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Estimation of direct and maternal variance components of lamb weights at 90 days

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Abstract - Weights at 90 days were simulated for Barbarine lambs using various data and pedigree structures. The herd size, number of years and ram pedigree information were modified to cover probable structures of field data: Herds included between 100 and 2000 animals over 4 to 20 years with complete or missing ram information. Direct, maternal, permanent and residual variance components were estimated by Bayesian analysis via Gibbs sampling applied to an animal model that included the fixed effects of year and month of lambing, litter size, the age of the dam and sex of the lamb. A total of 30000 samples were generated. A burn-in period of 2000 rounds was used and then one out of 10 iterations was kept for subsequent analysis. Posterior means of direct and maternal variance effects ranged from 0,83 to 3,86 and from 2,30 to 4,34, respectively. Heritability estimates, in the same order, were between 0,06 and 0,29 and 0,16 and 0,28. In manner similar to direct estimates, maternal component estimates were closer to input parameters (3, 3,5, 9 and 7 for direct, maternal, permanent and residual variance, respectively) for increased herd sizes and number of years and complete ram pedigree.

Key words: Barbarine / growth / maternal effect / Sheep breed.

1. Introduction

Barbarin is the major fat tail breed in Tunisia, Bedihaf-romdhani et al. (2008) indicate that they are 4 millions breeding ewes and 60% are fat tail Barbarin. Accurate estimation of these genetic parameters and in particular genetic correlations requires large across-generation data sets for each relevant population which are not always available. Pooling estimates from several populations may provide more reliable parameter estimates than those obtained from a single population if there is stability across populations. Under low input production systems, small heritability estimates were very often due to a large phenotypic variance and consequently the existing genetic variance (small or medium) is not exploited (Bedihaf-romdhani et Djemali 2006). A large results variability are observed for the direct heritability of weaning weight (90 days), Djemali et al. (1995) using three methods (MIVQUE(0), ML and REML) found 0,27 to 0,36, Ben Gara (2000) think that the heritability is about 0,24 and Bedihaf-romdhani and Djemali (2006) by means of an animal model with direct genetic effect and an animal model with direct and maternal effects between 0,307 and 0,369.

Schenkel and Schaeffer (2000) indicated that selection may increase the mean square error of the estimates of variance components, amplifying the uncertainty about genetic parameters. The Bayesian methods can fully take into account the uncertainty about dispersion parameters by considering the marginal posterior density of those parameters (Gianola and Fernando1986; Wang et al.1993 and Sorensen et al., 1994)

Gibbs sampling is a Monte Carlo numerical integration method that allows inferences to be made about joint or marginal distributions, even if appropriate densities cannot be explicitly formed (Geman and Geman 1984). The great appeal of the Bayesian analyses *via* Gibbs sampling is that it yields Monte Carlo estimates of the full marginal posterior distribution of all parameters of interest, for instance breeding values, from which the probabilities that the parameter lies between specified values can be computed (Van Tassel et al.1994; Sorensen 1996).

The cycle of generating each parameter is repeated. Eventually, the Gibbs sampler converges to the posterior distribution, and the values drawn after that convergence are considered random samples from the posterior distribution. The number of rounds discarded before the values are considered samples from the posterior distribution is usually called the burn-in period (Van Tassell and Van Vleck 1996).

Bayesian analyses *via* Gibbs sampling are becoming more and more feasible as computer power increases and as better algorithms are developed. The applicability of Bayesian methods for genetic evaluation is already possible routinely for moderately sized problems (Schenkel et al. 2002).

The objective of this study was to determinate estimated variance components of lamb growth at 90 days with a simulated data (different scenarios) and using a Markov Chain Monte Carlo Bayesian method.

2. Materials and methods

2.1. Data Simulation

Simulation of a Barbarin Herd:

- Fertility: 0,9
- Prolificacy: 1,3
- Mortality: 0,0
- Initial herd size: N
- Sex ratio: 0,05

Variance components:

- Direct genetic additive variance: 3 Kg^2
- Maternal genetic additive variance: 3,5 Kg^2
- Direct-maternal covariance: -0,5 Kg^2
- Permanent environmental effect variance: 1 Kg^2
- Residual variance: 7 Kg^2
- h^2_d: 0,207
- h^2_m: 0,241

Animal genetic value of the base herd:

$$\mathbf{g_i = L'z_i}$$

i= 1,……,N

With L' such as G_0=L'L and $\mathbf{z_i}$~N(0_2, 1_2)

The permanent maternal effect :

$$\mathbf{p_i = r_i \sqrt{\sigma^2_p}}$$

With r~N(0,1)

Lambing year's effect is determinate like this:

a_n~N(0,1) and the effect of month, sex and type of birth and age of the ewe are taken from a Tunisian Barbarin semi-arid results (Ben Gara, no published references).

Descendant generation's simulation:

The descendants come from hazard mating of the reproductive animals kept every year with a phenotypic selection. The yearly reform rate is about 17%.

The breeding values of a descendant are calculated like this:

Then $\mathbf{g_i = (g_s + g_d) \times \frac{1}{2} + L'\phi_i}$

with $\boldsymbol{\phi}_i = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}$ et $\theta_j = z_j \times \sqrt{\frac{1}{2}}$

where $z_j \sim N(0,1)$

s and d are respectively the sire and the dam of the animal i.

The phenotypic value of the animal i is calculated in this way:

$Ph_i = g_i(1) + g_d(2) + p_d + e_i + \Sigma f_i$

With $g_i(1)$ Direct genetic additive effect of the animal i

$g_d(2)$ Maternal genetic additive variance effect of the dam d

p_d permanent environmental effect of the dam d

e_i residual value of the animal i

and Σf_i The whole of fixed effects affecting the performance of the animal i (year, month, sex and type of birth , age of the ewe).

With $\mathbf{e_i = r_i \sqrt{\sigma_e^2}}$ and $r_i \sim N(0,1)$

The table below gives us an idea about the number of lambs simulated, the base herd range between 100 and 2000, the number of years is between 4 and 20. Example for a base herd of 100 ewes and with 4 years of reproduction we obtain 495 lambs.

Table 1. Description of the data simulated

Base herd	**Number of years**					
	4	**6**	**8**	**10**	**12**	**20**
100	495	700	914	1131	1356	2260
250	1299	1859	2,398	2969	3509	5714
300	1518	2163	2,819	3487	4167	6883
500	2478	3534	4,597	5693	6826	11364
1000	5025	7147	9372	11645	13874	22944
1200	6097	8684	11414	14120	16833	27716
1500	7446	10606	13887	17243	20613	34192
2000	10175	14645	19106	23698	28280	46478

2.2. Analyses

The linear mixed model used in this analysis was:

$$y = Xb + Wp + Z_m m + Z_a a + e \qquad (1)$$

With $W = Z_m$

m : Vector of maternal genetic additive effect q

a : Vector of direct genetic additive effect q

p : Vector permanent environnemental effect p

N : Number of observation

We define :

$$\mathbf{G_0^{-1}} = \begin{bmatrix} \sigma_m^2 & \sigma_{a,m} \\ \sigma_{a,m} & \sigma_a^2 \end{bmatrix} = \begin{bmatrix} g^{m,m} & g^{m,a} \\ g^{m,a} & g^{a,a} \end{bmatrix}$$

$$\mathbf{Var}\begin{bmatrix} \mathbf{p} \\ \mathbf{m} \\ \mathbf{a} \end{bmatrix} = \begin{bmatrix} \sigma_p^2 & \\ \mathbf{G_0 \otimes} & \mathbf{A} \end{bmatrix}$$ with $\otimes$ produit de Kronecker

$y \sim N(Xb + Wp + Z_m m + Z_a a, I\boldsymbol{\sigma}_p^2)$

$$\left.\begin{matrix} \mathbf{m} \\ \mathbf{a} \end{matrix}\right| \mathbf{A, G_0} \sim N(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{G_0 \otimes A})$$

$$\mathbf{p} | \boldsymbol{\sigma}_p^2 \sim N(0, \mathbf{I}\boldsymbol{\sigma}_p^2)$$

g'=(m'a') with 2 q order.

A priori distribution definition

p(b)~ a constant

$$\mathbf{p(\sigma_e^2 / v_e, S_e^2) \propto S_e^2 \chi_{v_e}^{-2}}$$

$$\mathbf{p(\sigma_p^2 / v_p, S_p^2) \propto S_p^2 \chi_{v_p}^{-2}}$$

$p(G_0/V,v) \propto IW_2(V,v)$

with v=-3 , V=0 in this way $p(G_0/V,v)$ is a uniform distribution

$$\sigma = \sigma_e^2 / \sigma_p^2$$
$$K_{m,m} = \sigma_e^2 g^{m,m}$$
$$K_{m,a} = \sigma_e^2 g^{m,a}$$
$$K_{a,a} = \sigma_e^2 g^{a,a}$$

$Xb + Z_m p + Z_m m + Z_a a = W\theta$

Then

$$\begin{cases} \theta_i / \theta_{-i}, \sigma_p^2, \sigma_m^2, \sigma_a^2, \sigma_e^2, y \sim N(\hat{\theta}_i, C_{ii}^{-1}\sigma_e^2) \\ C_{ii}\hat{\theta}_i = (W'_i y - C_{i,-i}\theta_{-i}) \end{cases}$$

$$C = \begin{bmatrix} X'X & X'Z_m & X'Z_m & X'Z_a \\ Z'_m X & Z'_m Z_m + \gamma I & Z'_m Z_m & Z'_m Za \\ Z'_m X & Z'_m Z_m & Z'_m Z_m + A^{-1}K_{m,m} & Z'_m Za + A^{-1}K_{m,a} \\ Z'_a X & Z'_a Z_a & Z'_a Z_m + A^{-1}K_{a,m} & Z'_a Z_a + A^{-1}K_{a,a} \end{bmatrix}$$

I

With :

$$\hat{b} = (X'R^{-1}X)^{-1} X'R^{-1}(y - Z_m\hat{p} - Z_m\hat{m} - Z_a\hat{a})$$
$$\hat{p} = (Z'_m R^{-1}Z_m + I\sigma_p^{-2})^{-1} Z'_m R^{-1}(y - X\hat{b} - Z_m\hat{m} - Z_a\hat{a})$$
$$\hat{m} = (Z'_m R^{-1}Z_m + A^{-1}\sigma_m^{-2})^{-1} Z'_m R^{-1}(y - X\hat{b} - Z_m\hat{p} - Z_a\hat{a})$$
$$\hat{a} = (Z'_a R^{-1}Z_a + A^{-1}\sigma_a^{-2})^{-1} Z'_a R^{-1}(y - X\hat{b} - Z_m\hat{p} - Z_m\hat{m})$$

With

$$b \sim N((\hat{b}, (X'R^{-1}X)^{-1})$$
$$p \sim N((\hat{p}, (Z'_m R^{-1}Zm + I\sigma_p^{-2})^{-1})$$
$$m \sim N(\hat{m}, (Z'_m R^{-1}Zm + A^{-1}\sigma_m^{-2})^{-1})$$
$$a \sim N(\hat{a}, (Z'_a R^{-1}Z_a + A^{-1}\sigma_a^{-2})^{-1})$$
$$\sigma_e^2 \sim \chi^{-2}(N + v_e, v_e S_e^2 + ee')$$
$$\sigma_p^2 \sim \chi^{-2}(p + v_p, v_p S_p^2 + pp')$$
$$G_0 \sim IW_2(CS_g^2 + V^{-1})^{-1} \quad , v + q)$$

And $S_g^2 = \begin{bmatrix} m'A^{-1}m & m'A^{-1}a \\ a'A^{-1}m & a'A^{-1}a \end{bmatrix}$

$$e = (y - Xb - Z_m p - Z_m m - Z_a a$$
$$V = S_{g_0} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$
$$v = mg_0 = -3$$

A Wishart distribution simulation

$W_p(S,n)$

We proceed with a Chodesky factorisation : $S=L'L$

We build an inferior triangle $T = \{t_{i,j}\}_{j=1,\ldots,p}^{i=1,\ldots,p}$

With $t_{i,j} = \sqrt{\chi^2_{n+1-i}}$

$$t_{i,j} \sim N(0,1)\ \mathrm{si}\ i \rangle j$$
$$\mathrm{et}\ t_{i,j} = 0\ \mathrm{si}\ i \langle j$$

Then $Q=L'TT'L \sim W_p(S,n)$

And $Q^{-1} \sim I\ W_p(S,n)$

The hyper parameter V(prior) is determinated in this way :

$$E(G_0/V,v) = \frac{V^{-1}}{(v-3)}$$

We choose $V^{-1} = (v-3)\tilde{E}(G_0 / V, v)$

And $\tilde{E}(G_0 / V, v)$ establish the *a priori* information base.

3. Results and discussions

3.1. Variance component estimates

Marginal distributions were used with herd's size 100 and 500 to determine: direct, maternal, permanent environment and residual variances. Estimated posterior and standard deviation of all of these criteria are presented in Table 2. Posterior means for direct variance effect ranged from 0,83 to 3,83. This estimate is similar with Mandal et al. (2006) results who reported 3,23 for pre-weaning weight (75 days) with a Muzaffarnagari sheep. A similar result (3,99) was founded by Mokhtari et al. (2008) for weight at 6 months of Kermani sheep. A lower direct genetic variance for the weight at 90 days (0.57) was estimated by an animal model with direct and maternal effects with barbarin lambs (Bedhiaf-Romdhani and Djemali 2006).

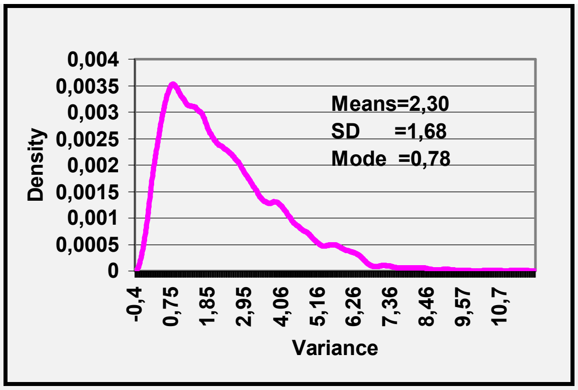

Figure 1. Posterior density function of direct variance (T100-G4) Complete ram information

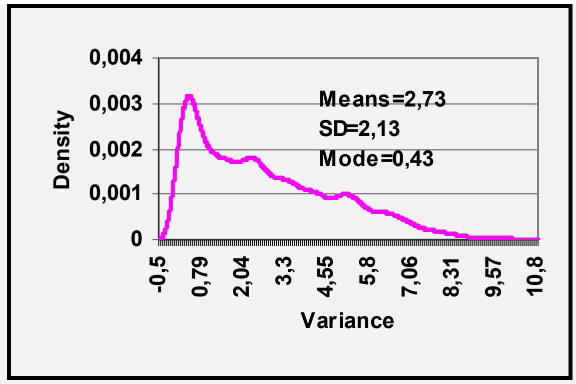

Figure 2. Posterior density function of direct variance (T100-SG-G4) sire ram missing information

Marginal distributions of direct variance for a herd size of 100 ewes and 4 years with complete ram information (T100-G4) and a sire ram missing information (T100-SG-G4) are presented in Figures. 1-2, respectively.

Direct variance ranged from -0,4 to 11,6 for the first design and from -0,5 to 10,9 for the second. With complete ram information the mode is about 0,78 and 0,43 with a sire ram missing information.

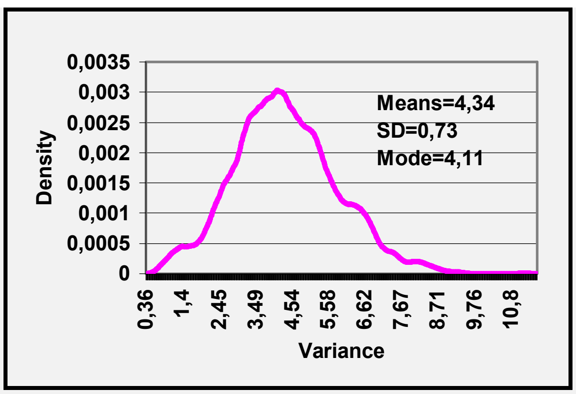

Figure 3. Posterior density function of maternal variance (T100-G4) Complete ram information

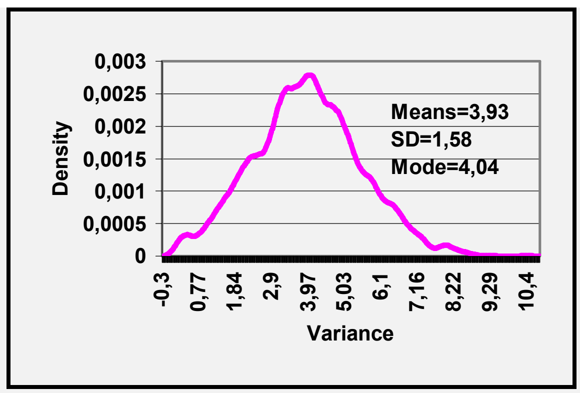

Figure 4. Posterior density function of direct variance (T100-SG-G4) sire ram missing information

Table 2. Estimated posterior and standard deviation of direct, maternal, permanent environment and residual variances

Design	σ^2_d		σ^2_m		σ_{md}		r_{dm}		σ^2_C		σ^2_e		h^2		m^2	
	Est	SD	Est	SD	Est	SD	Est	SD	Est	SD	Est	SD	Est	SD	Est	SD
T100-G4	2,30	2,82	4,34	2,19	-4,20 10^{-3}	3,97 10^{-2}	-4,25	4,19	1,30	1,07	7,40	1,14	0,15	1,06 10^{-2}	0,28	7,24 10^{-3}
T100-G6	2,04	1,80	3,83	1,61	-1,20 10^{-2}	2,26 10^{-2}	-3,52	2,99	1,26	0,91	7,15	0,73	0,14	7,62 10^{-3}	0,27	6,34 10^{-3}
T100-G8	1,93	1,81	3,27	1,02	-8,30 10^{-4}	1,24 10^{-2}	-8,47	2,23	1,01	0,46	7,20	0,64	0,14	8,77 10^{-3}	0,24	4,86 10^{-3}
T100-G10	1,69	1,45	3,35	1,19	-3,51 10^{-4}	9,48 10^{-3}	6,12	1,81	1,24	0,47	7,50	0,55	0,12	6,84 10^{-3}	0,24	5,25 10^{-3}
T100-G12	2,18	1,62	3,21	1,51	-1,21 10^{-3}	9,15 10^{-3}	-4,09	1,48	1,49	0,59	6,80	0,52	0,16	7,96 10^{-3}	0,23	6,99 10^{-3}
T100-G20	2,96	1,43	3,27	0,71	2,14 10^{-3}	8,20 10^{-3}	7,85 10^{-4}	8,86 10^{-4}	1,20	0,23	6,90	0,43	0,20	6,19 10^{-3}	0,23	3,01 10^{-3}
T100-SG-G4	2,74	4,54	3,93	2,48	-8,32 10^{-3}	3,95 10^{-2}	-1,44 10^{-3}	4,05 10^{-3}	1,46	1,37	6,52	2,82	0,19	2,10 10^{-2}	0,27	9,37 10^{-3}
T100-SG-G6	3,11	2,60	3,21	1,58	-1,96 10^{-2}	2,76 10^{-2}	-5,43 10^{-3}	2,91 10^{-3}	1,31	1,02	5,87	1,61	0,23	1,34 10^{-2}	0,24	7,37 10^{-3}
T100-SG-G8	2,98	1,97	2,47	0,91	1,17 10^{-3}	1,47 10^{-2}	-1,37 10^{-3}	2,21 10^{-3}	1,17	0,55	5,98	1,21	0,23	1,18 10^{-2}	0,19	5,07 10^{-3}
T100-SG-G10	2,98	1,98	2,35	0,99	-3,51 10^{-3}	1,16 10^{-2}	-5,64 10^{-4}	1,79 10^{-3}	1,48	0,59	6,16	1,23	0,23	1,12 10^{-2}	0,18	5,27 10^{-3}
T100-SG-G12	3,23	1,56	2,30	1,11	-5,37 10^{-3}	1,00 10^{-2}	-1,80 10^{-3}	1,46 10^{-3}	1,66	0,64	5,55	0,94	0,25	9,49 10^{-3}	0,18	6,13 10^{-3}
T100-SG-G20	3,53	1,02	2,71	0,47	-2,07 10^{-3}	8,23 10^{-3}	-4,65 10^{-4}	8,75 10^{-4}	1,09	0,25	5,87	0,61	0,27	5,66 10^{-3}	0,20	2,32 10^{-3}
T500-G4	3,01	0,79	3,01	0,44	-3,20 10^{-3}	7,53 10^{-3}	-9,62 10^{-4}	8,52 10^{-4}	0,91	0,27	6,86	0,29	0,22	3,73 10^{-3}	0,22	2,14 10^{-3}
T500-G6	2,31	0,28	3,26	0,23	-5,37 10^{-3}	4,47 10^{-3}	-1,81 10^{-3}	5,86 10^{-4}	0,56	0,12	7,37	0,13	0,17	1,40 10^{-3}	0,24	1,03 10^{-3}
T500-G8	2,51	0,26	3,71	0,21	-4,65 10^{-3}	4,12 10^{-3}	-1,44 10^{-3}	4,41 10^{-4}	0,31	7,70 10^{-2}	7,37	0,11	0,18	1,20 10^{-3}	0,27	8,82 10^{-4}
T500-G10	2,15	0,15	3,60	0,23	-3,96 10^{-3}	2,78 10^{-3}	-1,38 10^{-3}	3,63 10^{-4}	0,56	9,04 10^{-2}	7,63	7,41 10^{-2}	0,15	7,10 10^{-4}	0,26	9,20 10^{-4}
T500-G12	2,30	0,18	3,52	0,17	-2,64 10^{-3}	2,43 10^{-3}	-8,86 10^{-4}	3,01 10^{-3}	0,63	6,17 10^{-2}	7,53	7,37 10^{-2}	0,16	8,31 10^{-4}	0,25	7,31 10^{-4}
T500-G20	2,75	0,14	3,45	0,12	-9,17 10^{-4}	1,69 10^{-3}	-2,74 10^{-4}	1,75 10^{-4}	0,64	3,29 10^{-2}	7,19	5,16 10^{-2}	0,19	6,38 10^{-4}	0,25	4,91 10^{-4}
T500-SG-G4	2,34	2,20	2,73	0,79	-2,82 10^{-3}	4,89 10^{-3}	-9,46 10^{-4}	8,37 10^{-4}	1,24	0,50	7,23	1,28	0,17	1,20 10^{-2}	0,20	4,05 10^{-3}
T500-SG-G6	1,38	0,52	2,89	0,39	-2,94 10^{-3}	2,21 10^{-3}	-1,23 10^{-3}	5,72 10^{-4}	1,03	0,25	8,11	0,34	0,10	2,91 10^{-3}	0,21	1,95 10^{-3}
T500-SG-G8	0,99	0,44	3,84	0,25	-8,34 10^{-4}	1,64 10^{-3}	-2,33 10^{-4}	4,34 10^{-4}	0,36	0,10	8,54	0,29	7,23 10^{-2}	2,31 10^{-3}	0,28	1,10 10^{-3}
T500-SG-G10	0,83	0,15	3,72	0,22	-8,49 10^{-4}	1,07 10^{-3}	-5,16 10^{-4}	3,60 10^{-4}	0,51	0,10	8,66	0,12	6,03 10^{-2}	8,06 10^{-4}	0,27	9,46 10^{-4}
T500-SG-G12	1,04	0,40	3,72	0,20	-8,97 10^{-4}	1,10 10^{-3}	-3,07 10^{-4}	2,98 10^{-4}	0,52	8,17 10^{-2}	8,48	0,25	7,49 10^{-2}	2,11 10^{-3}	0,27	8,86 10^{-4}
T500-SG-G20	2,03	0,18	3,42	0,12	-5,27 10^{-5}	1,18 10^{-3}	3,61 10^{-5}	1,72 10^{-4}	0,62	4,52 10^{-2}	7,67	0,11	0,15	9,31 10^{-4}	0,25	5,22 10^{-4}
T1000-G4	3.26	0,54	2,47	0,48	-4,11 10^{-3}	3,14 10^{-3}	-1,54 10^{-3}	3,94 10^{-4}	1,87	0,43	6,93	0,19	0,17	1,20 10^{-2}	0,20	4,05 10^{-3}
T1000-G6	3,14	0,26	3,19	0,26	-2,92 10^{-3}	2,94 10^{-3}	-9,01 10^{-4}	2,97 10^{-4}	1,04	0,15	6,87	9,49 10^{-2}	0,10	2,91 10^{-3}	0,21	1,95 10^{-3}
T1000-G8	3,38	0,20	2,75	0,14	-2,46 10^{-3}	1,91 10^{-3}	-7,72 10^{-4}	2,08 10^{-4}	1,28	7,27 10^{-2}	6,71	6,81 10^{-2}	7,23 10^{-2}	2,31 10^{-3}	0,28	1,10 10^{-3}
T1000G10	3,14	0,16	3,23	0,14	-3,34 10^{-3}	1,78 10^{-3}	-1,04 10^{-3}	1,76 10^{-4}	0,99	6,17 10^{-2}	6,96	5,71 10^{-2}	6,03 10^{-2}	8,06 10^{-4}	0,27	9,46 10^{-4}
T1000G12	2,93	8,65 10^{-2}	3,36	0,11	-4,93 10^{-3}	1,42 10^{-3}	-1,56 10^{-3}	1,45 10^{-4}	0,93	4,44 10^{-2}	7,06	3,34 10^{-2}	7,49 10^{-2}	2,11 10^{-3}	0,27	8,86 10^{-4}
T1000G20	2,99	8,89 10^{-2}	3,34	7,70 10^{-2}	-3,65 10^{-3}	8,660 10^{-4}	-1,15 10^{-3}	8,65 10^{-5}	0,97	2,17 10^{-2}	7,05	2,95 10^{-2}	0,15	9,31 10^{-4}	0,25	5,22 10^{-4}
T1500-G4	2,66	0,25	3,38	0,17	-1,64 10^{-3}	2,51 10^{-3}	-5,08 10^{-4}	2,78 10^{-4}	0,56	0,10	6,93	9,32 10^{-2}	0,22	2,26 10^{-3}	0,17	3,94 10^{-4}
T1500-G6	2,41	0,13	3,25	0,15	-1,88 10^{-3}	1,50 10^{-3}	-6,33 10^{-4}	1,93 10^{-4}	0,71	9,83 10^{-2}	7,23	5,38 10^{-2}	0,22	1,12 10^{-3}	0,22	1,17 10^{-4}
T1500-G8	2,61	0,10	3,07	8,82 10^{-2}	-2,84 10^{-3}	1,27 10^{-3}	-9,72 10^{-4}	1,59 10^{-4}	0,84	4,20 10^{-2}	7,19	4,13 10^{-2}	0,24	8,68 10^{-4}	0,19	6,16 10^{-4}
T1500-G10	2,65	3,79 10^{-2}	3,02	6,90 10^{-2}	-3,01 10^{-3}	9,27 10^{-4}	-1,06 10^{-3}	1,16 10^{-4}	0,90	3,31 10^{-2}	7,20	2,07 10^{-2}	0,22	7,11 10^{-4}	0,22	5,87 10^{-4}
T1500-G12	2,46	6,20 10^{-2}	3,30	7,16 10^{-2}	-2,38 10^{-3}	7,54 10^{-4}	-8,25 10^{-4}	9,28 10^{-5}	0,76	3,03 10^{-2}	7,30	2,56 10^{-2}	0,20	3,82 10^{-4}	0,23	4,57 10^{-4}
T1500-G20	2,57	5,31 10^{-2}	3,29	4,06 10^{-2}	-2,47 10^{-3}	5,13 10^{-4}	-8,38 10^{-4}	6,05 10^{-5}	0,80	1,38 10^{-2}	7,21	1,79 10^{-2}	0,21	3,71 10^{-4}	0,23	2,94 10^{-4}
T2000-G4	3,86	0,27	3,09	0,28	-2,70 10^{-3}	2,44 10^{-3}	-8,05 10^{-4}	2,07 10^{-4}	1,05	0,25	6,67	9,00 10^{-2}	0,26	1,10 10^{-3}	0,21	1,28 10^{-3}
T2000-G6	3,48	0,13	3,02	0,16	-3,47 10^{-3}	1,48 10^{-3}	-1,09 10^{-3}	1,42 10^{-4}	1,17	0,12	6,90	4,77 10^{-2}	0,24	5,31 10^{-4}	0,21	7,04 10^{-4}
T2000-G8	3,18	0,10	2,90	8,35 10^{-2}	-3,13 10^{-3}	1,03 10^{-3}	-1,01 10^{-3}	1,12 10^{-4}	1,13	4,31 10^{-2}	7,01	3,49 10^{-2}	0,22	4,55 10^{-4}	0,20	3,74 10^{-4}
T2000-G10	3,14	8,47 10^{-2}	2,79	8,10 10^{-2}	-2,16 10^{-4}	7,69 10^{-4}	-7,37 10^{-4}	8,83 10^{-5}	1,17	3,70 10^{-2}	7,01	2,80 10^{-2}	0,22	3,78 10^{-4}	0,20	3,63 10^{-4}
T2000-G12	2,90	5,61 10^{-2}	3,01	6,27 10^{-2}	-1,94 10^{-4}	6,46 10^{-4}	-6,55 10^{-4}	7,40 10^{-5}	1,09	2,71 10^{-2}	7,10	2,07 10^{-2}	0,20	2,55 10^{-4}	0,21	2,79 10^{-4}
T2000-G20	2,90	2,85 10^{-2}	3,19	3,46 10^{-2}	-3,07 10^{-3}	4,10 10^{-4}	-1,01 10^{-3}	4,44 10^{-5}	1,08	1,29 10^{-2}	7,03	1,08 10^{-2}	0,20	1,28 10^{-4}	0,22	1,46 10^{-4}

σ^2_d Direct genetic additive variance,
σ^2_m Maternal genetic additive variance,
σ_{md} Direct-maternal covariance,
σ^2_C Permanent environmental effect variance
σ^2_e Residual variance
h^2 Direct heritability
m^2 Maternal heritability

Maternal variance estimates ranged between 2,0503 and 4,3426. This estimates is higher than most estimates reported in many research works on estimation of genetic parameters of lamb growth (Neser et al.2001;Bedhiaf-Romdhani and Djemali 2006;Mandal et al., 2006; Mokhtari et al. 2008).The marginal distributions of the maternal variance is about 3,9289 for a complete raw information and it varied between -0,3 and 10,6, with a sire raw missing information this value is about 4,342 and varied from 0,36 and 11.5 (Figures 3 and 4).

The permanent environmental variance estimates varied from 0,3137 and 1,875, these values are similar with major works (Neser et al. 2001;Bedhiaf-Romdhani and Djemali 2006;Mandal et al. 2006; Mokhtari et al. 2008). The marginal distributions of this criteria is ranged between -0.2 and 6.02 with a complete raw information and -0,3 and 7,14 with a sire raw missing information (Figures 5 and 6).

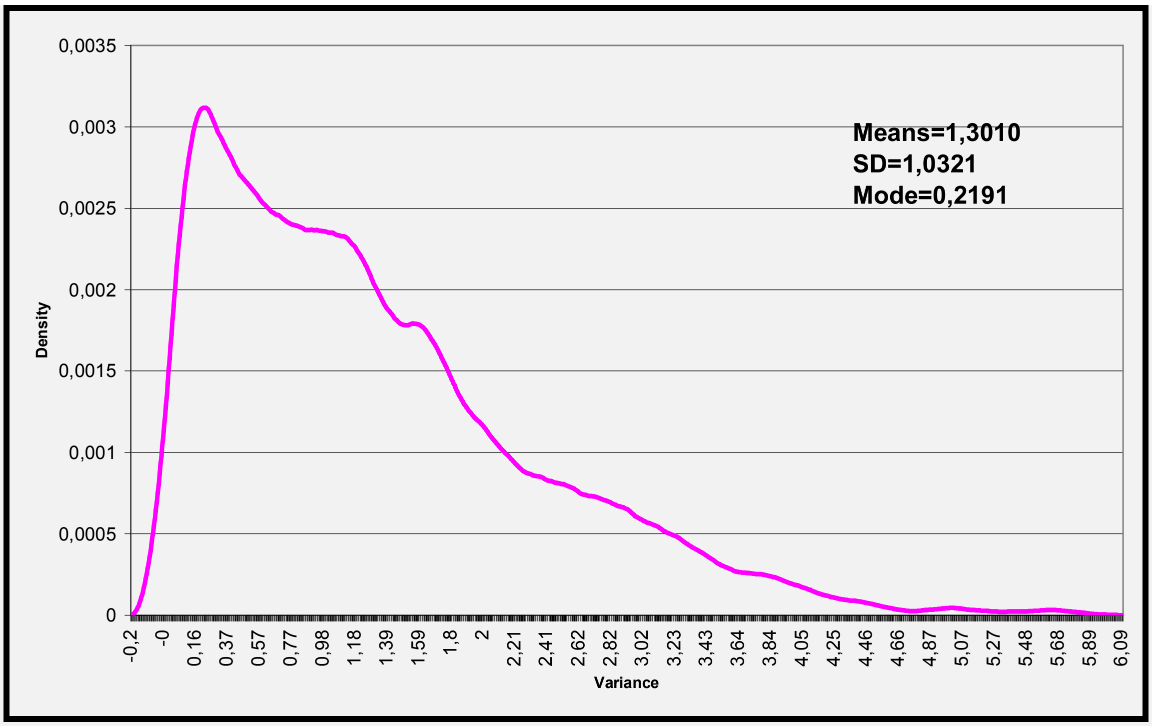

Figure 5. Posterior density function permanent environmental variance (T100-G4) Complete ram information

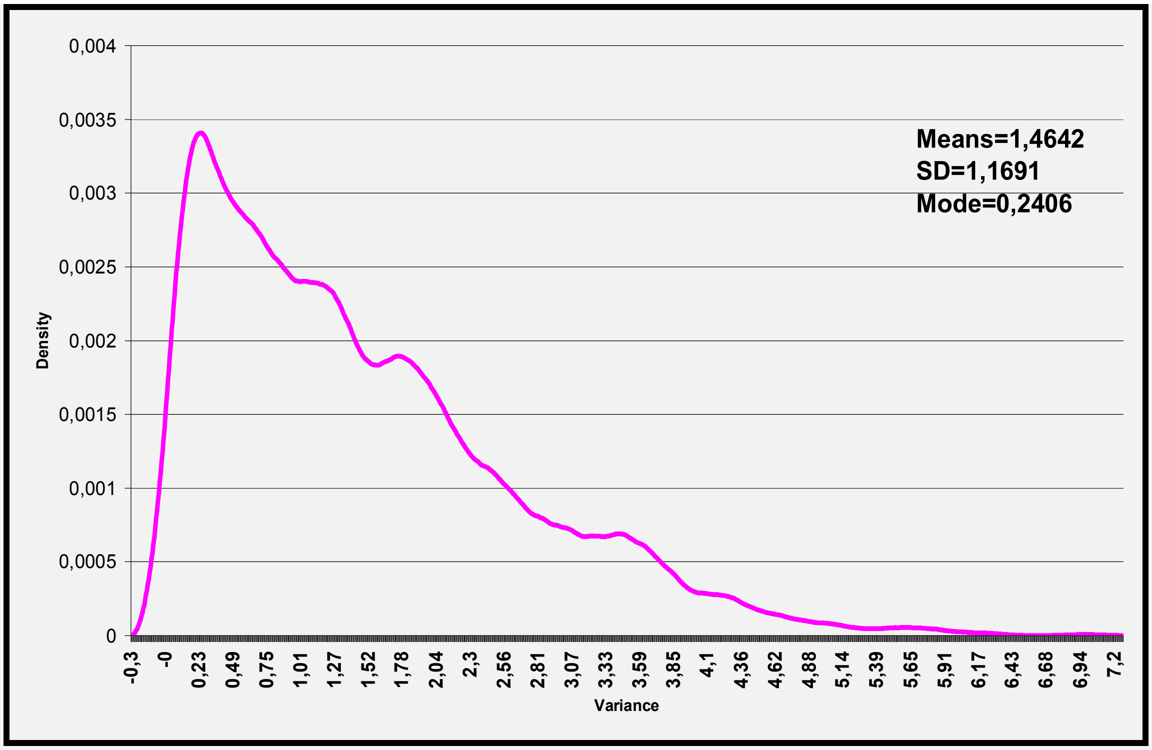

Figure 6. Posterior density function of permanent environmental variance (T100-SG-G4) sire ram missing information

The residual variance estimates ranged between 5,5483 and 8,6613. Only Mandal et al. (2006) results are lower with 4,550. Bedhiaf-romdhani and Djemali (2006), Mokhtari et al.(2008) and Rachidi et al.(2008) have the same results (between 5,35 and 7,25). Neser et al.(2001) and Ozcan et al.(2005) results are higher with 13,58 and 22,53 respectively.

3.2. Heritability's

Direct heritability estimates for weaning weight of Barbarin lambs varied from 0,1026 to 0,2916. The same results are reported by more research teams and it ranged between 0,058 and 0,40 (Table 3). The marginal distributions estimate for complete raw information is about 0,1481 with minima of -0,0208 and maxima of 0.66. For a sire raw missing information the direct heritability was 0,1868, the lower value is -0,0309 and the higher is 0,7 (Figures 7 and 8).

Table 3. Summary of published estimates of genetic parameters for lamb weaning weight

Breed	h^2	m^2	r_{am}	Author
Dorper	0,20±0,07	0,10±0,07	-0,58	Neser et al.(2001)
Turkish merino	0,12±0,04	0,04±0,02	-0,92	Ozcan et al.(2005)
Barbarin	0,058	0,108	0,412	Bedhiaf-Romdhani and Djemali (2006)
Muzzaffarangari	0,40	0,04	-1,00	Mandal et al.(2006)
Beulah Specklefaced				
Kermani	0,23±0,03	0,11±0,03	-0,73±0,10	Husain et al.(2007)
	0,33±0,05	0,05±0,03	-0,41±0,23	Rachidi et al.(2008)

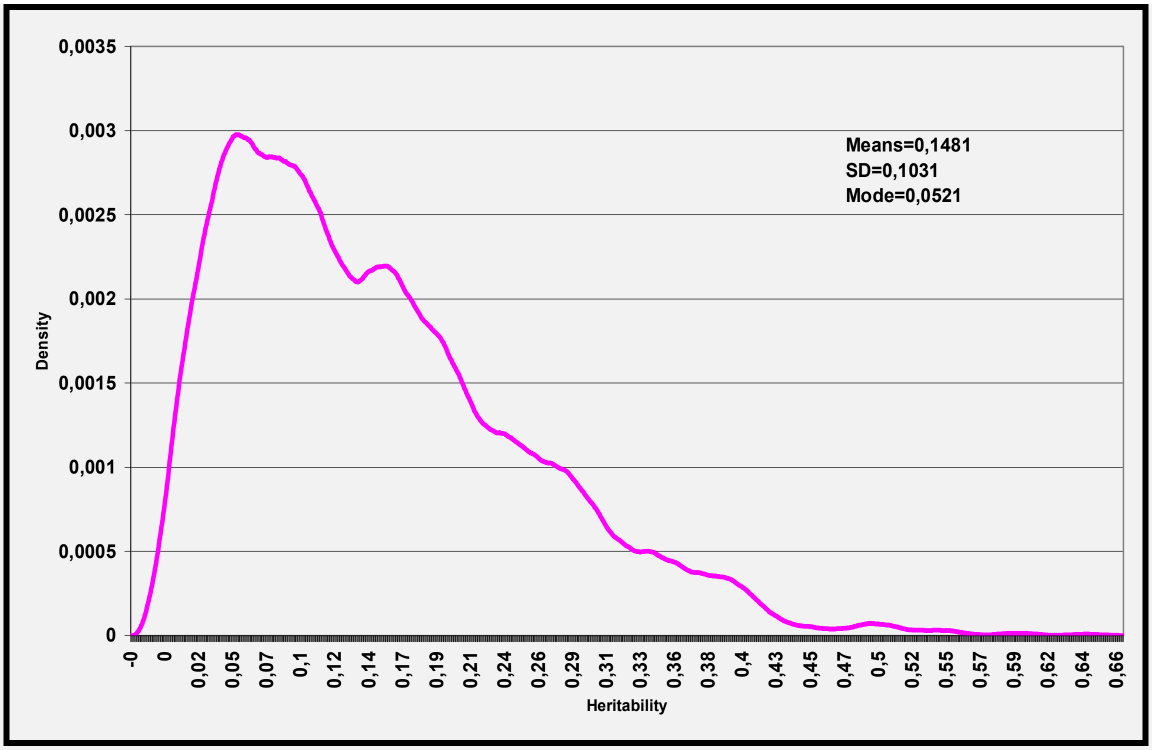

Figure7. Posterior density function of direct heritability (T100-G4) Complete ram information

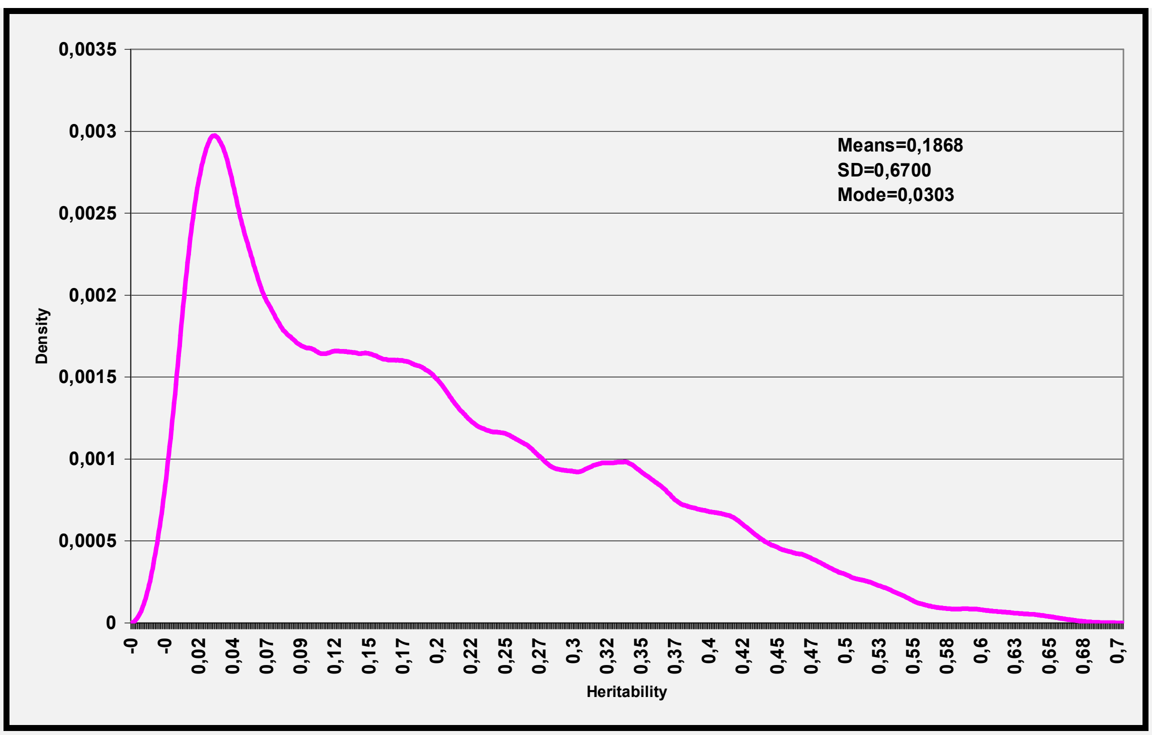

Figure 8. Posterior density function of direct heritability (T100-SG-G4) sire ram missing information

The maternal heritability estimation ranged between 0.155 and 0.2813,all published estimates in Table 3 varied from 0,04 to 0,11. The marginal distributions estimates varied from 0,03 to 0,54 with a complete raw information and it starting from -0,016 to 0,53 (figures 9 and 10).

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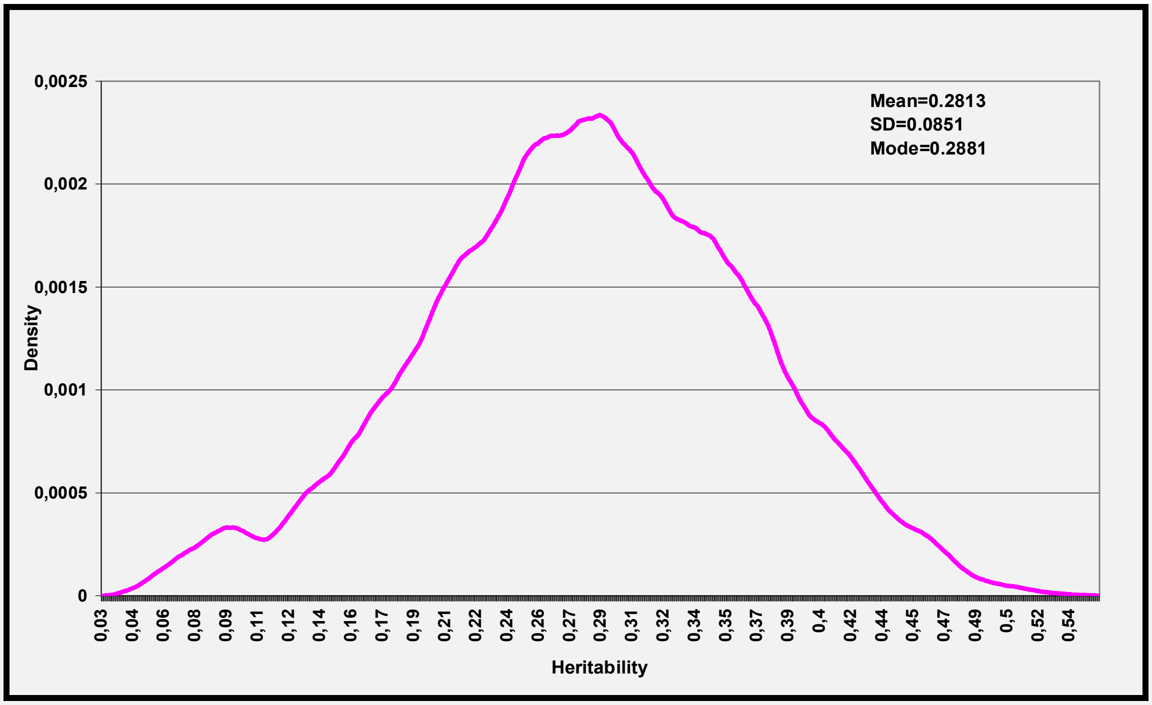

Figure 9. Posterior density function of maternal heritability (T100-G4) Complete ram information

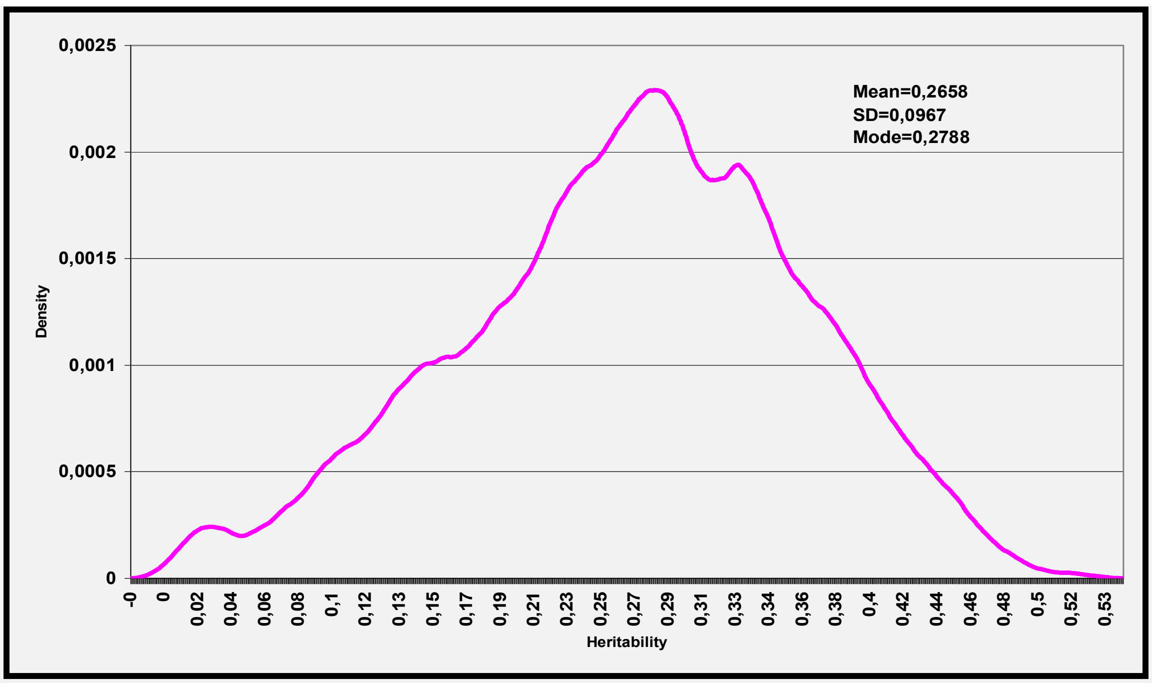

Figure 10. Posterior density function of maternal heritability (T100-SG-G4) sire ram missing information

4. Conclusion

The estimation of genetic parameters by Bayesian methodology via Gibbs sampling applied to a multitrait animal model to explain the largest variability of results in major works on weaning weight of lambs.

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