

Bayesian Estimation of Shrubs Diversity in Rangelands under Two Management Systems in Northern Syria

Abdoul Aziz Niane¹, Murari Singh^{1*}, Paul C. Struik²

¹Bio-Diversity and Integrated Gene Management Program, International Center for Agricultural Research in the Dry Areas (ICARDA), Aleppo, Syria

²Centre for Crop Systems Analysis, Wageningen University, Wageningen, The Netherlands

Email: *m.singh@cgiar.org

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Abstract

The diversity of shrubs in rangelands of northern Syria is affected by the grazing management systems restricted by the increase in human and livestock populations. To describe and estimate diversity and compare the rangeland grazing management treatments, two popular indices for diversity, the Shannon index and the Simpson index, were studied for the four combinations of two sites, Hammam and Obeisan, and two grazing methods, Closed and Open, using frequentist and Bayesian approaches. We simulated the *a priori* and *a-posteriori* distributions of the Shannon and Simpson diversity indices, where from a range of values for a constant in the *a priori* distribution the best value normalizing the distribution of the diversity indices was chosen. The Bayesian diversity estimates were higher than their frequentist counterparts and had lower standard errors. The grazing methods at each site and sites under each grazing method delivered significant diversity of shrub species. The Bayesian estimates resulted in lower p-values than the frequentist approach for two cases reflecting in Bayesian method's higher power. Bayesian approach is recommended as it has a wider framework for inference on diversity studies.

Keywords

Arid Rangelands; Species Abundance; Diversity; Shannon Index; Simpson Diversity Index; Bayesian Method

*Corresponding author.

1. Introduction

The arid Mediterranean rangelands are known for their high plant species diversity [1]. Due to increased human and livestock population pressure and technological development for exploitation of natural resources, these rangelands are under tremendous threat. The rangelands, established historically as common property resources, are used for grazing by small ruminants, especially sheep and goats. Overgrazing of rangelands by these small ruminants causes degradation [2]-[4]. This results in reduced performance and a gradual reduction in biodiversity and its spatial distribution [5]-[7]. In addition to overgrazing, wind and irregular rainfall make rangelands fragile and vulnerable to top-soil and plant bio-diversity loss. Suitable rangeland management approaches can be implemented to restore or rehabilitate the diversity [8] [9]. Above ground vegetation replenishment depends on aerial seed, rain and viable soil seed banks [10]-[12]. It is essential to study the status of plant biodiversity in the rangelands under various management practices in order to develop recommendations on the preservation of plant diversity.

A study was undertaken at two sites in the Syrian arid rangelands to investigate the effect of range rehabilitation methods on above ground vegetation density and species diversity. Standard diversity indices such as Shannon index of diversity and Simpson reciprocal diversity index are commonly used instead of the observed plant population density and richness [13]-[16]. In context of partitioning the diversity into that at sub-divisions of a larger area, a new weighted Gini-Simpson index which behaves well for partitioning of biodiversity when the number of species is large is introduced in [17]. These measures are based on the frequentist approach. Several factors, which underlie the rangeland environment, affect the emergence, reproduction and identification of the emerged plant species and the diversity of the species in that area. With climate change, the biophysical aspects and weather - especially the drought behavior of the environment - are changing and these changes affect the diversity. Therefore, it is more realistic to consider the prevalence or abundances of the species as random variable rather than assuming a fixed constant. A Bayesian approach, as it is based on distribution of parameters as prior information, is thus more suitable for estimation of the diversity indices. For a set of chosen priors, the objectives of this study were to: 1) describe the diversity in the study regions; 2) estimate the diversity using Bayesian method; and 3) compare the rangeland grazing management treatments for the changes in the diversity.

2. Materials and Methods

2.1. Study Locations

A study was undertaken at two sites located within the Aleppo province between the 35.657372°N and 37.612917°E, and 35.611903°N and 37.499980°E geographical coordinates. The study was conducted in 2006/07 and 2007/08 using the modified Daubenmire quadrat method [18] and the point intercepts method [19]. The areas studied were located within range rehabilitation areas in which continuous, rotational and full protection from grazing methods had been implemented for about 20 years. We present the analysis of data from the two sites and two grazing managements implemented by the Syrian Steppe Directorate, using halophyte shrub transplanting and rotational grazing. At each site and grazing management combination, a representative macro-plot of 3 ha was used for 9 soil samples and grow-out tests were carried out to identify the shrub species and their abundances. The details of the procedures are described by [20] [21]. **Table 1** presents the observed distribution of the number of individuals per plant species found at the two sites, Hammam and Obeisan, in Syria and under two contrasting management practices (closed and open system) in 2007.

2.2. Diversity Indices

We estimate the diversity using Shannon and Simpson indices [13] given in the following. In a given year, site (community) and a management system, let there be s plant species with a_i the observed abundance of i -th species, and $N = \sum_{i=1}^s a_i$ be the observed total number of individual plants of all the species ($i = 1, 2, \dots, s$). Further, denote by $p_i = a_i/N$, the proportion of plants belonging to i -th species. Let π_i be the true but unknown proportion in the population of the i -th species at the site/environment under study ($i = 1, 2, \dots, s$).

The Shannon index of diversity is given by $-\sum_{i=1}^s \pi_i \ln(\pi_i)$ and is estimated by $H = -\sum_{i=1}^s p_i \ln(p_i)$ and has a

Table 1. Distribution of species abundance using growing out method in 2007.

Site	Management																	
1	Hamмам	Closed	Abundance	55	37	33	26	25	20	16	15	10	8	6	2	1		
			No of species (f_j) (total = 23)	1	2	1	1	1	1	1	1	1	1	2	2	1	8	
	Open	Abundance	69	34	29	10	6	5	3	2	1							
		No of species (total = 13)	1	1	1	1	1	2	3	1	2							
2	Obeisan	Closed	Abundance	82	48	35	34	30	23	17	13	10	9	8	6	3	2	1
			No of species (total = 21)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3
	Open	Abundance	445	51	27	21	12	10	9	8	3	2	1					
		No of species (total = 20)	1	1	1	2	1	2	2	1	2	2	5					

standard error of $se(H) = \left(\left(\sum_{i=1}^s p_i (\ln(p_i))^2 - \left(\sum_{i=1}^s p_i \ln(p_i) \right)^2 \right) / N - (s-1) / (2N^2) \right)^{1/2}$. H can alternately be computed as, $H = -\sum_{j=1}^M f_j (j/N) \ln(j/N)$ where f_j is the number of species appearing j times; M is the maximum number of appearance of any species. Also, $N = \sum_{j=1}^M jf_j$.

Another measure, Simpson index of diversity (SID) is given in terms of an index called Simpson's D , as $SID = 1 - D$ where $D = \sum_{i=1}^s p_i^2$. Standard error of SID , $se(SID)$, can be obtained by estimating the square-root of the variance:

$$\text{Var}(D) = \sum_{i=1}^s \text{Var}(p_i^2) + 2 \sum_{i < j} \text{Cov}(p_i^2, p_j^2) = \sum_{i=1}^s \left[E(p_i^4) - \{E(p_i^2)\}^2 \right] + 2 \sum_{i < j} \left[E(p_i^2 p_j^2) - E(p_i^2) E(p_j^2) \right]$$

In the above, the variance and expected values can be expressed in terms of multinomial distribution parameters [22]. The estimates, shown as caps, of various expected values can be given by:

$$\begin{aligned} \hat{E}(p_i^2) &= p_i^2 + p_i(1-p_i)l \\ \hat{E}(p_i^4) &= l_1 l_2 l_3 p_i^4 + 6l_1 l_2 l p_i^3 + 7l_1 l^2 p_i^2 + l^3 p_i \\ \hat{E}(p_i^2 p_j^2) &= l_1 l_2 l_3 p_i^2 p_j^2 + l_1 l_2 l p_i p_j (p_i + p_j) + l_1 l^2 p_i p_j, (i \neq j) \end{aligned}$$

where $l = 1/N, l_i = 1-il, i = 1, 2, 3$.

2.3. Bayesian Method and Estimation of Diversity Index

The Bayesian setting requires an estimation of parameters of the proportion of abundance of each species within a system of given number of species and the total abundance (N). Distribution of (a_1, \dots, a_s) can be seen as multinomial distribution with $s-1$ components with s proportions $(\pi_1, \pi_2, \dots, \pi_s)$ where $\pi_s = 1 - \sum_{i=1}^{s-1} \pi_i$. We briefly describe a Bayesian method for estimation of a single parameter say θ using an observed data vector say $y = (y_1, \dots, y_n)$. In our case, e.g., θ may stand for $\pi_i (i = 1, 2, \dots, s)$. Let the probability in case of discrete distribution or the likelihood of observing y based on a value of the parameter θ be given by $f(y|\theta)$, called likelihood of y which is a function of θ . In Bayesian framework, one introduces a degree of belief in the parameter θ in terms of its probability distribution function say $g(\theta)$, called a *a priori* distribution of θ , or, simply a prior for θ . The inference about θ is obtained in terms of the probability distribution of θ given the data y and is expressed as $f(\theta|y) \propto g(\theta)f(y/\theta)$, and called the *a posteriori*, or simply a posterior, density function of θ , which is obtainable from the famous Bayes' Theorem available in standard texts [23]-[25]. Using this *a posteriori* density, one can obtain the expected value of θ as an estimate of θ , standard error and its confidence intervals. In case of multiple parameter situation, say $\underline{\theta} = (\theta_1, \theta_2, \dots, \theta_r)$, as in the present case, the generalization of the *a posteriori* distribution of θ_k say, based on an assumed joint prior $g(\underline{\theta})$, is given by

$$f(\theta_k|y) = \int \dots \int g(\underline{\theta}) f(y|\underline{\theta}) d\theta_1 \dots d\theta_{k-1} d\theta_{k+1} \dots d\theta_r / \int \dots \int g(\underline{\theta}) f(y|\underline{\theta}) d\theta_1 \dots d\theta_r$$

There are numerical challenges in the evaluation of the multiple integral required in Bayesian estimation, and these challenges are addressed in vast resources of algorithmic tools and computational codes; see, for example, [23] [25] [26].

In the present context, we proceed as follows. For a fixed N , we assume a multinomial distribution of (a_1, \dots, a_s) with parameter vector $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ where $\pi_s = 1 - \sum_{i=1}^{s-1} \pi_i$. The probability function of these is given by

$$p(a_1, \dots, a_s; N; \pi_1, \pi_2, \dots, \pi_s) = N! \pi_1^{a_1} \pi_2^{a_2} \dots \pi_s^{a_s} / (a_1! a_2! \dots a_s!) \text{ when } \sum_{i=1}^s a_i = N, \text{ and} \\ = 0, \text{ otherwise.}$$

The marginal distribution of $a_i \sim \text{Binomial}(N, \pi_i)$. A Dirichlet distribution is commonly used as a prior for proportions in components of a system. We assume that $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ follow $s-1$ dimensional Dirichlet distribution with parameter vector $\underline{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_s)'$, where $\pi_s = 1 - \sum_{i=1}^{s-1} \pi_i$. The *a priori* probability density function (*pdf*) of the Dirichlet distribution of the random proportions $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ of the i -th species is

$$f(\pi_1, \pi_2, \dots, \pi_{s-1}; \alpha_1, \alpha_2, \dots, \alpha_s) = \Gamma\left(\sum_{i=1}^{i=s} \alpha_i\right) \pi_1^{\alpha_1-1} \pi_2^{\alpha_2-1} \dots \pi_s^{\alpha_s-1} / \prod_{i=1}^{i=s} \Gamma(\alpha_i) \text{ where } \pi_i > 0, \sum_{i=1}^{s-1} \pi_i < 1, \pi_s = 1 - \sum_{i=1}^{s-1} \pi_i, \text{ and} \\ = 0, \text{ otherwise}$$

In above, the random variable and its assumed value is denoted by the same symbol. In this case, it is easy to see that the posterior of $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ $\left| (a_1, \dots, a_s) \right.$ is also a Dirichlet distribution with parameter vector $\underline{\beta} = (\alpha_1 + a_1, \alpha_2 + a_2, \dots, \alpha_s + a_s)'$ with the *pdf* given by

$$f(\pi_1, \pi_2, \dots, \pi_{s-1} | a_1, a_2, \dots, a_s) = \Gamma\left(\sum_{i=1}^{i=s} \alpha_i + a_i\right) \pi_1^{\alpha_1+a_1-1} \pi_2^{\alpha_2+a_2-1} \dots \pi_s^{\alpha_s+a_s-1} / \prod_{i=1}^{i=s} \Gamma(\alpha_i + a_i) \text{ where } \pi_i > 0, \sum_{i=1}^{s-1} \pi_i < 1, \\ \pi_s = 1 - \sum_{i=1}^{s-1} \pi_i, \text{ and} \\ = 0, \text{ otherwise.}$$

Thus, the above prior is a conjugate prior. A frequentist estimate of π_i , based on maximum likelihood estimate or method of moments is given by $p_i = a_i/N$, while an *a priori* estimate would be $\alpha_i / \sum_{i=1}^s \alpha_i$. Using the above prior on π_i 's, the *a posteriori* estimate/expectation of π_i is given by $E(\pi_i | a_1, \dots, a_s) = E(\pi_i | a_i) = (a_i + \alpha_i) / (N + \alpha_0)$, where $\alpha_0 = \sum_{i=1}^s \alpha_i$. While the *a posteriori* distribution of $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ is available in exact form, the *a posteriori* distribution of H or SID is not. However, its distribution can be simulated using the random values of $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ using the Dirichlet distribution with parameter vector $\underline{\beta} = (\alpha_1 + a_1, \alpha_2 + a_2, \dots, \alpha_s + a_s)'$. The expressions for exact mean and variance of the Shannon index has been given by [27] where α_i 's are kept constant. Realizing the fact that *a posteriori* estimates of π_i 's depend on α_i 's also, it may be worthwhile to allow variation in α_i 's. Since the α_i 's are predetermined known values, we can have various models to choose from. There are many theoretical models for π_i 's such as random uniform model, geometric series, logarithmic series, broken stick model, Zipf-Mandelbrot model etc. [13] [28]. We therefore take the following three classes of priors for choosing α_i 's: 1) constant ($\alpha_i = 1, 3, 5$ or 10 for all the species), 2) α_i unequal derived as a random sample from uniform (0.5, k) where $k = 1, 3, 5, 10$, and 3) geometric series and kept within a chosen range given by $\alpha_i = \text{low} + (\text{high} - \text{low}) \left(r^{(i-1)} - r^{(s-1)} \right) / \left(1 - r^{(s-1)} \right)$, where the four sets of values (low, high, r) were (1, 2, 0.2), (1, 3, 0.2), (1, 3, 0.8), (5, 10, 0.5). The number of simulation runs was taken as 10,000. The computations were carried out using R-language [29] and the codes used are available on request.

2.4. The Estimates of Diversity Indices

Using the selected values of α_i in the Dirichlete distribution as prior parameters to obtain the resulting *a post-*

a priori distribution of H and SID, simulations were used to obtain the required probability density function and summary statistics such as mean, median and 95% confidence limits.

3. Results

For the four combinations of the sites (Hamman and Obeisan) and grazing methods (Closed, Open), observed number of shrub species were: 23 under the closed area (no grazing), referred to as “Closed”, and 13 under an area open for grazing at Hamman, referred to as “Open”, while at Obeisan, the number of species found were 21 and 20 under Closed and Open grazing systems, respectively (**Table 1**). The maximum number of abundances varied from 55 to 445 over the four combinations. We simulated the distributions of H and SID based on the prior distribution and posterior distribution of $\underline{\pi} = (\pi_1, \pi_2, \dots, \pi_s)'$ in terms of density plots and mean, standard deviation, skewness, kurtosis and quantiles (data and figures not included). For $\alpha_i = 1, 3, 5, 10 (i = 1, \dots, s)$, the *a posteriori* distributions of H and SID at Hamman showed a shift to the left of their *a priori* distributions. For $\alpha_i = 1$, the *a priori* distributions covered the range of values of the diversity indices under the *a posteriori* distribution. The distribution patterns were similar for both the grazing management methods. Thus $\alpha_i = 1$ was chosen for the *a priori* distribution of H and SID. The *a priori* and *a posteriori* distributions of the diversity indices were obtained when α_i were chosen from as a sample from Uniform (0.5, k) where $k = 1, 3, 5, 10$. For this site, Hamman, the two distribution curves overlapped reasonably well for all these choices of k . Similarly for values of α_i from the geometric series, in majority of cases, the overlap between the *a priori* and the *a posteriori* distribution took place for the range of the indices. A wider spread in the *a priori* distributions was noticed in comparison with the *a posteriori* distributions.

3.1. The Choice of α_i

Although any of the parameters determining the *a priori* distribution could be taken, however, to determine α_i , we identified those parameter values for which the density graphs showed a high degree of overlap with the *a priori* distribution. Although the data need not determine the *a priori* distribution, the overlap consideration pointed to the information for choosing a more reasonable prior than taking arbitrarily from a much wider range of priors. The *a posteriori* probability density of diversity indices are presented for the selected priors in **Figures 1-3** and their mean, standard deviation, skewness, kurtosis, quantiles at 2.5%, median and 97.5% in **Table 2**. **Figures 1-3** show that *a priori* distribution of H/SID has larger skewness and kurtosis compared to the *a posteriori* distributions. As can be expected, there is a difference between the *a priori* and *a posteriori* distributions based on the selected values of α_i . However, the three *a posteriori* distributions also showed differences. For Hamman under the Closed grazing system, the mean H and SID varied, over the three priors, in the range 2.60 - 2.62 and 0.91 - 0.92, respectively (**Table 2**). The 95% confidence intervals for H were (2.51, 2.69), (2.53, 2.61) and (2.53, 2.70) for the three priors $\alpha_i (i = 1 \dots s)$ from Uniform (0.5, 3), geometric series (rate = 0.2, low = 1, high = 3) and equal value fixed at 1, respectively.

3.2. Best Prior

Since the H is a sum of random variables, the central limit theorem supports a normal approximation for its distribution for a large number of species classes. Each *a priori* distribution results in *a posteriori* distribution. To provide an estimate, a criterion is needed to select the most suitable distribution out of the posterior distributions considered for a given site and management combination. We took the sum of squares of skewness (γ_1) and kurtosis (γ_2) (SSSK) as a criterion, $SSSK = \gamma_1^2 + \gamma_2^2$. In case the SSSK is equal for any two posteriors, the preference was given to the low skewness model followed by a low kurtosis. **Table 3** summarizes the Bayesian estimates, selected using the SSSK criterion and frequentist estimates of the two diversity estimates for the site and grazing system combinations. Of the four cases, only for one case of Obeisan and Closed system, the same prior, *i.e.* α_i from Uniform (0.5, 1), was found most suitable for the estimation of H and SID indices. In each case, the Bayesian estimates of diversity were slightly higher than their frequentist counterparts and with lower standard error.

The two grazing management options were compared for diversity at each of the sites, and the sites were compared for each management using the indices estimated by the Bayesian and frequentist approach. To compare the two indices, we computed p-values based on the normal approximation of the difference of their esti-

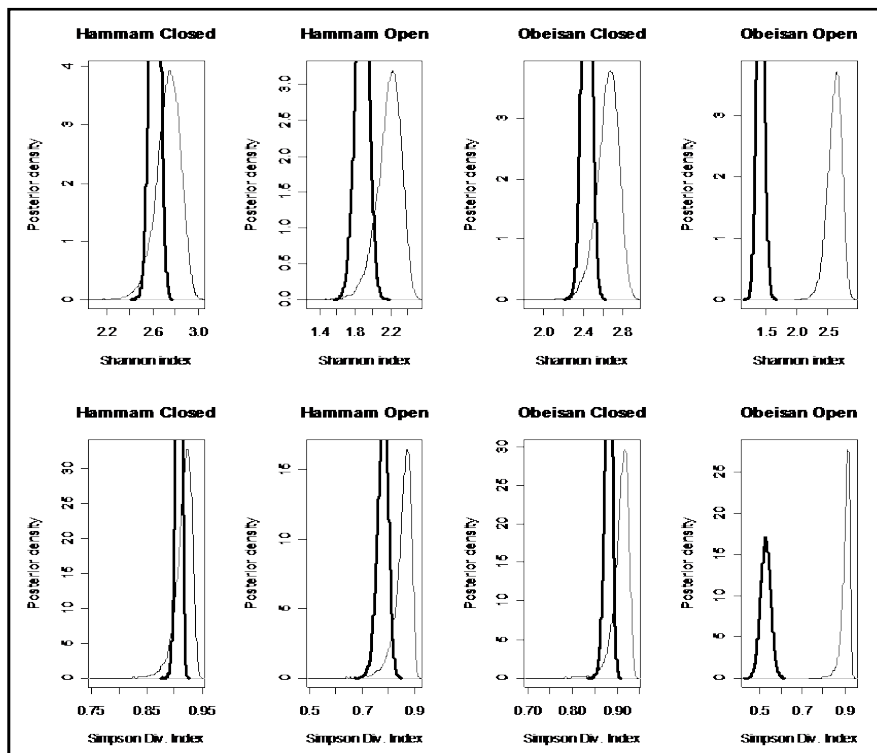


Figure 1. Prior and posterior density of Shannon and Simpson indices for various flattening parameters α_i (equal) = 1.

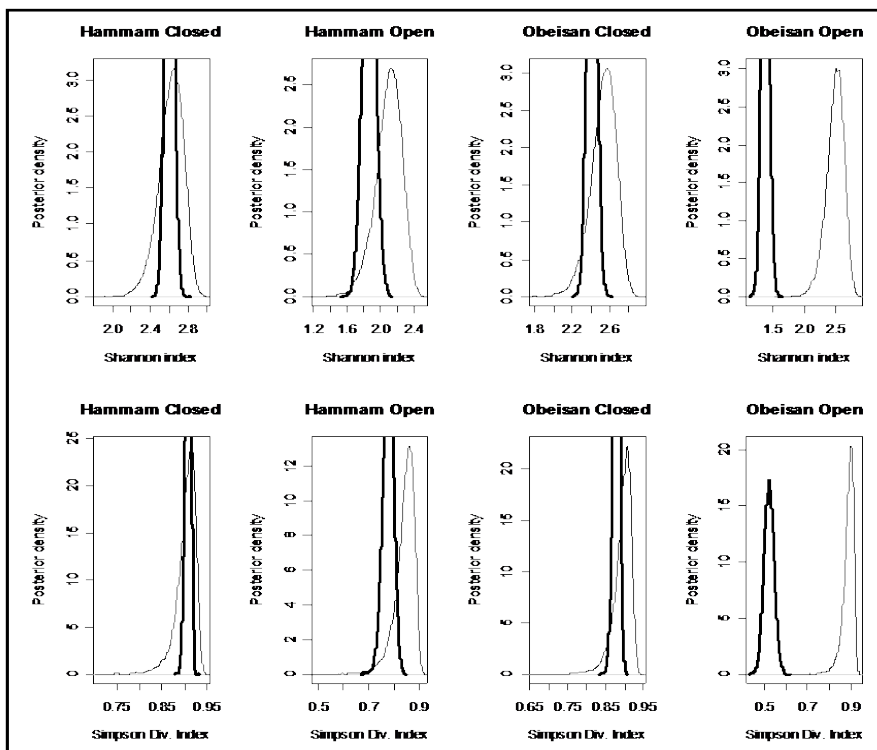


Figure 2. Prior and posterior density of Shannon and Simpson indices for various flattening parameters α_i (unequal) generated as a random sample from uniform (0.5, $k = 1$).

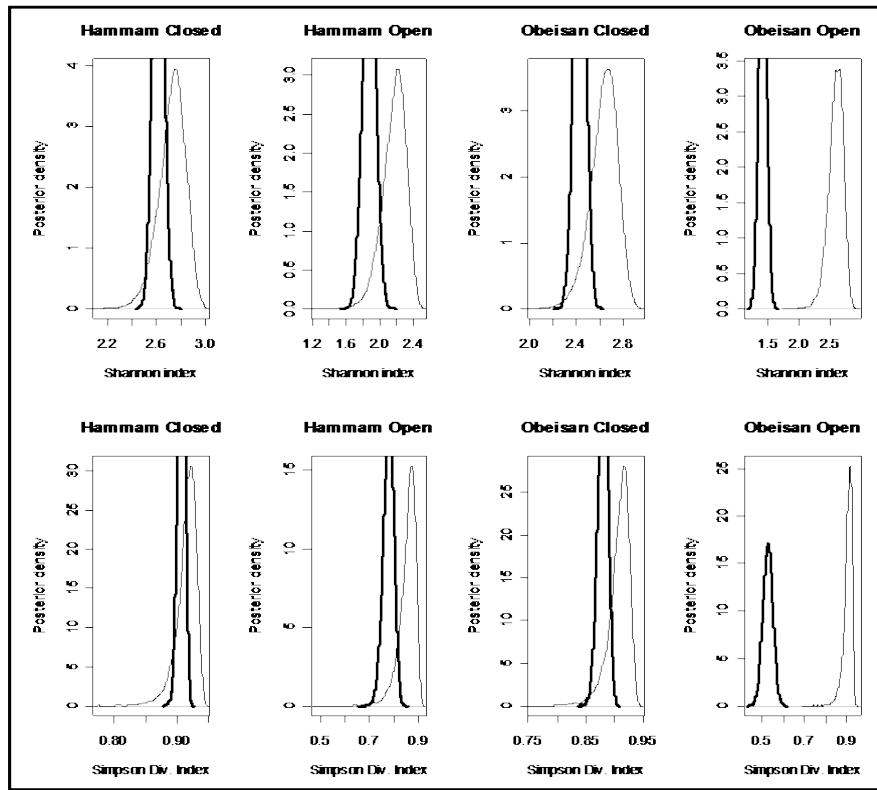


Figure 3. Prior and posterior density of Shannon and Simpson indices for various flattening parameters α_i (unequal) generated as a random sample from geometric distribution and restricted in the range (lower = 1, upper = 3, $r = 0.2$).

Table 2. Posterior distribution summary for diversity indices based on selected prior distributions. Methods: Uniform means a random sample of α_i ($i = 1, 2, \dots, s$) from Uniform distribution (0.5, 3), Fixed means where each α_i was equal to 1; Geometric means α_i s follow geometric series with rate $r = 0.2$ and cover the range (1, 3). SSSK = sum of squares of skewness and kurtosis ($\gamma_1^2 + \gamma_2^2$). H: Shannon index. SID: Simpson index of diversity. Low95% (Upp95%) = lower 95% (upper 95%) confidence limit. Bold case refers to the prior with lowest value of SSSK.

Site	Grazing Management	Mean	SD	Skewness	Kurtosis	SSSK	Low95%	Median	Upp95%	Method	Index	Distribution
Hamмам	Closed	2.61	0.132	-0.61	0.72	0.89	2.32	2.63	2.84	Uniform	H	Prior
Hamмам	Closed	2.72	0.110	-0.63	0.77	0.99	2.48	2.73	2.91	Geometric	H	Prior
Hamмам	Closed	2.73	0.105	-0.61	0.82	1.04	2.51	2.74	2.91	Fixed	H	Prior
Hamмам	Closed	2.60	0.044	-0.07	0.05	0.01	2.51	2.60	2.69	Uniform	H	Posterior
Hamмам	Closed	2.61	0.043	-0.04	0.08	0.01	2.53	2.61	2.70	Geometric	H	Posterior
Hamмам	Closed	2.62	0.043	-0.10	-0.04	0.01	2.53	2.62	2.70	Fixed	H	Posterior
Hamмам	Closed	0.90	0.021	-1.65	5.06	28.31	0.85	0.91	0.93	Uniform	SID	Prior
Hamмам	Closed	0.91	0.017	-1.69	5.56	33.80	0.87	0.92	0.94	Geometric	SID	Prior
Hamмам	Closed	0.92	0.015	-1.55	5.36	31.19	0.88	0.92	0.94	Fixed	SID	Prior
Hamмам	Closed	0.91	0.005	-0.38	0.34	0.26	0.90	0.91	0.92	Uniform	SID	Posterior
Hamмам	Closed	0.91	0.005	-0.36	0.39	0.28	0.90	0.91	0.92	Geometric	SID	Posterior
Hamмам	Closed	0.91	0.005	-0.38	0.33	0.25	0.90	0.91	0.92	Fixed	SID	Posterior
Hamмам	Open	2.09	0.155	-0.66	0.77	1.03	1.74	2.11	2.35	Uniform	H	Prior
Hamмам	Open	2.16	0.140	-0.71	0.86	1.24	1.85	2.18	2.39	Geometric	H	Prior
Hamмам	Open	2.18	0.134	-0.73	0.96	1.46	1.87	2.20	2.40	Fixed	H	Prior

Continued

Hamмам	Open	1.86	0.075	-0.04	0.02	0.00	1.71	1.86	2.01	Uniform	H	Posterior
Hamмам	Open	1.87	0.076	-0.05	-0.04	0.00	1.72	1.87	2.02	Geometric	H	Posterior
Hamмам	Open	1.88	0.074	-0.13	-0.02	0.02	1.73	1.88	2.02	Fixed	H	Posterior
Hamмам	Open	0.84	0.039	-1.58	4.55	23.24	0.74	0.85	0.89	Uniform	SID	Prior
Hamмам	Open	0.85	0.035	-1.67	5.46	32.59	0.77	0.86	0.90	Geometric	SID	Prior
Hamмам	Open	0.86	0.032	-1.72	6.15	40.75	0.78	0.86	0.90	Fixed	SID	Prior
Hamмам	Open	0.78	0.021	-0.33	0.31	0.21	0.73	0.78	0.81	Uniform	SID	Posterior
Hamмам	Open	0.78	0.021	-0.35	0.21	0.17	0.73	0.78	0.81	Geometric	SID	Posterior
Hamмам	Open	0.78	0.020	-0.41	0.31	0.26	0.74	0.78	0.82	Fixed	SID	Posterior
Obeisan	Closed	2.53	0.137	-0.65	0.84	1.13	2.22	2.54	2.76	Uniform	H	Prior
Obeisan	Closed	2.63	0.116	-0.66	0.79	1.05	2.37	2.64	2.83	Geometric	H	Prior
Obeisan	Closed	2.65	0.109	-0.66	0.92	1.27	2.40	2.66	2.83	Fixed	H	Prior
Obeisan	Closed	2.41	0.049	-0.01	0.02	0.00	2.32	2.41	2.51	Uniform	H	Posterior
Obeisan	Closed	2.43	0.048	-0.05	0.01	0.00	2.34	2.43	2.53	Geometric	H	Posterior
Obeisan	Closed	2.44	0.048	-0.10	0.03	0.01	2.34	2.44	2.53	Fixed	H	Posterior
Obeisan	Closed	0.89	0.024	-1.69	5.42	32.20	0.83	0.90	0.93	Uniform	SID	Prior
Obeisan	Closed	0.91	0.019	-1.59	4.54	23.13	0.86	0.91	0.93	Geometric	SID	Prior
Obeisan	Closed	0.91	0.017	-1.70	6.51	45.22	0.87	0.91	0.93	Fixed	SID	Prior
Obeisan	Closed	0.88	0.008	-0.31	0.17	0.13	0.86	0.88	0.89	Uniform	SID	Posterior
Obeisan	Closed	0.88	0.008	-0.34	0.17	0.15	0.86	0.88	0.89	Geometric	SID	Posterior
Obeisan	Closed	0.88	0.008	-0.44	0.33	0.30	0.86	0.88	0.90	Fixed	SID	Posterior
Obeisan	Open	2.48	0.140	-0.68	0.97	1.40	2.16	2.49	2.71	Uniform	H	Prior
Obeisan	Open	2.58	0.119	-0.72	1.20	1.95	2.32	2.59	2.78	Geometric	H	Prior
Obeisan	Open	2.60	0.113	-0.62	0.62	0.77	2.34	2.61	2.78	Fixed	H	Prior
Obeisan	Open	1.39	0.060	0.04	0.00	0.00	1.27	1.39	1.50	Uniform	H	Posterior
Obeisan	Open	1.41	0.061	0.01	-0.01	0.00	1.29	1.41	1.53	Geometric	H	Posterior
Obeisan	Open	1.41	0.061	0.01	-0.05	0.00	1.29	1.41	1.53	Fixed	H	Posterior
Obeisan	Open	0.89	0.026	-1.79	6.34	43.45	0.82	0.89	0.92	Uniform	SID	Prior
Obeisan	Open	0.90	0.021	-1.85	7.22	55.59	0.85	0.91	0.93	Geometric	SID	Prior
Obeisan	Open	0.90	0.019	-1.55	4.48	22.49	0.86	0.91	0.93	Fixed	SID	Prior
Obeisan	Open	0.52	0.023	-0.01	0.00	0.00	0.48	0.52	0.57	Uniform	SID	Posterior
Obeisan	Open	0.53	0.023	-0.04	0.02	0.00	0.48	0.53	0.57	Geometric	SID	Posterior
Obeisan	Open	0.53	0.023	-0.03	-0.05	0.00	0.48	0.53	0.57	Fixed	SID	Posterior

Table 3. Estimates and standard errors of diversity indices under frequentist and selected Bayesian models. H: Shannon index. SID: Simpson index of diversity. SE: standard error.

Site	Management	S	N	Bayesian estimates				Frequentist estimates			
				Parameters (α_j) generated using distribution				H	SE	H	SE
Hamмам	Closed	23	312	Geometric				2.61	0.043	2.56	0.045
Hamмам	Open	13	171	Uniform				1.86	0.075	1.80	0.080
Obeisan	Closed	21	329	Uniform				2.41	0.049	2.38	0.050
Obeisan	Open	20	638	Geometric				1.41	0.061	1.33	0.061
								SID	SE	SID	SE
Hamмам	Closed	23	312	Fixed				0.91	0.005	0.90	0.006
Hamмам	Open	13	171	Geometric				0.78	0.021	0.76	0.023
Obeisan	Closed	21	329	Uniform				0.88	0.008	0.87	0.009
Obeisan	Open	20	638	Uniform				0.52	0.023	0.50	0.024

mates (Table 4). The two methods and the two sites show statistically significant differences at 1%, the commonly used level of significance. In most of the cases the p-values were extremely small. However, for the comparison of the two sites under no-grazing (closed), the p-values under the Bayesian approach were lower than those under the frequentist approach. This indicates that use of prior information can result in higher power for the comparisons.

4. Discussion

Bayesian approach is a more general and realistic framework for drawing a statistical inference which utilizes the prior information about the parameters involved. With the availability of computing power, *a posteriori* distributions of parameters of interest can be obtained in general practice even when involving large number of nuisance parameters. This study, examined the *a posteriori* distributions of two measures of diversity commonly used in practice. Choice of the prior is an issue that would normally be subjective. However, if the *a priori* distribution and the *a posteriori* distribution overlap with high probability on axis of indices then it would be a desirable feature just like a conjugate prior is desirable one in practice. If the probability of their overlap is very low then this indicates that our assumed prior is drifting too much away from the observed reality. The sets of priors used in this study for proportion of species as parameters of the Dirichlet distribution covered a wide range of distribution of diversity indices. The *a priori* distribution of resulting diversity measures provided a reasonable envelope for their *a posteriori* distributions.

The selection of the best prior favoured those for which the resulting posterior distribution is close to normality. Since the indices are sums of random variables, their asymptotic distribution could be approximated by normal distribution. One way to examine an effective closeness to normal distribution is in terms of skewness and kurtosis, therefore, a combined index of skewness and kurtosis, as their sum of squares, was introduced. Other ways or methods of creating indices may be worthwhile.

Further, the diversity measures are based on the fact that the number of species was fixed and equal to the same as that which has been observed. There are methods which estimate the number of species using the sample data on the abundances of observed species [30] [31]. Therefore, it would be more realistic to allow for random distribution of not only the proportion or abundance of a given species, but also of the number of species in a given geographical region during a given period of time.

5. Conclusion

A number of priors for the proportion of species were used in obtaining the Bayesian estimates and confidence interval of the two diversity indices. The Bayesian estimates of the diversity were larger, with smaller standard errors, compared to the estimates based on the frequentist approach which ignores any prior information. Significant differences were observed between the diversities of the two sites under each system of grazing management, and also between the two grazing managements at each site. At least in two comparisons, the Bayesian approach resulted in lower p-values. It is recommended that the use of Bayesian approach should be exploited in the estimation of diversity.

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Table 4. P-values for comparing the grazing methods and sites for the diversity. H: Shannon index. SID: Simpson index of diversity.

Comparison	within	H		SID	
		Frequentist	Bayesian	Frequentist	Bayesian
Closed vs. Open	Hammam	2.22E-16	<2.22E-16	1.08E-09	1.40E-09
Closed vs. Open	Obesian	<2.22E-16	<2.22E-16	<2.22E-16	<2.22E-16
Hammam vs. Obesian	Closed	0.005792	0.0019225	0.0052731	0.002657
Hammam vs. Obesian	Open	2.55E-06	0.0023331	3.33E-15	4.44E-16

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