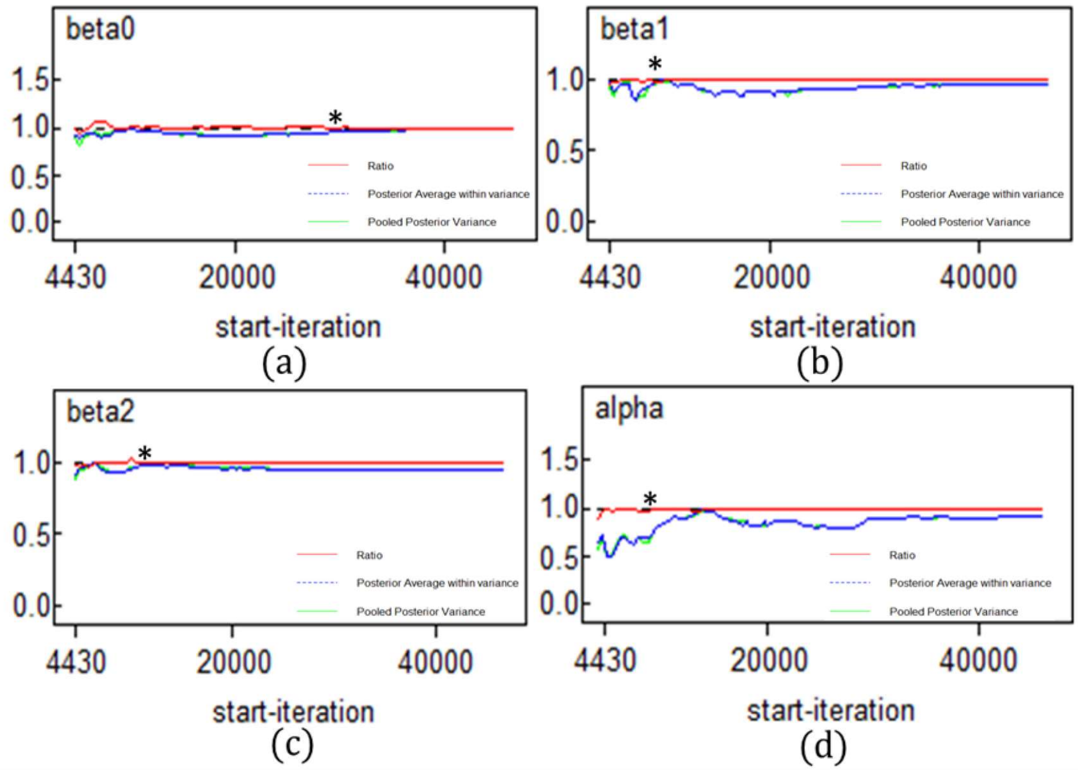


Figure 25 BGR Plots after 60 iterations

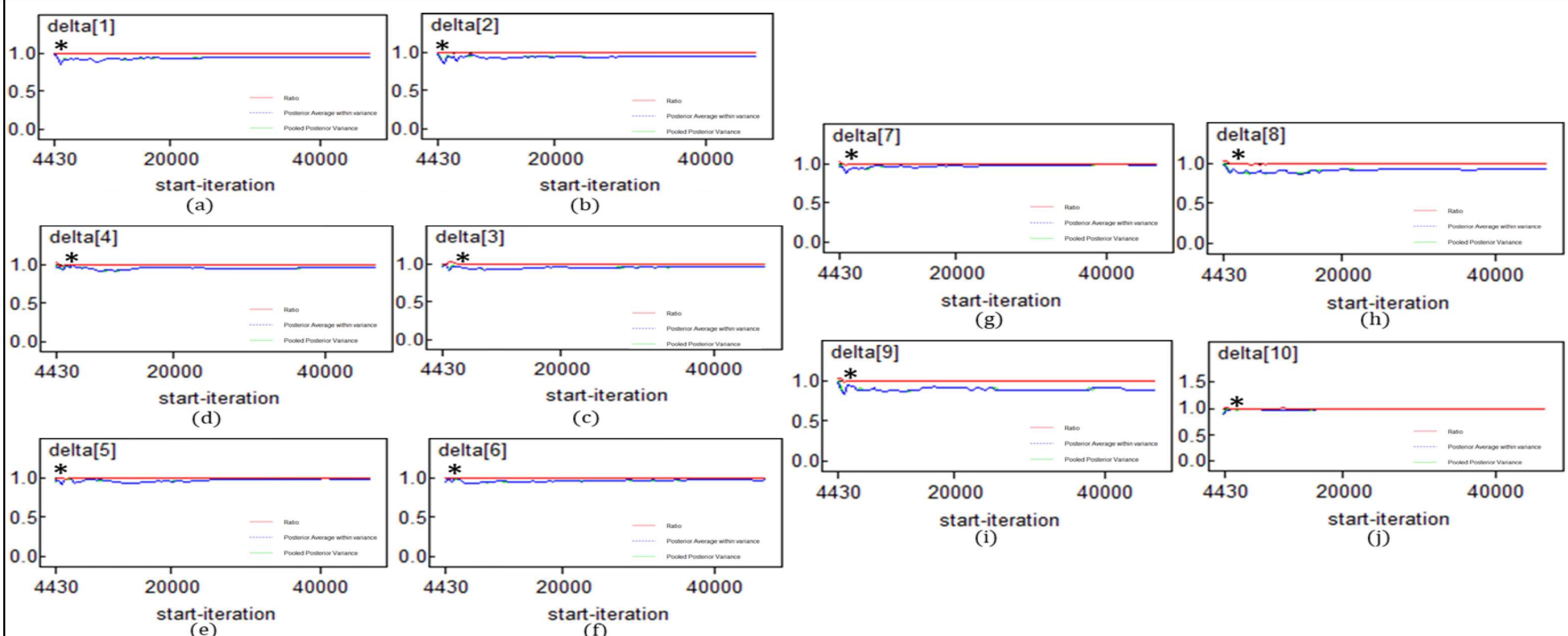


Table 11. BZINB S-T Model with 60,000 iterations

Parameter	Mean	SD	MC Error	2.5%	Median	97.5%
α	0.04581	0.02183	3.655E-4	-0.09118	0.04512	0.05176
β_0	2.323	0.5786	0.01201	0.532	2.307	2.524
β_1	0.003376	0.001255	2.347E-5	9.375E-4	0.003351	0.005951
β_2	0.001	0.00105	1.448E-5	0.001069	0.00107	0.003067
δ_1	0.01129	0.01872	1.392E-4	-0.02377	0.009757	0.0519
δ_2	-0.02587	0.02466	2.509E-4	-0.08492	-0.02161	0.0107
δ_3	-0.01291	0.0197	1.558E-4	-0.05718	-0.01088	0.02239
δ_4	0.01291	0.02065	1.883E-4	-0.02168	0.01002	0.05949
δ_5	0.01291	0.02065	1.883E-4	-0.02168	0.01002	0.05949
δ_6	-0.01527	0.02222	1.687E-4	-0.06522	-0.01295	0.02414
δ_7	0.005205	0.02661	2.37E-4	-0.04691	0.004522	0.05918
δ_8	0.00282	0.01942	1.522E-4	-0.03307	9.592E-4	0.0466
δ_9	-0.0149	0.03709	3.398E-4	-0.1043	-0.008742	0.04187
δ_{10}	0.04629	0.02252	3.112E-4	0.005043	0.04566	0.09256
deviance	326.7					

BZINB S-T Model

Based on the parameter estimation in Table 5.12, the model for the DHS cases using the BZINB S-T model is given by

$$\text{DHF Cases} = \log(e_{st}) + \left(2.323 + 0.003376 \times x_{rain(st)} + 00.08608 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$$

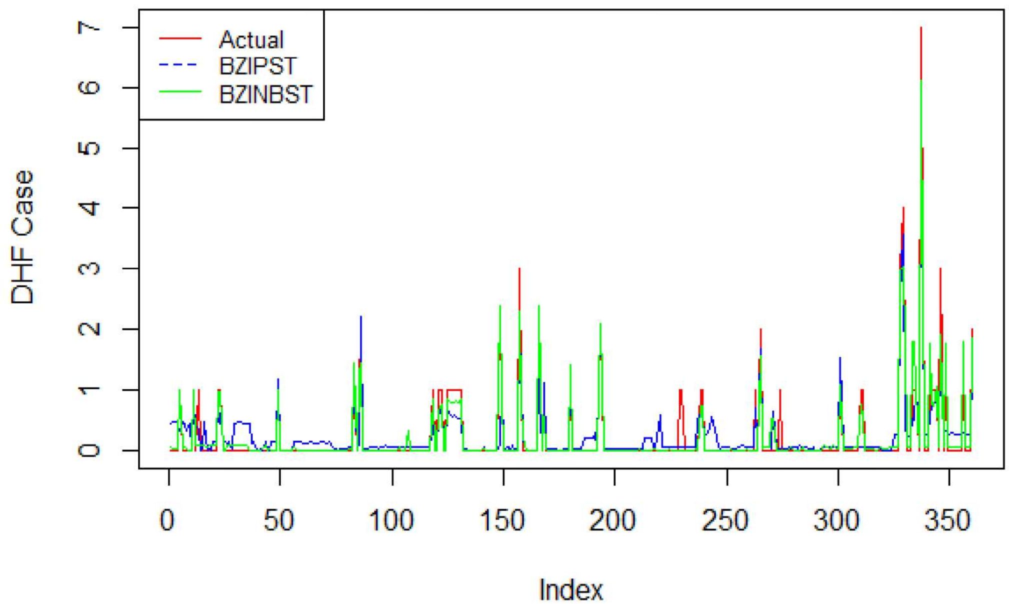
Observing all parameters, we can infer that the effect of both explanatory variables, the rainfall (β_1) and population density (β_2) have an important contribution to the prediction of DHF in Caraga Region.

BZINB S-T Model

To give an actual estimation of DHF Cases, suppose that the rainfall is 11.1 mm., the population density is 190 (these are actual values of rainfall and population density in Caraga Region), with $\alpha = 0.04581$, $\beta_1 = 0.0003145$, $\beta_2 = 0.08608$, $\beta_0 = 2.323$, $u_{11} = -0.0046$, $v_{11} = 0.0068$, $\delta_1 = 0.01129$ and $\log(e_{11}) = 0.0028$.

Given these information, the expected count of the DHF cases in Tandag, Caraga Region is 0.07 or round off to 0, which quite similar to the actual data collected from Caraga Region.

Figure 26 DHF Actual Values VS BZIP S-T Model VS BZINB S-T Model (Predicted Values)



Summary and Conclusion

Summary of the Effect of the Overrelaxation Algorithm on the Rate of Convergence of the Model Parameter Estimates

Model	Number of Iterations
BZINBST (DHF Kendari) $\text{DHF Cases} = \log(e_{st}) + \left(1.357 + 0.05546 \times x_{rain(st)} + 0.001222 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	100,000 Iterations
BZINBST(with Overrelaxation) $\text{DHF Cases} = \log(e_{st}) + \left(1.304 + 0.05597 \times x_{rain(st)} + 0.001255 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	60,000 Iterations

Summary of the Effect of the Overrelaxation Algorithm on the Rate of Convergence of the Model Parameter Estimates

Model	Number of Iterations
BZINBST with Overrelaxation (DHF Caraga) $\text{DHF Cases} = \log(e_{st}) + \left(2.323 + 0.003376 \times x_{rain(st)} + 00.08608 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	60,000 Iterations
BZIPST with Overrelaxtion (DHF Caraga) $\text{DHF Cases} = \log(e_{st}) + \left(1.499 + 0.003145 \times x_{rain(st)} + 0.08608 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	10,000 Iterations

Summary of the Effect of the Overrelaxation Algorithm on the Rate of Convergence of the Model Parameter Estimates

Model	Number of Iterations
BZIPST DHF Cases $= \log(e_{st}) + \left(1.104 + 0.04351 \times x_{rain(st)} + 0.002325 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	30,000 Iterations
BZIPST (with Overrelaxtion) DHF Cases $= \log(e_{st}) + \left(1.031 + 0.03882 \times x_{rain(st)} + 0.002425 \times x_{pop.density(st)} + u_{st} + v_{st} + (\alpha + \delta_s)t_z\right)$	10,000 Iterations

[1] Agresti, A. (2003). *Categorical Data Analysis*. Hoboken, NJ: John Wiley & Sons.

[2] Agresti, A. (2006). *An Introduction to Categorical Data Analysis*. FL: Wiley-Interscience.

[3] Arora, M. (2018). *Extended Poisson Models for Count Data with Inflated Frequencies* (Unpublished doctoral dissertation). Department of Mathematics and Statistics, Old Dominion University, Norfolk, Virginia, United State of America.

[4] Blangiardo, M., & Cameletti, M. (2015). *Spatial and Spatio-temporal Bayesian Models with R - INLA*. Hoboken, NJ: John Wiley & Sons. a

[5] C MacNab, Y., Qiu, Z., Gustafson, P., Dean, C. B., Ohlsson, A., & Lee, S. K. (2004). Hierarchical Bayes Analysis of Multilevel Health Services Data: A Canadian Neonatal Mortality Study. *Health Services and Outcomes Research Methodology*, *5*(1), 5-26. doi:10.1007/s10742-005-5561-1

[6] Cameron, A. C., & Trivedi, P. K. (1998). *Regression Analysis of Count Data*. Cambridge, NJ: Cambridge University Press.

[7] Cameron, A. C., & Trivedi, P. K. (2013). *Regression Analysis of Count Data*. Cambridge, England: Cambridge University Press.

[8] Casella, G., & Berger, R. L. (2002). *Statistical Inference*. FL: Duxbury Press.

[9] Chiang, J., Chib, S., & Narasimhan, C. (1998). Markov chain Monte Carlo and models of consideration set and parameter heterogeneity. *Journal of Econometrics*, *89*(1-2), 223-248. doi:10.1016/s0304-4076(98)00062-1

[11] Conlon, E., & Louis, T. (1999). Addressing multiple goals in evaluating regionspecific risk using Bayesian methods. In A Lawson, A Bigger, D Bohning, E Lesaffre, J Viel, R Bertollini (eds), Disease mapping and risk assessment for public health. Chichester. *John Wiley*, 21-47.

[12] Consul, P. C. (1988). *Generalized Poisson Distributions*. Boca Raton, FL: CRC Press.

[13] Cressie, N. (2010). Smoothing Regional Maps Using Empirical Bayes Predictors. *Geographical Analysis*, *24*(1), 75-95. doi:10.1111/j.1538-4632.1992.tb00253.x

[14] Dellaportas, P., & Smith, A. F. (1993). Bayesian Inference for Generalized Linear and Proportional Hazards Models via Gibbs Sampling. *Applied Statistics*, *42*(3), 443. doi:10.2307/2986324

[15] Dunson, D. B. (2001). Commentary: Practical Advantages of Bayesian Analysis of Epidemiologic Data. *American Journal of Epidemiology*, *153*(12), 1222-1226. doi:10.1093/aje/153.12.1222

[16] Fernandes, M. V., Schmidt, A. M., & Migon, H. S. (2009). Modelling zero-inflated spatio-temporal processes. *Statistical Modelling: An International Journal*, *9*(1), 3-25. doi:10.1177/1471082x0800900102

[17] Frome, E.L., Kutner, M.H, & Beauchamp, J.J. (1973). Regression analysis of Poisson-distributed data. *JASA 68*, 935-940.

[18] Gelfand, A. E., & Smith, A. F. (1989). Sampling Based Approaches to Calculating Marginal Densities. doi:10.21236/ada208388

[19] Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). *Bayesian Analysis*, *1*(3), 515-534. doi:10.1214/06-ba117a

[20] Gilks, W. (1995). Markov Chain Monte Carlo in Practice. doi:10.1201/b14835

[21] Greene, W. H. (1994). *Accounting for Excess Zeros and Sampled Selection in Poisson and Negative Binomial Regression Models* (EC-94-10). NJ: Department of Economics, Stern School of Business, New York, University.

[22] Gustafson, P., Hossain, S., & Macnab, Y. C. (2006). Conservative prior distributions for variance parameters in hierarchical models. *Canadian Journal of Statistics*, *34*(3), 377-390. doi:10.1002/cjs.5550340302

[23] Hadjicostas, P., & Berry, S. M. (1999). Improper and proper posteriors with improper priors in a Poisson-gamma hierarchical model. *Test*, *8*(1), 147-166. doi:10.1007/bf02595867

[24] Hilbe, J. M. (2014). *Modeling Count Data*. Cambridge, England: Cambridge University Press.

[25] Joe, H., & Zhu, R. (2005). Generalized Poisson Distribution: the Property of Mixture of Poisson and Comparison with Negative Binomial Distribution. *Biometrical Journal*, *47*(2), 219-229. doi:10.1002/bimj.200410102

[26] Kalktawi, H. S. (2017). *Discrete Weibull Regression Model for Count Data*. NJ.

[27] Lambert, D. (1992). Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing. *Technometrics*, *34*(1), 1. doi:10.2307/1269547

[28] Mukhsar, Abapihi, B., Sani, A., Cahyono, E., Adam, P., & Aini Abdullah, F. (2016). Extended convolution model to bayesian spatio-temporal for diagnosing the DHF endemic locations. *Journal of Interdisciplinary Mathematics*, *19*(2), 233-244. doi:10.1080/09720502.2015.1047591

[29] Mukhsar, Bahrddin Apabihi, Sitti Wirdhana Ahmad Bakkareng, Asrul Sani, & Edi Cahyono. (2017). Bayesian Zero-Infalted Generalized Poisoon Spatio-Temporal Modeling for Analysing DHF Endemic Area. *Global Journal of Pure and Applied Mathematics*, *13*(2017), 1069-1081.

[30] Mukhsar, Iriawan N., Ulama, B.S.S, & Sutikno. (2013). *New look for DHF Relative Risk Analysis Using Bayesian Poisson-Lognormal 2-Level Spatio- Temporal*. International Journal of Applied Mathematics and Statistics: SECER Publication, ISSN: 0973-1377 (Print), ISSN: 0973-7545 (Online), Vol. 47, No. 17, p 39-46.

[31] Mukhsar. (2018). The Bayesian Zero-Inflated Negative Binomial (τ) Spatio-Temporal Model To Detect An Endemic Dhf Location. *Far East Journal of Mathematical Sciences (FJMS)*, *109*(2), 357-372. doi:10.17654/ms109020357

[32] Naylor, J. C., & Smith, A. F. (1982). Applications of a Method for the Efficient Computation of Posterior Distributions. *Applied Statistics*, *31*(3), 214. doi:10.2307/2347995

[33] Payandeh Najafabadi, A. T, & MohammadPour, S. (2018). A k-inflated Negative Binomial Mixture Regression Model: Application to Rate Making System. *Asia Pacific Journal of Risk and Insuarance*, *12*(12). doi:10.1515/apjri-2017-0014

[34] Serra, Ian Jay, & Polestico, Daisy Lou-Lim. (2019). *On Extended Negative Binomial Distribution for Count Data with Inflated Frequencies* (Unpublished master's thesis). Mindanao State University- Iligan Institute of Technology, Iligan City, Philippines.

[35] Shoemaker, J. S., Painter, I. S., & Weir, B. S. (1999). Bayesian statistics in genetics: a guide for the uninitiated. *Trends in Genetics*, *15*(9), 354-358. doi:10.1016/s0168-9525(99)01751-5

[36] Wakefield, J. (2006). Disease mapping and spatial regression with count data. *Biostatistics*, *8*(2), 158-183. doi:10.1093/biostatistics/kxl008

[37] Willink, R., & Lira, I. (2005). A united interpretation of different uncertainty intervals. *Measurement*, *38*(1), 61-66. doi:10.1016/j.measurement.2005.01.001

[38] World Health Organization. (2017). Dengue and severe dengue (fact sheets).

[39] Yau, K. K., Wang, K., & Lee, A. H. (2003). Zero-Inflated Negative Binomial Mixed Regression Modeling of Over-Dispersed Count Data with Extra Zeros. *Biometrical Journal*, *45*(4), 437-452. doi:10.1002/bimj.200390024

[40] You, Y., & Rao, J. N. (2000). Hierarchical Bayes and related methods for model-based small area estimation Using Multi Level Models. *Journal of Survey Methodology, Statistics Canda*, 173-181. doi:10.22215/etd/1999-04296

[41] Angers, J., & Biswas, A. (2003). A Bayesian analysis of zero-inflated generalized Poisson model. *Computational Statistics & Data Analysis*, *42*(1-2), 37-46. doi:10.1016/s0167-9473(02)00154-8

[42] Gholami chaboki, B., Akbarzadeh baghan, A., Baghfalaki, T., Khoshnevisan, M., & Heydarpour meymeh, M. (2019). Bayesian Analysis of Doubly Inflated Poisson Regression for Correlated Count Data: Application to DMFT Data. *Epidemiology Biostatistics and Public Health*, *16*(4). doi:10.2427/13224

[43] Hodges, J.S. and Reich, B.J. (2010) Adding spatially-correlated errors can mess up the fixed effect you love. Am. Stat. 64, 325–334.

[44] Schmidt, A. M., & Nobre, W. S. (2018). Conditional autoregressive (CAR) model. Wiley StatsRef: Statistics Reference Online, 1-11. https://doi.org/10.1002/9781118445112.stat08048

Thank you!

http://www.psa.gov.ph/ncs

http://openstat.psa.gov.ph

https://twitter.com/PSAgovph

https://www.facebook.com/PhilippineStatisticsAuthority