

1 Article

2 **Latent GLM Tweedie Distribution in Butterflies**  
3 **Species Counts**4 **Rezzy Eko Caraka<sup>1,2,3,\*</sup>, Rung Ching Chen<sup>1,\*</sup>, Toni Toharudin<sup>2</sup>, Isma Dwi Kurniawan<sup>4</sup>, Asmawati**  
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15 **Abstract:** Background: The diversity of butterflies relies on the accessibility of food plants and the  
16 quality of their habitat. Methods: The purpose of this study was to evaluate the diversity butterfly  
17 based on latent GLM in 3 different Habitat. At the same time, we perform the step construction of  
18 Tweedie Distribution both in species levels and individual level. Results: Our finding can be shown  
19 by accuracy AIC, AICc, and BIC. Conclusions: In modelling with latent glm tweedie it can conclude  
20 that the our model is suitable for use at the species or individual level.21 **Keywords:** tweedie; GLM; species counts; butterfly24 **1. Introduction**25 Research on ecology is always interesting to study, especially in species modelling. The scope of the  
26 most essential Ecological studies is ideally about changes in the population of a species at different  
27 time vulnerable, the transfer of energy and matter of living things to one another, as well as the factors  
28 that influence and the occurrence of interrelationships between living things (animals, plants, and  
29 microorganisms, and The environment is a unity of space with all objects, power, conditions, and  
30 living things, as well as behaviours that affect the survival and well-being of humans and other living  
31 things. Ecology has a variety of levels, ranging from the smallest organisation or cell to large scale  
32 such as biosphere. Based on the composition of the types of organisms studied, Ecology can be  
33 divided into autecology and synecology. Aukelogi discusses the study of individual organisms or  
34 individual species whose emphasis is on the histories of life and behaviour in adjusting to the  
35 environment, for example, studying the life history of a species, and its adaptation to the  
36 environment. Meanwhile, Synecology discusses the study of groups or groups of organisms as a unit.  
37 For example, studying the structure and composition of plant species in swamp forests, studying the  
38 distribution patterns of wild animals in natural forests, tourist forests, or national parks.39 Ecosystems are dynamic, continually changing, can be fast, or can be for thousands of years. The area  
40 of the ecosystem varies significantly from small to large and large. The diversity of animals in  
41 Indonesia is high so that it is also known as Megabiodiversity. Insect is the most dominant fauna  
42 group in almost every habitat type, both in terms of diversity, abundance, and its role in the  
43 ecosystem. One member of Insecta who is very diverse and has an important role in the ecosystem is

44 the butterfly. Butterflies are diurnal insects belonging to the Order Lepidoptera. To date, there are at  
45 least 28,000 species of butterflies that have been described worldwide and nearly 80% are found in  
46 the tropics [1]. Indonesia as a mega-biodiversity country has a high level of endemic species of  
47 butterflies. The number of Indonesian butterfly species is estimated at 1,600 species. This number is  
48 only less than Brazil and Peru which have approximately 3,000 species [2].

49 Butterflies have a very important role in the ecosystem. This group is one of the important pollinators  
50 that help the process of pollinating various species of flowering plants. In addition to helping  
51 pollination, butterflies also play a role in increasing plant genetic variation. This is because butterflies  
52 can carry pollen from one individual plant to another so that cross-pollination can occur. In the food  
53 network, butterflies are a source of food for various predatory fauna located at higher trophic levels  
54 such as birds, reptiles and amphibians. Butterflies also have important economic value. Larvae from  
55 several species of butterflies can produce high economic value silk. Many species of butterflies have  
56 beautiful colors and shapes so that many are used as a tourist attraction. Besides having important  
57 ecological and economic functions, butterflies are also a bio-indicator of the balance of an ecosystem.  
58 Butterflies are very sensitive to changing environmental conditions so they are often used as key  
59 indicators in monitoring changes in ecosystems. In addition, butterflies can also be used as indicators  
60 to assess the success of ecosystem restoration [3].

61 The existence of butterflies is greatly influenced by the condition of the habitat where they live. In  
62 general, the diversity and abundance of butterflies tend to be high in locations with diverse  
63 vegetation structures. Butterflies also tend to prefer open spaces that have water sources [4].

64 One of the diversity that is classified as high is a butterfly. The existence of butterflies is strongly  
65 influenced by the carrying capacity of existing habitats including physical and biotic components.  
66 This causes the butterfly is one of the insects of the order Lepidoptera which has a beautiful shape  
67 and colour pattern with wings covered with varying fine scales. Butterflies are one type of insect that  
68 has essential value as pollinators and prey for insectivorous animals [5]. Butterflies are one of the  
69 pollinators in the process of flower fertilisation. Ecologically this has contributed to maintaining the  
70 balance of the ecosystem so that changes in diversity and population density can be used as an  
71 indicator of environmental quality [6]. Butterflies are fascinating insects, colourful, and present  
72 everywhere. The larvae are clustered on a host and the transformation of their larvae into butterflies  
73 is very easily observed.

74 On the other hand, some species species that are rarely found actually prefer dense forest habitat that  
75 has not been disturbed. This pattern of population distribution makes butterflies very interesting to  
76 be used as statistical object modeling species counts. One of the main problems in modeling species  
77 counts is that there are often quite a lot of data with zero values and there are also latent variables  
78 outside the observation that also influence so that the statistical method that can be used is very  
79 limited. In this work we will perform latent glm with laplace approximation [7] and tweedie  
80 distribution to see the diversity of butterfly in three different habitat.

81

## 82 **2. Materials and Methods**

### 83 **Tweedie Latent GLM**

84

85 In general, statistical modelling is abstract which is a simple concept from a theory that is generally  
86 used in the scientific family, research technology on the relationship between real phenomena is the  
87 basis of the goals of science and plays a vital role in everyday life. Nowadays regression analysis is a

88 popular tool for finding out these relationships. Regression analysis is one method for determining  
 89 the causal relationship between one variable and another. The cause variable is called the  
 90 independent variable, the explanatory variable or the  $X$  variable [8]. While the affected variable is  
 91 known as the affected variable, the dependent variable, the dependent variable, the response variable  
 92 or the  $Y$  variable. Estimated regression curves are used to explain the relationship between  
 93 explanatory variables and response variables. The most commonly used approach is the parametric  
 94 approach. The assumption underlying this approach is that the regression curve can be represented  
 95 by a parametric model [9].

96 In parametric regression, it is assumed that the shape of the regression curve is known based on  
 97 theory, previous information, or other sources that can provide detailed knowledge. If the model of  
 98 the parametric approach is assumed to be correct, then the parametric estimation will be very  
 99 efficient. However, if it is wrong, it will lead to misleading data interpretations. In addition,  
 100 parametric models have limitations in predicting unexpected data patterns. If the assumptions of the  
 101 parametric curve are not met, then the regression curve can be assumed using a regression model  
 102 from the nonparametric approach. The nonparametric approach is a model estimation method which  
 103 is based on an approach that is not bound by certain assumptions of the regression curve shape. The  
 104 classical regression analysis has the requirement to fulfil linearity assumptions and the assumption  
 105 of normally distributed data. This analysis aims to determine the direction of the relationship  
 106 between the independent variable with the dependent variable whether positive or negative as well  
 107 as to predict the value of the dependent variable if the value of the independent variable has increased  
 108 or decreased. The data used is usually interval or ratio scale. If the number of independent variables  
 109 is more than one, multiple linear regression analysis is used. In practice in the field, the data found  
 110 often does not meet the assumptions required by classical linear regression. The generalized linear  
 111 model (GLM) is an extension of the linear regression model assuming the predictor has a linear effect  
 112 but does not assume a certain distribution of the response variable and is used when the response  
 113 variable is a member of an exponential family.

114 Natural exponential families (NEFs) are an essential part of theoretical statistics. For several decades,  
 115 they have been studied and classified.. Many authors then looked at their classification according to  
 116 the form of their variance function (i.e. the writing of their variance as a function of the mean  
 117 parameter). For example, [10], [11], [12] who gave a complete description of all the NEFs of R d of  
 118 quadratic variance function. A very particular case of these families, when they generate an  
 119 exponential dispersion model, are those of Tweedie models. These laws, introduced by Tweedie  
 120 (1984) [13] [14] The variance function is very specific and is given by equation (1):  
 121

$$122 \quad V(m) = m^p \quad (1)$$

123

124 With  $p \in ]-\infty, 0] \cup [1, +\infty$  [Tweedie laws are involved in a significant number of fields of  
 125 application. They are indeed linked, by the relation (1.1), to the law of Taylor's power. The latter  
 126 appears in both biology and physics and states that the power of the average gives the empirical  
 127 variance. In particular, the links between Tweedie models and Taylor's power law in physical science  
 128 are brought to light [15]. To make these laws accessible to practitioners, [16]) proposed a package  
 129 for the R software [17] who proposed a method for estimating the densities of Tweedie laws, which  
 130 are not explicable for the most part, by Fourier inversion.

131 We will now introduce the family of Tweedie laws. This family contains some well-known laws such  
 132 as the normal law, the gamma law, the law of Poisson or the inverse Gaussian law. To begin, put  $d =$   
 133 1. We recall that for  $\lambda > 0$ , the NEFs  $(\mu\lambda)$  generates the family of laws  $ED^*(\theta, \lambda)$  called the exponential  
 134 dispersion model and whose elements are written

135 
$$\exp[\theta x - \lambda k_\mu(\theta)]\mu_\lambda d(x) \quad (2)$$

136 This family of laws is called additive. Indeed, it is easy to see that for every  $\lambda_1, \lambda_2, \dots, \lambda_n$  of  $\Lambda_\mu$

137 
$$ED^*\left(\theta, \sum_{i=1}^n \lambda_i\right) \underset{138}{=} \sum_{i=1}^n ED^*(\theta, \lambda_i), \quad (3)$$

139 where  $\underset{138}{=}$  designates equality in law. The corresponding family  $ED(m, \sigma^2) \underset{139}{=} \frac{1}{ED^*(\theta, \lambda_i)}$  with  $m = \tau(\theta)$   
 140 and  $\sigma^2 = \frac{1}{\lambda}$  is called the exponential reproductive dispersion model.

141 Generalized Linear Models (GLM) aims to determine the causal relationship, the effect of  
 142 independent variables on the dependent variable ([18], [19]). The superiority of GLM compared to  
 143 ordinary linear regression lies in the distribution (curve shape) of dependent variables [20]. Variable  
 144 dependent on GLM is not socialized with a normal distribution (symmetrical bell curve), but  
 145 distributions that belong to an exponential family, namely; Binomial, Poisson, Negative Binomial,  
 146 Normal, Gamma, Gaussian Inverse. In GLMs, the distribution of responses can be of various types,  
 147 which are included in the Exponential Family. A random variable  $Y$ , included in the distribution that  
 148 is incorporated in the Exponential Family, if it has a form

149 
$$f_Y(y; \theta, \phi) = \exp\{(y\theta - b(\theta))/a(\phi) + c(y, \phi)\} \quad (4)$$

150 with certain functions  $a(\cdot)$ ,  $b(\cdot)$  and  $c(\cdot)$ . If  $\phi$  is known, then the form of equation (4) is an Exponential  
 151 Family with canonical parameters  $\theta$ .

152 The GLLVM model is generally used to model the type of data where the response variable is large  
 153 enough [21],  $p > n$  where  $p$  is the number of respondent variables and  $n$  is the number of observations  
 154 [22]. If we assume that the response variables are independent of each other, then we can do the glm  
 155 analysis as usual individually or can jointly use the manyglm () function available in the mvabund  
 156 package [23]. So that the regression equation will be obtained as many as  $p$  pieces. However, the fact  
 157 is in ecology that these response variables are not mutually exclusive. To be able to model the types  
 158 of correlated responses we need a combined model and one of them is to introduce random effects  
 159 into the model [24], [25], [26]. In general, the GLLVM model is defined as follows:

160 
$$g(\mu_{ij}) = \eta_{ij} = \tau_i + \beta_{0j} + \mathbf{x}^T \boldsymbol{\beta}_j + u_i^T \boldsymbol{\lambda}_j \quad (5)$$

161 Each butterfly goes through four phases in its life cycle which starts from the egg, caterpillar, pupa  
 162 and imago stages. The change from caterpillar to cocoon and into butterfly involves a major change  
 163 in the appearance of the butterfly called metamorphosis [27]. Butterfly classification and diversity,  
 164 namely:

- 165 • Order: Lepidoptera
- 166 • Suborder: Rhopalocera
- 167 • Superfamily: Hesperioidae and Papilionoidea
- 168 • Family Hesperioidae: Hesperiidae
- 169 • Family Papilionoidea: Papilionidae, Pieridae, Lycaenidae, Nymphalidae

170  
171  
172  
173  
174**Table 1.** Species Counts

Habitat A (Flowing Water)		N	Habitat B (Puddle)		N	Habitat C (No Watter)		N
<i>Lampides boeticus</i>	Lycanidae	3	<i>Jamides tiglath</i>	Lycanidae	4	Leptosia Nina	Lycanidae	1
<i>Jamides tiglath</i>	Lycanidae	1	<i>Lampides boeticus</i>	Lycanidae	4	Euplea Eunice	Nymphalidae	2
<i>Jamides celeno</i>	Lycanidae	3	<i>Danaus chrysippus</i>	Nymphalidae	1	Junonia Hedonia	Nymphalidae	5
<i>Neptis cliniooides</i>	Nymphalidae	1	<i>Euploea Mulciber</i>	Nymphalidae	5	Hypolimnas Bolina	Nymphalidae	3
<i>Junonia almana</i>	Nymphalidae	20	<i>Hypolimnas Bolina</i>	Nymphalidae	5	Ideopsis Vulgaris	Nymphalidae	1
<i>Athyina nefre</i>	Nymphalidae	1	<i>Ideopsis Vulgaris</i>	Nymphalidae	1	Troides Helena	Papilionidae	1
<i>Euploea eunice</i>	Nymphalidae	2	<i>Junonia orithya</i>	Nymphalidae	4	Calopsilia pomona	Pieridae	43
<i>Ideopsis vulgaris</i>	Nymphalidae	1	<i>Catopsilia pomona</i>	Pieridae	61	Eurema sp.	Pieridae	36
<i>Euploea climenia</i>	Nymphalidae	5	Eurema sp.	Pieridae	17			
<i>Danaus chrysippus</i>	Nymphalidae	3						
<i>Neptis hylas</i>	Nymphalidae	5						
<i>Euploea mulciber</i>	Nymphalidae	1						
<i>Papilio helenus</i>	Papilionidae	2						
<i>Pachliopta aristolochiae</i>	Papilionidae	1						
<i>Papilio memnon</i>	Papilionidae	1						
<i>Graphium sarpedon</i>	Papilionidae	1						
<i>Papilio demoleus</i>	Papilionidae	1						
<i>Graphium agamemnon</i>	Papilionidae	1						
<i>Papilio polytes</i>	Papilionidae	1						
<i>Eurema sp.</i>	Pieridae	54						
<i>Catopsilia pomona</i>	Pieridae	63						

175  
176

## RESULTS AND DISCUSSION

### Species Level

177 The highest abundance of individuals and species of butterflies in Habitat A (flowing water) is  
 178 thought to be due to the suitable location for life, in addition to that available sunlight, so the amount  
 179 of vegetation that grows is different. That the number of species is sufficiently affected by the canopy  
 180 cover and intensity of sunlight. Variation of canopy cover provides a suitable place for butterflies so  
 181 that species of butterflies in locations that have water become more diverse. At the same time, in  
 182 order to survive, the butterfly must drink. Flower nectar is a drink that butterflies like because it  
 183 contains sugar which can be used as an energy source. In addition to nectar, some butterflies also like  
 184 to drink water vapour from sand and water vapour from rotted fruit. To form a latent model in this  
 185 paper using the Gaussian inverse. However, in other studies using the Poisson distribution. One  
 186 assumption in the Poisson distribution is that the mean and variance have the same value  
 187 (equidispersion) [28]. The mean and variance of a data count are often not the same whether the mean  
 188 is higher than the variance (overdispersion) or the mean is smaller than the variance  
 189 (underdispersion). In other words, the assumption of equidispersion is often violated. Chopped data  
 190

191 often shows a quite large variance because it contains a lot of zero values (extra zeros) or a distribution  
 192 that is greater than the values in the data or both. Overdispersion cases if ignored can lead to  
 193 underestimation of the estimated standard error, which can result in errors in decision making some  
 194 hypothesis testing. For example, a predictor variable has a significant effect, but in reality it has no  
 195 significant effect. Based on Table 2, the intercept, theta latent values and parameters of the dispersion  
 196 are obtained.

197 In this paper, we will use the tweedie distribution or also said that the Gaussian inverse distribution  
 198 is a continuous distribution and is a family of exponential distributions. This distribution has one  
 199 mode and has curves that tilt to the right, sometimes even the right tail curve of this distribution is  
 200 very long. The opportunity density function is as follows:

$$201 \quad f(v; \delta, \tau) = (2\pi v^3)^{-\frac{1}{2}} \exp -\frac{(\delta v - 1)^2}{2\tau v}, v \geq 0, \delta > 0, \tau > 0 \quad (6)$$

202 The parameters  $\delta$  and  $\tau$  are known as shape parameters. The expected value and variance of the  
 203 Gaussian inverse distribution are  $E(V) = \frac{1}{\delta}$  and  $Var(V) = \frac{\tau}{\delta^3}$ . Skewness and kurtosis of the Gaussian  
 204 inverse distribution are  $3\sqrt{\frac{\tau}{\delta}}$  and  $\frac{15\tau}{\delta}$ , respectively. This distribution is named Gaussian inverse by  
 205 Tweedie because its cumulative generating function is the opposite of the Gaussian distribution. To  
 206 evaluate the models we use AIC, AICc, and BIC. The AIC is defined as

$$207 \quad AIC = 2k - 2 \ln(l) \quad (7)$$

208 and its corrected form for small sample sizes,

$$209 \quad AIC_c = AIC + \frac{2k(k + 1)}{N - k - 1} \quad (8)$$

210 as well as its Bayesian alternative,

$$212 \quad BIC = -2 \ln(l) + \ln(N) * k \quad (9)$$

213 where  $l$  denotes the number of parameters and  $k$  denotes the maximized value of the likelihood  
 214 function. For model comparison, the model with the lowest AIC score is preferred.  
 215 The *absolute* values of the AIC scores do not matter. These scores can be negative or positive.

216

217 **Table 2.** Parameter Estimation GLLVM

	Intercept	theta.LV1	Dispersion parameters
<b>Lycanidae</b>	1.562320	-0.4909974	6.893565e-01
<b>Nymphalidae</b>	2.877803	-0.6032400	3.188624e-06
<b>Pieridae</b>	4.498928	-0.1745962	5.485229e-02
<b>Papilionidae</b>	0.513864	-1.0766610	1.871521e+00

218

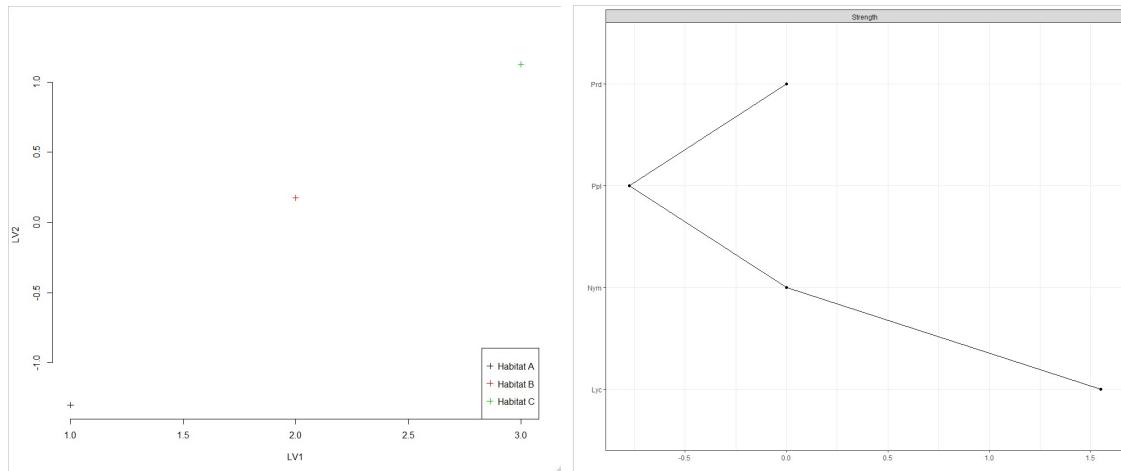
219 Then also obtained values from species ordination based on habitats A, B, and C. It can be seen clearly  
 220 in Table 3 and Figure 1 that the difference in the number of species in this habitat for habitat A has  
 221 negative ordinance compared to B and C. It can be assumed that statistically clear differences the  
 222 number of butterflies at location A with B and C.

223

224 **Table 3.** Habitat Ordination

Habitat	Ordination
<b>Habitat A (Flowing Water)</b>	-1.3025632
<b>Habitat B (Puddle)</b>	0.1744208
<b>Habitat C (No Watter)</b>	1.1281974

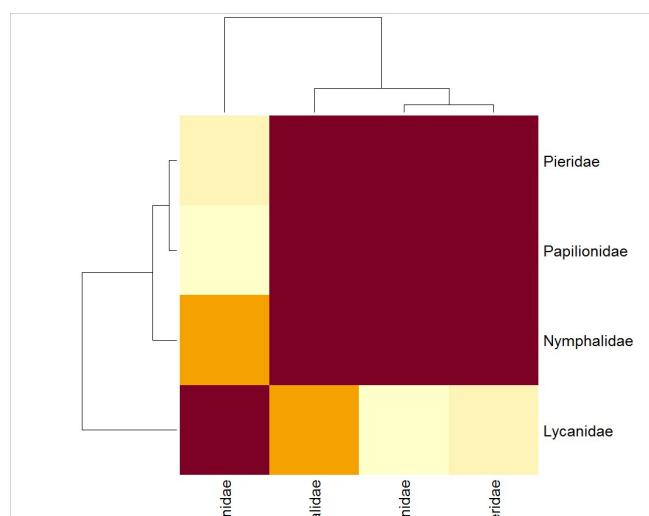
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226

227 **Figure 1. Ordination Habitat (left), Strength Species (right)**

228



229

230 **Figure 2. Heatmap Based on Species**

231

232 In Figure 1 the right can be seen the centrality of this species and can be seen that *Lycanidae* is more  
 233 dominant than *Papilionidae*. *Lycanidae* can be found in all habitats A, B, and C. While *Papilionidae* is  
 234 only found in specific habitats. To evaluate the model, log-likelihood is obtained, AIC 92.22747, AICc  
 235 61.02747, BIC 81.41082.

236

237 **Individual Level**

238 Then we analysis at an individual level because this information is crucial considering the different  
 239 conditions of each habitat. For example, in location C, there are a large number of *Calopsilia Pomona*,  
 240 but that cannot be obtained at other locations. We also use the Tweedie distribution to get LV  
 241 parameters and disperse parameters which can be seen in Table 4

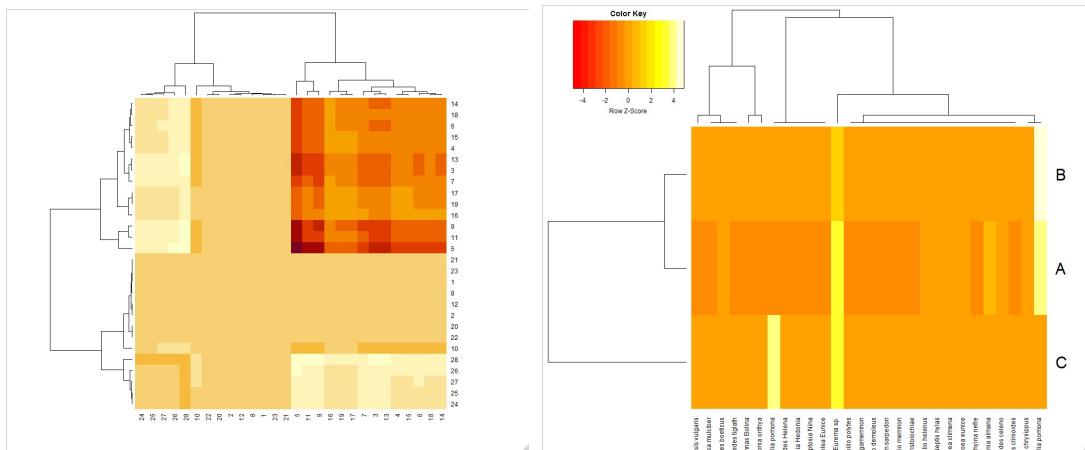
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243

Table 4. Individual Butterflies Counts

No	Name	Hab	Hab	Hab	Intercept	theta.LV1	Dispersion
		A	B	C			parameters
1	<i>Lampides boeticus</i>	3	4	0	0.1918613	1.824132919	0.0000000
2	<i>Jamides tiglath</i>	1	4	0	0.1196806	1.390784277	0.0554530
3	<i>Jamides celeno</i>	3	0	0	-22.3256231	36.40333227	0.0000000
4	<i>Neptis clinoides</i>	1	0	0	-19.3633553	30.06868128	0.0001116
5	<i>Junonia almana</i>	20	0	0	-30.3595546	51.85249351	0.0000000
6	<i>Athyina nefre</i>	1	0	0	-20.8599137	32.40316633	0.0001140
7	<i>Euploea eunice</i>	2	0	0	-21.1510486	33.900739	0.0000000
8	<i>Ideopsis vulgaris</i>	1	1	0	-1.4365198	2.456160331	0.0000028
9	<i>Euploea climena</i>	5	0	0	-26.2246992	43.26507266	0.0000000
10	<i>Danaus chrysippus</i>	3	1	0	-3.6491945	7.324644478	0.0000000
11	<i>Neptis hylas</i>	5	0	0	-24.1491405	40.03382187	0.0000000
12	<i>Euploea mulciber</i>	1	5	0	0.2214806	1.548258021	0.2973333
13	<i>Papilio helenus</i>	2	0	0	-23.0294663	36.88284706	0.0000000
14	<i>Pachliopta aristolochiae</i>	1	0	0	-20.2489731	31.45031725	0.0001126
15	<i>Papilio memnon</i>	1	0	0	-19.6198712	30.46891488	0.0001117
16	<i>Graphium sarpedon</i>	1	0	0	-15.4576646	23.96637522	0.0001165
17	<i>Papilio demoleus</i>	1	0	0	-17.4575418	27.09332625	0.0001142
18	<i>Graphium agamemnon</i>	1	0	0	-19.9752136	31.02327873	0.0001121
19	<i>Papilio polytes</i>	1	0	0	-17.4013016	27.0054651	0.0001143
20	<i>Eurema sp.</i>	54	17	36	3.5768664	0.008946943	0.1708117
21	<i>Catopsilia pomona</i>	63	61	0	2.9489731	2.022838075	0.0029583
22	<i>Hypolimnas Bolina</i>	0	5	3	0.9453342	-0.10337632	0.4775907
23	<i>Junonia orithya</i>	0	4	0	-0.3713151	1.998601509	2.1260480
24	<i>Leptosia Nina</i>	0	0	1	-23.0476328	-12.07378698	0.0000532
25	<i>Euplea Eunice</i>	0	0	2	-22.226489	-12.0148352	0.0000000
26	<i>Junonia Hedonia</i>	0	0	5	-24.6583221	-13.77211016	0.0000000
27	<i>Troides Helena</i>	0	0	1	-24.0393129	-12.59557446	0.0000525
28	<i>Calopsilia pomona</i>	0	0	43	-33.6748127	-19.62356859	0.0000000

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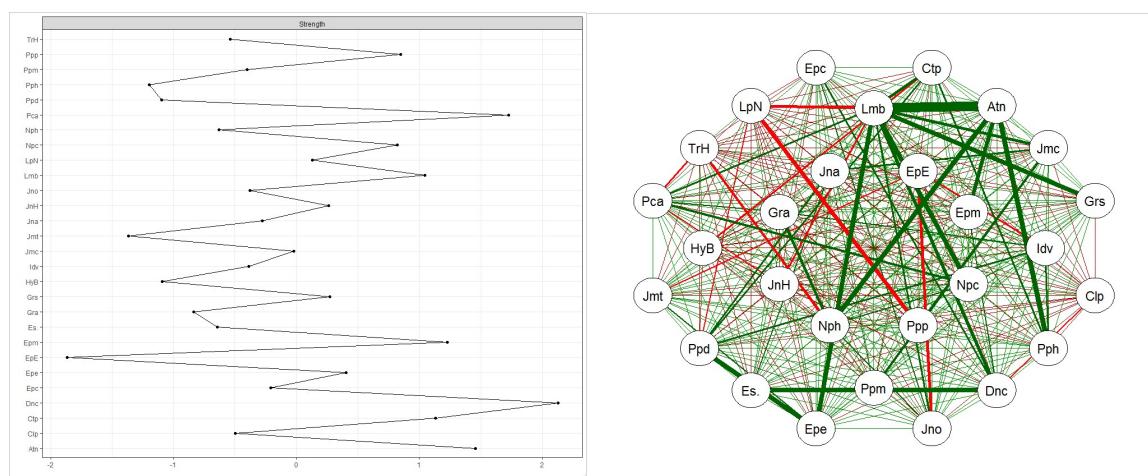


245

246 **Figure 3. Heatmap Based on Individual (left) and location (right)**

247

248 With this simulation we get the negative AIC: -2.2518e+16, AICc: -2.2518e+16, BIC: -2.2518e+16,  
 249 and log-likelihood 1.1259e+16. This is because our likelihood is a continuous probability function, it  
 250 is not uncommon for the maximum value to be greater than 1, so we calculate the logarithm of the  
 251 value, we can get a positive number and (if that value is greater than  $k$ ) get a negative AIC. At the  
 252 same time, in figure 4 we can see the strength and correlation in individual level  
 253



254

255 **Figure 4. Strength Individual (left) and Correlation (right)**

256

257 **Discussion**

258 The species richness of butterflies in habitat A is a different when compared to Habitat b and habitat  
 259 C. The high species richness in Habitat A is thought to be because the area is overgrown by nectar-  
 260 producing flowering plants such as *Melastoma malabatricum*, and *C. rutidosperm*, *banyan* (*Ficus sp.*),  
 261 *Caesalpinia pulcherrima*, and *Plumeria sp.* Habitat modification is one thing that must be considered to  
 262 maintain the abundance of butterflies [29] assert that butterfly abundance will be higher in areas with  
 263 moderate disturbance, where disturbance creates forest gaps. Moreover, forest encourages plant  
 264 growth due to incoming sunlight, and this plant growth will provide a food source for animals. This  
 265 causes the abundance of species to increase. According to [30] treated forests and grasslands are two  
 266 of several habitats Which has the highest number of butterflies. The abundance of butterfly species is  
 267 closely related to the abundance of plant food sources. A consistent species found in all habitat types

268 is *Eurema* sp. However, The only species found in Habitat C are *Leptosia Nina*, *Euplea Eunice*, *Junonia*  
269 *Hedonia*, *Troides Helena*, and *Calopsilia Pomon*. In modelling with latent glm it can be seen that the  
270 model is suitable for use at the species or individual level. Butterflies increase the opening of their  
271 wings to get sunlight and increase body temperature by sunbathing in cold weather. When this cold  
272 weather the butterflies always spread their wings to dry so that they can fly lightly and easily,  
273 whereas if the body's temperature rises the butterflies will find shelter. The range of temperatures  
274 that can support the life of a butterfly is between 21°C - 34°C.  
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