

4 **A case study of *Eucalyptus globulus* fingerprinting**  
5 **for breeding**6 **Maria Margarida Ribeiro · Leopoldo Sanchez ·**  
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11

12 **Abstract**13 • **Introduction** Tree genetic improvement programs usually  
14 lack, in general, *pedigree* information. Since molecular  
15 markers can be used to estimate the level of genetic  
16 similarity between individuals, we genotyped a sample of a  
17 Portuguese *Eucalyptus globulus* breeding population—a  
18 reference population of 125 individuals—with 16 micro-  
19 satellites (SSR).  
20 • **Materials and methods** Using genotypes from the  
21 reference population, we developed a simulation approach  
22 to recurrently generate ( $10^5$  replicates) virtual offspring  
23 with different relatedness: selfed, half-sib, full-sib andunrelated individuals. Four commonly used pairwise sim- 24  
ilarity coefficients were tested on these groups of simulated 25  
offspring. Significant deficits in heterozygosity were 26  
found for some markers in the reference population, 27  
likely due to the presence of null alleles. Therefore, the 28  
impact of null alleles in the relatedness estimates was 29  
also studied. We conservatively assumed that all 30  
homozygotes in the reference population were carriers 31  
of null alleles. 32  
• **Results** All estimators were unbiased, but one of them 33  
was better adjusted to our data set, even when null alleles 34  
were considered. The estimator's accuracy and precision 35  
were validated with individuals of known pedigree obtained 36  
from controlled crosses made with the same reference 37  
population's parents. Additionally, a clustering algorithm 38  
based on the estimator of choice was constructed, in order to 39  
infer the relatedness among 24 *E. globulus* elite individuals. 40  
We detected four putatively related elite individuals' pairs 41  
(six pairs considering the presence of null alleles). 42  
• **Conclusions** This work demonstrates that in the absence 43  
of pedigree information, our approach could be useful to 44  
identify relatives and minimize consanguinity in breeding 45  
populations. 46

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2070-220 Cartaxo, Portugal**Keywords** Microsatellites · *Eucalyptus globulus* · Null 47  
alleles · Relatedness 48**1 Introduction** 49*Eucalyptus globulus* ssp. *globulus* (hereafter *E. globulus*) is 50  
an economically important species for pulpwood produc- 51  
tion, actively bred in many countries (Eldridge et al. 1994), 52  
including Portugal, where the first formal breeding program 53  
for the species began in 1966 (Borralho et al. 2007). In general, 54

55 the foundation of breeding populations aims to capture, as  
 56 close as possible, the genetic diversity of the original  
 57 population. However, breeding activities will rapidly reduce  
 58 genetic diversity due to selection intensity, linkage and  
 59 random drift in finite populations (Lefèvre 2004). Moreover,  
 60 inbreeding depression is known to be severe in this species  
 61 (Hardner and Potts 1995; Costa e Silva et al. 2010). To  
 62 ensure that levels of coancestry and inbreeding among  
 63 selected trees are kept to a minimum, it would be  
 64 advantageous to know the relatedness among parents of  
 65 unknown *pedigree*, particularly in early stages of breeding  
 66 programs (Ballou and Lacy 1995). In the absence of  
 67 known pedigree information, estimates of relatedness  
 68 between individuals can be obtained through the use of  
 69 molecular markers. Codominant microsatellite markers  
 70 (SSR) are particularly suitable for this purpose, as they  
 71 can be used to estimate individuals' pairwise relatedness,  
 72 based on probability ratios of identity in state between  
 73 individuals and an unrelated reference population. These  
 74 estimates are very useful to infer the level of relatedness  
 75 among sub-populations of elite material, to assure the  
 76 deployment of unrelated elite clones and/or for the  
 77 design of controlled crosses between putatively unrelated  
 78 parents.

79 Estimators of pairwise relatedness were first consid-  
 80 ered for DNA data by Lynch (1988). This first estimator  
 81 was modified by Li et al. in order to accommodate  
 82 codominant markers (1993). Band sharing by chance is  
 83 difficult to separate from band sharing by descent, and a  
 84 method-of-moments (MM) estimator for pairwise related-  
 85 ness was developed by Queller and Goodnight (1989).  
 86 Afterwards, more accurate and precise MM estimators  
 87 were developed by Ritland (1996) and Lynch and Ritland  
 88 (1999). Recently, Wang (2002) introduced a new estima-  
 89 tor, an improved version of the one proposed by Li et al.  
 90 (1993), but Csillery et al. (2006) demonstrated that its  
 91 performance was poor. Other estimators, including max-  
 92 imum likelihood methods (ML), were proposed to esti-  
 93 mate relatedness in the absence of known pedigree  
 94 structure (Queller and Goodnight 1989; Li et al. 1993;  
 95 Lynch and Ritland 1999; Wang 2002; Milligan 2003;  
 96 Thomas 2005; Oliehoek et al. 2006) and were used in  
 97 different areas of research (reviewed by Blouin 2003 and  
 98 Thomas 2005). Their performance was compared in  
 99 several studies using simulated and empirical datasets  
 100 (Lynch and Ritland 1999; Van de Castele et al. 2001;  
 101 Wang 2002; Milligan 2003; Csillery et al. 2006). These  
 102 studies agree in that no single estimator is universally  
 103 superior to the others in terms of bias and variance and  
 104 that the performance rank order of the estimators depends  
 105 on the estimation of the true relatedness value, the  
 106 informativeness of the markers (number of *loci* and number  
 107 and frequencies of alleles per *locus*) and the sample size used

108 to estimate allele frequencies. For the commonly available  
 109 markers in most studies (~ 5 to 20 microsatellites), the  
 110 MM estimators are preferred because the ideal proper-  
 111 ties of ML methods are only achieved asymptotically  
 112 (Lynch and Ritland 1999; Wang 2002; Milligan 2003).  
 113 Additionally, the presence of null alleles in SSR markers  
 114 can introduce a bias in the estimation of relatedness  
 115 (Wagner et al. 2006). However, little is known on the  
 116 actual impact of null alleles on the behaviour of relatedness  
 117 estimators.

118 In this study, we compared three commonly used MM  
 119 coefficients to estimate pairwise similarity: Ritland  
 120 (1996) (R), Queller and Goodnight (1989) (Q) and Lynch  
 121 and Ritland (1999) (LR), and a band sharing method: Li et  
 122 al. (1993) (L), in the context of a Portuguese *E. globulus*  
 123 breeding population. We followed a Monte Carlo simula-  
 124 tion strategy and, unlike previous studies in the literature,  
 125 considered two different criteria to identify the best  
 126 performing estimator: (1) smaller average overlapping  
 127 areas between every two density distribution relatedness  
 128 categories and (2) smaller impact from the presence of  
 129 null alleles.

130 We have used 16 publicly available SSR markers to  
 131 screen 125 putatively unrelated individuals from an elite  
 132 breeding population of *E. globulus*. The assumption of  
 133 Hardy-Weinberg equilibrium in breeding populations of  
 134 artificial origin might not hold true. However, this issue  
 135 was overcome by measuring relatedness on the randomly  
 136 generated *in silico* individuals from the existing parents in  
 137 the reference breeding population.

138 In order to define a threshold to transform the continuous  
 139 range given by the pairwise methods into genealogical  
 140 relatedness (e.g. Blouin et al. 1996; Kozfkay et al. 2008),  
 141 the density distributions of the simulated selfed, half-sib,  
 142 full-sib and unrelated offspring were obtained. The selected  
 143 threshold corresponds to the interception of the probability  
 144 distribution curves of the unrelated and the half-sib  
 145 individuals. This critical value is only coincident with the  
 146 cut-off defined by Blouin et al. (1996) when the density  
 147 distributions are absolutely symmetric, which is not always  
 148 the case (e.g. Kozfkay et al. 2008). An additional  
 149 population of 24 elite trees from the genetic improvement  
 150 program was genotyped, as a practical application of the  
 151 methodology developed here.

152 The objectives of this study are to provide estimates  
 153 of the genetic parameters of the SSR used, including its  
 154 discriminant power (*D*), to select the better suited  
 155 relatedness estimator across unrelated (UR), half-sib  
 156 (HS), full-sib (FS) and individuals generated by selfing a  
 157 single parent (SF), to validate the estimator's precision and  
 158 accuracy with individuals of known pedigree (HS, FS and SF),  
 159 and to study the impact of null alleles in the relatedness  
 160 estimates.

161 **2 Material and methods**

162 2.1 Plant material and DNA extraction

163 The *E. globulus* population of 125 putatively unrelated  
 164 individuals (hereafter reference population, RP), includes  
 165 12 individuals used in controlled crosses to produce the  
 166 validation population. The remaining 113 were putatively  
 167 unrelated *E. globulus* individuals representative of the  
 168 genetic improvement population of RAIZ (Forestry and  
 169 Paper Research Institute, Portugal) (Borrvalho et al. 2007).  
 170 This group includes 47 trees originally selected in planta-  
 171 tions in Portugal (referred herein as “Portuguese land race”)  
 172 and 66 trees from 13 Australian native races (classification  
 173 follows Dutkowski and Potts (1999)). The validation  
 174 population comprised three half-sib families, three full-sib  
 175 families and four selfed families (each family with  
 176 individuals generated by selfing a single parent), from  
 177 controlled crosses made between 12 putatively unrelated  
 178 individuals of the Portuguese land race. Each family had six  
 179 offspring. An extra set of 24 elite clones was also  
 180 genotyped. These 24 elite trees were used as a practical  
 181 application of the proposed methodology. They were  
 182 selected from RAIZ *E. globulus* breeding population and  
 183 are to be used for deployment. Total genomic DNA was  
 184 extracted as in Marques et al. (1998). DNA concentration  
 185 was estimated by comparison of the fluorescence intensities  
 186 of ethidium bromide-stained samples to those of  $\lambda$ DNA  
 187 standards, on 1% agarose gels.

188 2.2 SSR, PCR conditions and sizing of PCR products

189 Sixteen publicly available eucalypt SSR (Appendix 1<sup>1</sup>)  
 190 were selected for its allele number and effective number of  
 191 alleles (Table 1). SSR primer design was described  
 192 elsewhere (EMBRA 1–20 in Brondani et al (1998),  
 193 EMCRC1-12 in Steane et al. (2001) and EMBRA 21–70  
 194 in Brondani et al. (2002)). Each SSR marker was  
 195 assigned to a consensus linkage group based on *E.*  
 196 *globulus* genetic linkage maps (unpublished results) and  
 197 a consensus map of a *Eucalyptus grandis* × *Eucalyptus*  
 198 *urophylla* pedigree (Brondani et al. 2006). EMCRC5 was  
 199 the only unmapped marker in this study. Three SSR  
 200 (EMBRA 6, EMBRA 11 and EMBRA 12) mapped to the  
 201 same linkage group (no. 1, see Appendix 1), but in  
 202 different locations (unpublished results). The remaining  
 203 seven SSR mapped to different linkage groups. Despite  
 204 the fact that we expect high SSR synteny in the eucalypt  
 205 *Symphomyrtus* subgenus (Marques et al. 2002), we  
 206 performed linkage disequilibria tests for all loci combina-

tions with the Genepop version 4.0.7 (Rousset 2008). The  
*p* values were obtained by the contingency table approach  
 (Fisher’s exact test), and the number of dememorization  
 steps was 10,000, with 1,000 batches and 100,000 iterations  
 per batch. The significance level, with a probability of type I  
 error of 1%, took into account the number of tests performed  
 by using the Bonferroni correction (Sokal and Rohlf 1997).  
 The Hardy–Weinberg test was made by estimating the exact  
*p* values by the Markov chain method, with the same  
 dememorization steps, batches and iterations per batch  
 referred in the foregoing. The null allele frequencies per  
 loci were estimated by using a maximum likelihood EM  
 algorithm. Both were computed with the Genepop software.

Polymerase chain reaction amplification of SSR loci  
 was carried out in 96-well V-bottom plates. Each reaction  
 contained 0.2, 0.15 and 0.1  $\mu$ M of primer (for SSR in  
 groups 1, 2 and 3, respectively—Appendix 1), 0.5 U of  
 Taq DNA polymerase (Promega, Madison, WI, USA),  
 0.2 mM of each dNTP (otherwise as specified in  
 Appendix 1, Promega, Madison, WI, USA), 1 $\times$  reaction  
 buffer (Promega, Madison, WI, USA), 2 mM of MgCl<sub>2</sub>  
 (Promega, Madison, WI, USA), DMSO 5.0% (Sigma)  
 and 20 ng of template DNA in a final 10- $\mu$ l volume.  
 Forward primers were IRD800 (5'-fluoresceine) labelled.  
 Reactions were cycled in an MJ Research PT-100  
 Thermal Controller with a heated lid, 94°C for 30 s,  
 followed by 15 cycles of variable annealing temperature  
 (“touch down”): 94°C for 30 s, 30 s of annealing  
 (from 56°C, with a decrease of 0.2°C every cycle), and  
 72°C for 45 s; then 20 cycles of 94°C for 30 s, 53°C  
 for 30 s and 72°C for 45 s; and finally 72°C for 7 min.  
 Amplification products were denatured by adding 10  $\mu$ L of  
 formamide buffer (98% formamide deionized, 10 mM EDTA  
 pH 8.0, 60 mg bromophenol blue), heated 5 min at 70 C  
 (Termomixer Confort, Eppendorf), and 0.8  $\mu$ L of the  
 samples was loaded in 6% acrylamide denaturing gel  
 (50% Long-Ranger-, with 10.5 g Urea and 2.5 ml TBE  
 (10 $\times$ )). Fragments were separated using a LI-COR automatic  
 DNA sequencer (model 4200 Gene Reader) at 1,500 V, 25 W  
 constant power, 45°C of plate temperature and a 1 $\times$  TBE  
 running buffer, for approximately 2 h. RFLPscan was used to  
 retrieve the gel image, and the presence of the bands was  
 visually scored with the help of a LA4000-44B LI-COR  
 ladder.

2.3 Relatedness estimators

The coancestry coefficient ( $\theta$ ) between individuals *x* and *y*  
 is the probability that two randomly chosen homologous  
 alleles are identical ‘by descent’ (Lynch and Walsh 1998).  
 In a diploid mating system, the coefficient of coancestry  
 multiplied by 2 equals the coefficient of relatedness,  $r_{xy}$ ,  
 which is the expected fraction of alleles identical by

<sup>1</sup> Appendix is available online only at [www.asf-journal.org](http://www.asf-journal.org).

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**Table 1** Diversity parameters for the 16 SSR loci in the reference population, ordered according to its discriminant power (*D*)

	$N_a$	$N_e$	$H_e$	$H_o$	$F_{is}$	Sig.	Null	$D$	t1.2
EMBRA23	21	12.8	0.93	0.89	0.04	NS	0.031	0.991	t1.3
EMBRA12	19	13	0.93	0.89	0.04	NS	0.025	0.991	t1.4
EMCRC8	18	12.8	0.93	0.84	0.09	S	0.049	0.987	t1.5
EMBRA18	21	11.5	0.92	0.90	0.01	NS	0.011	0.987	t1.6
EMCRC11	16	8.9	0.89	0.83	0.07	NS	0.032	0.981	t1.7
EMBRA6	15	8.8	0.89	0.78	0.12	S	0.055	0.976	t1.8
EMCRC10	18	8.6	0.89	0.65	0.26	S	0.130	0.960	t1.9
EMBRA11	21	9.4	0.90	0.87	0.02	NS	0.029	0.960	t1.10
EMBRA2	15	6.2	0.84	0.76	0.1	NS	0.044	0.959	t1.11
EMBRA8	14	6.2	0.84	0.76	0.1	NS	0.046	0.956	t1.12
EMCRC7	14	4.8	0.79	0.70	0.11	NS	0.048	0.932	t1.13
EMBRA20	13	4.7	0.79	0.62	0.21	S	0.091	0.929	t1.14
EMCRC2	15	4.5	0.78	0.62	0.2	S	0.107	0.915	t1.15
EMBRA5	21	5.2	0.82	0.50	0.34	S	0.158	0.898	t1.16
EMCRC5	21	5.5	0.81	0.53	0.37	S	0.165	0.898	t1.17
EMBRA19	6	3.4	0.71	0.54	0.24	S	0.155	0.855	t1.18
Mean	16.8	7.9	0.85	0.73	0.15		0.074	0.948	t1.19

Sig. refers to the significance resulting from the HWE test (after Bonferroni correction, where NS means not significant and S significant), and null refers to null allele frequency estimates  
 $N_a$  number of alleles per locus,  $N_e$  effective number of alleles,  $H_e$  expected heterozygosity,  $H_o$  observed heterozygosity,  $F_{is}$  fixation index

258 descent between two (related) individuals. Alleles are  
 259 identical by descent if they recently descend from a  
 260 single ancestral allele. Alleles that are identical by state  
 261 (IBS) might not be identical by descent if they coalesce  
 262 further back than the reference pedigree or arose  
 263 independently via mutation (see Blouin 2003 for details).  
 264 In fact, the estimated relatedness measures how much  
 265 higher (or lower) the probability of recent coalescence is  
 266 for any given pair ( $x, y$ ), relative to the average probability  
 267 for all pairs. The expected relatedness is 0.67 for selfed,  
 268 0.5 for full-sibs, 0.25 for half-sibs and 0 for unrelated  
 269 individuals. For example, on average, a pair of siblings  
 270 (FS) shares one out of two alleles identical by descent  
 271 (Squillace 1974; Falconer and Mackay 1996; Blouin 2003).

272 Lynch (1988) relatedness estimator based on band  
 273 sharing and modified by Li et al. (1993) (L) is:

$$r_{xy} = \frac{S_{xy} - s_0}{1 - s_0} \text{ and } s_0 = \sum_{i=1}^n p_i^2 (2 - p_i), \quad (1)$$

274 where  $S_{xy}$  is the similarity index  $S_{xy} = n_{xy}/2(1/n_x + 1/n_y)$ ,  $n_{xy}$   
 275 is the number of shared alleles between individuals  $x$  and  $y$ ,  
 276  $n_x$  is the number of alleles of  $x$ ,  $n_y$  is the number of alleles  
 277 of  $y$  and  $S_0$  is the number of shared alleles in the reference  
 278 population, based on the allele frequencies ( $p_i$  is the  
 279 frequency of the  $i$ th allele).  
 280  
 281  
 282

Ritland (1996) (R) coancestry estimator of individuals  $X=(A_1, A_2)$  and  $Y=(A_3, A_4)$  can be written as: 281 282

$$\theta_{xy} = \frac{1}{4(n_i - 1)} \times \left[ \left( \frac{\delta(A_1, A_3) + \delta(A_1, A_4)}{p(A_1)} \right) + \left( \frac{\delta(A_2, A_3) + \delta(A_2, A_4)}{p(A_2)} \right) - 1 \right] \quad (2)$$

283 where  $\delta$ , the Kronecker operator, is defined for alleles  $A_i$  and  
 284  $A_j$ :  $\delta(A_i, A_j) = 1$  if  $A_i = A_j$ , and  $\delta(A_i, A_j) = 0$  if  $A_i \neq A_j$ . We have six  
 285 operators to compare two individuals (two within and four  
 286 between individuals) in the same locus,  $p(A_i)$  being the  
 287 frequency of the  $A_i$  allele in the considered locus and  
 288 reference population and  $n_i$  the total number of alleles in the  
 289 considered locus and reference population (Ritland 2000). 290

The Queller and Goodnight (1989) (Q) relatedness estimator is based on the same Kronecker operator and is described as: 291 292 293

$$r_{xy} = \frac{(\delta(A_1, A_3) + \delta(A_1, A_4) + \delta(A_2, A_3) + \delta(A_2, A_4) - p(A_1) - p(A_2))}{2(1 + \delta(A_1, A_2) - p(A_1) - p(A_2))} \quad (3)$$

294 Still based on Kronecker operators, Lynch and Ritland (1999) developed another relatedness estimator (LR) which is defined as follows: 295 296 297 298

$$r_{xy} = \frac{(p(A_1)\delta(A_2, A_3) + \delta(A_2, A_4)) + (p(A_2)\delta(A_1, A_3) + \delta(A_1, A_4)) - 4p(A_1)p(A_2)}{(1 + \delta(A_1, A_2))(p(A_1) + p(A_2)) - 4p(A_1)p(A_2)} \quad (4)$$

303  
304

306 2.4 Estimation of genetic parameters and simulation  
307 methods

308 For each SSR locus in the RP, the number of alleles ( $N_a$ ),  
309 the effective number of alleles ( $N_e=1/(1-H_e)$ ), the observed  
310 heterozygosity ( $H_o$ ) and the expected heterozygosity  
311 ( $H_e$ ) (Nei 1987) were computed with a FORTRAN  
312 program developed in this study, hereafter called Zeta  
313 (available upon request from LS). The fixation index  
314 ( $F_{is}$ ) (Weir and Cockerham 1984) was estimated with the  
315 Genepop software version 4.0.7.

316 The distribution of relatedness  $r$ -values estimated with  
317 the L, R, Q and LR coefficients was obtained by generating  
318  $10^5$  replicates of UR, HS, FS and SF individuals, from  
319 where mean and sampling variance values were calculated.  
320 Each replicate consisted of two in silico individuals. These  
321 individuals were obtained assuming free recombination and  
322 segregation out of parental SSR genotypes. Parents were  
323 sampled at random. In the UR group, four distinct parents  
324 were sampled and single-pair mated in order to obtain two  
325 unrelated offspring. For the HS group, three distinct parents  
326 were sampled, and one of them mated to the other two, in  
327 order to obtain one offspring from each mating. With the  
328 FS group, only two parents were sampled and mated, in  
329 order to obtain two full-sib individuals. Finally, in the SF's  
330 group, one parent was sampled and selfed twice, in order to  
331 get two offspring.

332 The relatedness between any two in silico individuals,  
333 measured in each replicate, the  $r$ -value ( $r_{xy}$ ), was computed  
334 using a weighted multilocus average:

$$\bar{r}_{xy} = \frac{\sum_i r_{xy(i)} / \text{Var}(r_{xy(i)})}{\sum_i 1 / \text{Var}(r_{xy(i)})},$$

336 where  $r_{xy(i)}$  is the estimator's value for the  $i$ th locus,  
337 according to one of the four estimators (L, R, Q or LR, in  
338 Eqs. 1, 2, 3 or 4, respectively), and  $\text{Var}(r_{xy(i)})$  is the Monte  
339 Carlo sampling variance for the same locus over  
340 replicates, which was used as a weighting factor for  
341 the multilocus average. Therefore, variable loci will  
342 account for less in the average, compared to less  
343 variable loci. A sampling variance was also calculated  
344 for the multilocus average ( $\text{Var } r_{xy}$ ), as the Monte Carlo  
345 variance over replicates.

346 In order to evaluate the informativeness of each SSR  
347 marker for fingerprinting, we estimated its discriminant  
348 power ( $D$ ) by using Zeta.  $D$  was the number of replicates in  
349 which a given marker was able to discriminate between two  
350 simulated individuals with a given level of relatedness, over  
351 the total number of  $10^5$  replicated pairs. The discriminant  
352 power was obtained for each marker and for each

relatedness group. This indicates the likelihood of discrim- 353  
ination of any two individuals derived from the reference 354  
population, over relatedness classes. 355

356 To study the impact of null alleles, we assumed an 357  
extreme simulation scenario where each putative homozy- 358  
gote in the RP was a carrier of one null allele. Pairwise 359  
relatedness estimators ( $r_{xym}$ ) were obtained with the proce- 360  
dure explained before and were compared to the 361  
corresponding cases without null alleles. 361

362 From each  $r$ -value distribution obtained from Zeta, based 362  
on  $10^5$  replicates, we randomly sampled 10,000 replicates 363  
(one tenth) and used them to draw density distributions. For 364  
each L, R, Q or LR estimator, we placed the four resulting 365  
density distributions from each relatedness group along the 366  
same axis and calculated the overlapping areas, i.e. UR- 367  
HS, UR-FS, UR-SF, HS-FS, HS-SF and FS-SF. The total 368  
overlapped area obtained per relatedness estimator was an 369  
indicator of its resolving power in distinguishing among 370  
relatedness classes. A similar procedure was carried out 371  
assuming null alleles. Based on the density distribution 372  
curves, we have also computed the exact percentiles at 373  
2.5% and 97.5% to frame the simulated multilocus  $r$ -values 374  
for each relatedness group and coefficient. Density distri- 375  
butions and corresponding overlapping areas were comput- 376  
ed with density functions written in the R statistical 377  
package (R Development Core Team 2008). 378

379 Most pairwise methods provide estimates within a 379  
continuous range that need to be converted into genealog- 380  
ical relatedness (UR, HS, FS and SF). This can be done 381  
through the use of arbitrary thresholds between relatedness 382  
classes, usually the midpoint between means of two 383  
consecutive relatedness classes (e.g. 0.125: UR-HS) 384  
(Blouin et al. 1996). We established the relatedness groups 385  
by looking at the overlapping area between density 386  
distributions and defining the relatedness value according 387  
to the interception point between any two overlapping 388  
distributions. This interception point was taken as the 389  
threshold between the two given relatedness classes 390  
(subsequently called the 'critical value'). This critical value 391  
minimizes both  $\beta$  and  $\alpha$  errors ( $\beta$  is the overlapping area to 392  
the left of the critical value and  $\alpha$  is the one to the right) 393  
(Kozfkay et al. 2008). Given that our interest was to know 394  
whether a given pair of individuals was unrelated or 395  
related to some extent, only one threshold between UR 396  
and the rest of the relatedness classes was obtained per 397  
estimator (L, R, Q or LR). The decision of accepting or 398  
rejecting the null ( $H_0$ : 'the pair are unrelated individuals') 399  
or the alternative hypotheses ( $H_1$ : 'the pair are half-sib 400  
individuals') was made comparing the observed  $r$ -value to 401  
the threshold. The threshold value was used to decide 402  
which pairs of the 24 trees from the elite population 403  
were related to some extent, at least at the half-sib level 404

405 (indicated by the comparison of the estimated pairwise  
406  $r$ -value with the threshold value), using the pairwise LR  
407 values (Fig. 5).

408 The relatedness estimator with the smallest percent-  
409 age of overlapping density probabilities and lower  
410 impact from the presence of null alleles was selected  
411 for further analysis with the 24 individuals of the elite  
412 population.

413 The validation population (three HS, three FS and four SF  
414 families) relatedness estimators were calculated using the  
415 SPAGeDi version 1.2 software (Hardy and Vekemans 2002).  
416 The pairwise relatedness matrix of the LR coefficient  
417 estimates for the 24 elite clones was used to perform an  
418 unweighted pair group method with arithmetic mean  
419 (UPGMA) dendrogram. The UPGMA tree topology was  
420 tested by comparing the elite clones LR pairwise matrix  
421 and the correspondent cophenetic matrix through a  
422 Mantel test (Sokal 1979). A normalized  $Z$  test was  
423 performed. The observed value after 1,000 permutations  
424 should be significantly larger than that expected by  
425 chance, in order for an association to be accepted.  
426 NTSYSpc version 2.1 (Rohlf 2000) was used to compute  
427 the UPGMA and the Mantel test.

428 **3 Results**

429 **3.1 SSR loci**

430 The effective number of alleles per loci ( $N_e$ ) in the reference  
431 population ranged from 6 to 21, with an average of 16.8  
432 (Table 1). The observed heterozygosity ( $H_o$ ) values  
433 ranged from 0.5 to 0.9. Loci with the same number of  
434 alleles ( $N_a$ ) exhibited different effective number of alleles  
435 ( $N_e$ ) and also different discriminant power ( $D$ ) (loci with  
436 21 alleles show  $N_e$  ranging from 5.2 to 12.8, Table 1). As  
437 an example, the allele frequency distributions of loci  
438 EMBRA5 and EMBRA23 (same  $N_a$  different  $N_e$ ) are  
439 displayed in Appendix 2. Locus EMBRA23 has a more even  
440 allele frequency distribution compared to locus EMBRA5,  
441 which results in differences in  $N_e$ , though they have the same  
442  $N_a$ . EMBRA5 has few high frequent alleles and many alleles  
443 with very low frequencies. Loci that displayed higher  
444 values of  $N_a/N_e$  also showed higher values in  $H_e/H_o$  ratio  
445 (i.e. EMBRA5, EMCRC5, EMBRA20 and EMCRC2) and  
446 are among the loci with lowest  $D$ .

447 High  $F_{is}$  values—the loss of heterozygosity due to non-  
448 random mating of parents —reflected differences between  
449 observed and expected heterozygosity. We need to note  
450 here that the reference population included individuals  
451 selected in stands after phenotypic evaluation and without  
452 pedigree information. Loci displayed different deviations  
453 from Hardy–Weinberg expectations (HWE), and half of

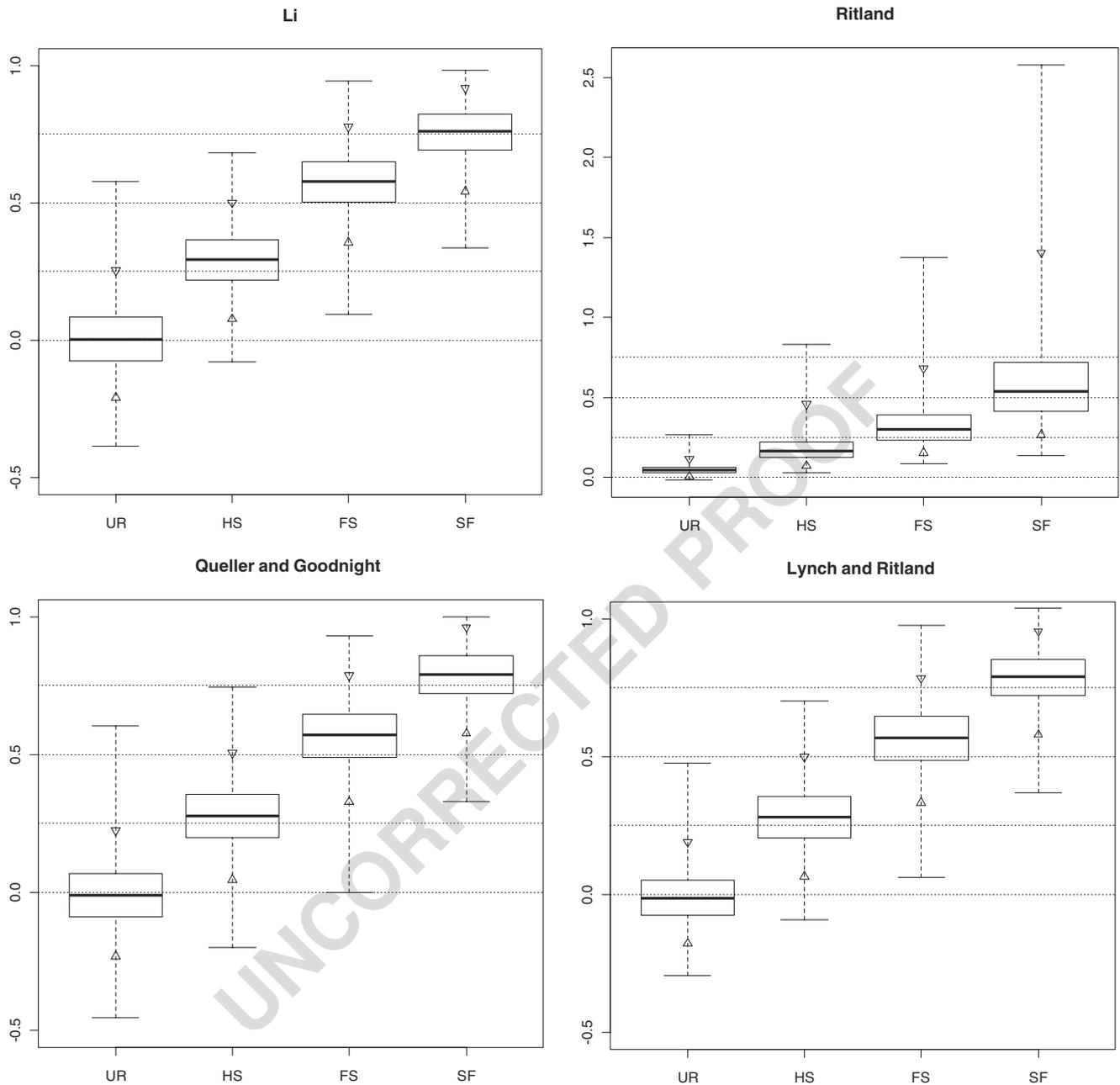
454 them were not under HWE. The presence of null alleles is  
455 one complementary hypothesis for departures from HWE.  
456 Table 1 shows null allele frequencies above 5% and  
457 significant HWE deviations for EMBRA6, EMCRC10,  
458 EMBRA20, EMCRC2 EMBRA5, EMCRC5 and  
459 EMBRA19. All loci combinations gave non-significant  
460 *linkage disequilibrium* values after the Bonferroni correc-  
461 tion. The only locus without mapping information  
462 (EMCRC5) appeared not linked to any other marker.  
463 Therefore, we assumed that all the markers used in this  
464 study have independent segregation.

465 **3.2 Relatedness estimators**

466 All estimators revealed similar levels of upward bias  
467 (the distance between the expected relatedness value and  
468 the observed mean) (Fig. 1), more evident in the higher  
469 relatedness class (FS and SF). Despite these biases,  
470 expected values fell well within exact percentiles at  
471 2.5% and 97.5% for all four estimators and relatedness  
472 classes. R showed a different behaviour, with overlapping  
473 exact percentiles at 2.5% and 97.5% for all the relatedness  
474 classes. According to this information, unrelated individ-  
475 uals could be distinguished from FS and SF individuals,  
476 and HS could be distinguished from SF individuals, for  
477 all estimators except R. The LR estimator produced  
478 slightly smaller exact percentiles at 2.5% and 97.5%  
479 (confidence percentiles=CP) than the Q estimator, in  
480 particular the UR class. The L estimator had slightly  
481 smaller confidence percentiles than LR, but not in the case of  
482 the unrelated individuals. Considering the percentage of  
483 overlapping areas of the density distributions of  $r$ -values  
484 (without taking into account the presence of null alleles),  
485 on average, the R coefficient had the highest mean  
486 overlapping distributions' area (OD) across relatedness  
487 groups (20.8%) and the LR estimator the lowest (11.6%),  
488 as shown in Table 2. The percentage of overlapping area  
489 was higher, for the comparison between FS–SF (36.5%),  
490 followed by the HS–FS and the UR–HS. The lowest  
491 OD was found in the UR–SF, with no overlapping  
492 areas for LR and Q estimators. Therefore, the over-  
493 lapping area for LR was generally the lowest, with the  
494 exceptions in the comparison UR–HS where it equalled  
495 R and in HS–FS where the L coefficient had a slightly  
496 better performance.

497 Considering nonparametric tests the overlapping areas,  
498 the worst behaving coefficient is R. LR proved to be the  
499 best overall performing relatedness estimator displaying  
500 the smallest average percentage of overlapping areas  
501 (11.6%), when compared with the other estimators' ODs  
502 (Table 2).

503 In Fig. 2, the density distributions for all relatedness  
504 estimators, without null alleles, are represented. L, Q and



**Fig. 1** Distribution of simulated multilocus  $r$ -values (*whiskers* for maxima and minima, *triangles* for exact percentiles at 2.5% and 97.5%, *bottom and top of the box* for the lower and upper quartiles, respectively, and *band near the middle of the box* for the median) in the different relatedness groups (unrelated, half-sibs, full-sibs

(FS) and individuals generated by selfing a single parent (SF) for different relatedness/coancestry estimators: Li et al. (1993) (L), Ritland (1996) (R), Queller and Goodnight (1989) (Q) and Lynch and Ritland (1999) (LR)

505 LR show approximately similar densities, with LR having a  
 506 slightly narrower curve for UR. In general, these three  
 507 estimators show symmetrical curves for UR, with asym-  
 508 metry increasing progressively towards classes with higher  
 509 relatedness. In SF class of  $r$ -values, the right tail is slightly  
 510 shorter than the left tail, i.e. exhibiting negative skewness.  
 511 Considering the R estimator, the density curve was  
 512 extremely leptokurtic for UR  $r$ -values, and with increasing

513 platykurtic properties and positive skewness towards  
 514 classes with higher relatedness.

515 The LR pairwise relatedness values computed for the  
 516 groups of individuals with known pedigree (SF, full-sibs,  
 517 half-sibs and unrelated) are shown in Fig. 3, together with  
 518 the corresponding exact percentiles at 2.5% and 97.5%.  
 519 Observed LR relatedness appears slightly downward biased  
 520 for half-sib and full-sib groups, while SF shows upward

t2.1 **Table 2** Relatedness group overlapping distribution areas excluding and accounting for null alleles (percent)

t2.2		L		R		Q		LR		Mean	
		No nulls	Nulls								
t2.4	UR–HS	21.49	38.70	15.45	26.50	21.87	37.35	15.53	29.05	18.58	32.90
t2.5	UR–FS	1.32	8.95	2.23	7.10	1.40	8.08	0.67	4.27	1.40	7.10
t2.6	UR–SF	0.07	0.11	0.31	1.64	0.03	0.31	0.00	0.13	0.10	0.55
t2.7	HS–FS	19.38	40.38	44.35	53.25	21.78	40.11	21.00	36.16	26.63	42.47
t2.8	HS–SF	2.48	1.90	16.80	26.50	1.83	5.12	1.56	5.04	5.67	9.64
t2.9	FS–SF	38.35	16.17	45.50	60.40	31.13	30.23	30.87	34.02	36.46	35.20
t2.10	Mean	13.85	17.70	20.77	29.23	13.01	20.20	11.60	18.11		

See Figs. 2 and 4 for details

521 estimates, when compared to theoretical expectations. All  
 522 observed estimates fell within the exact percentiles at 2.5%  
 523 and 97.5%. Additionally, LR was also calculated for the  
 524 reference population of 125 putatively unrelated trees.  
 525 Results not shown graphically here indicate that 4.4% of  
 526 relatedness fell beyond what would be expected to be the  
 527 upper bound for unrelated pairs, based on the 97.5% exact  
 528 percentile for UR, with a  $\beta$  error of 8%.

529 **3.3 Impact of null alleles on relatedness estimators**

530 ODs per relatedness coefficient and across relatedness  
 531 classes when null alleles were assumed are shown in  
 532 Table 2. In general, the inclusion of null alleles led to  
 533 increases in OD, making it more difficult to differentiate the  
 534 four relatedness classes through the use of the estimators.  
 535 Only a few cases involving SF with L exhibited lower OD  
 536 with null alleles than without them. Considering the  
 537 resulting ODs per estimator, R remained the one with the  
 538 highest overlapping areas amongst density distributions of  
 539  $r$ -values. The other three estimators had similar ODs, with  
 540 L showing the smallest, closely followed by LR, and Q  
 541 being the second largest.

542 Density distributions are represented for all relatedness  
 543 estimators with null alleles in Fig. 4. In general, the  
 544 inclusion of null alleles led to distributions of larger  
 545 variances and correspondingly broader bell shapes. As a  
 546 consequence of that, the overlapping areas were larger  
 547 under the hypothesis of null alleles and also the mode  
 548 decreased, at least for L, Q and LR, in particular for the  
 549 higher relatedness classes. The only exception was the L  
 550 estimator and the SF class, for which the overlapping area  
 551 with other neighbouring distributions was smaller.

552 Therefore, in general, the presence of null alleles  
 553 resulted in increased difficulties to discriminate among  
 554 relatedness classes. All estimators showed this effect,  
 555 though in different extents, with L being the estimator with  
 556 the lowest impact in the case of the SF.

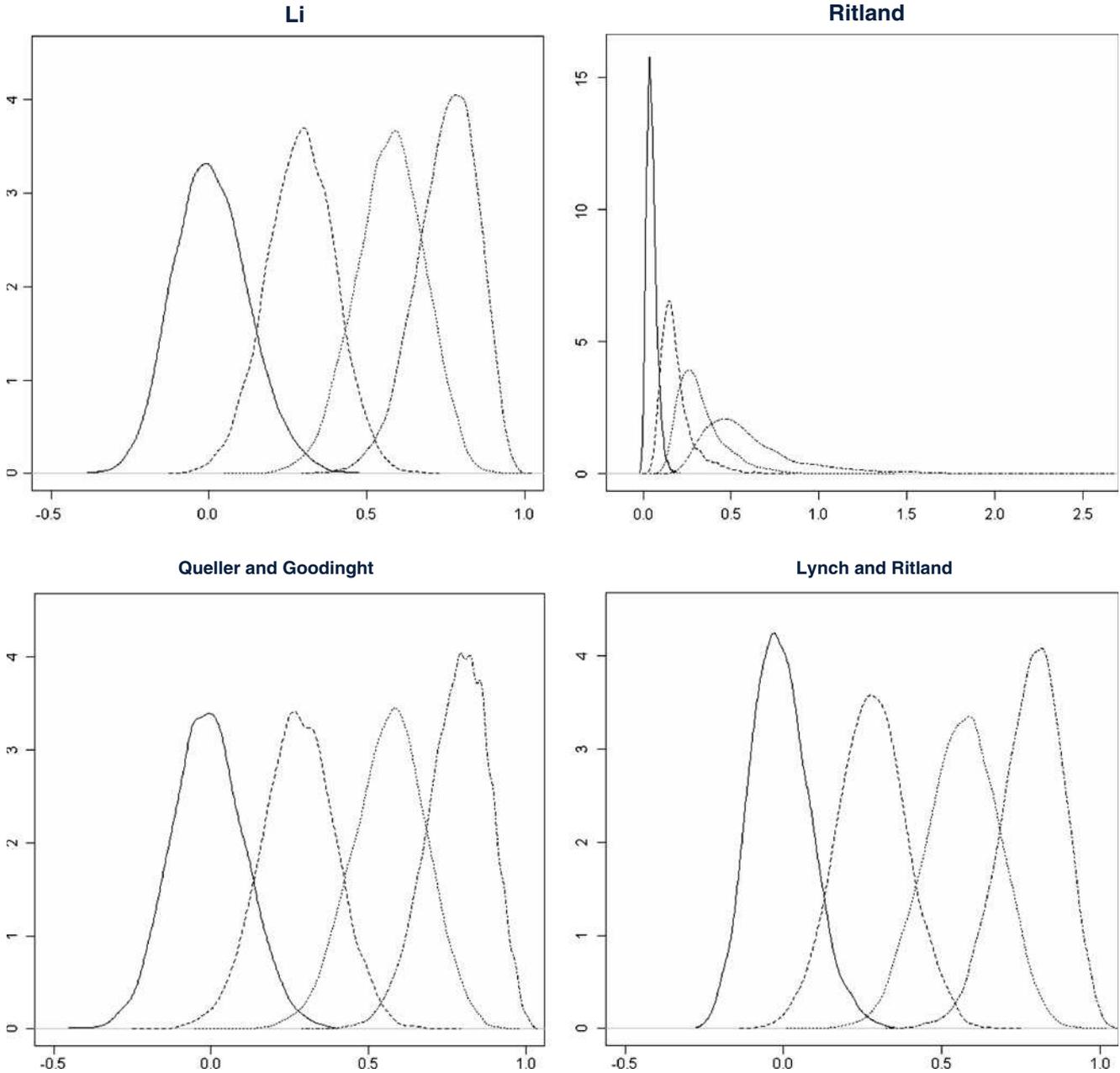
**3.4 Pairwise relatedness of elite clones**

557

558 After 1,000 permutations, the Mantel test showed that the  
 559 simulated LR values between pairs of elite clones were  
 560 larger than the observed values ( $r=0.65$ ;  $P<0.001$ ), a  
 561 moderate correlation yet significant. The average ( $\pm$ SD)  
 562 pairwise elite clone relatedness values computed with the  
 563 LR coefficient was  $-0.045\pm 0.067$ . Out of the 276 pairwise  
 564 LR values, only four (1.4%) pairwise comparisons between  
 565 elite clones had an LR estimator greater than the critical  
 566 value of 0.126. Most of the other values were close to zero  
 567 (Fig. 5), suggesting that levels of relatedness among  
 568 selected clones are generally low. The critical value of  
 569 0.126 comes from the interception between UR and HS  
 570 density distributions (Fig. 2). Therefore, pairs of individuals  
 571 with relatedness above this critical value may be considered  
 572 related to some degree, at least at a level close to HS. The  
 573 risk here is type II error, where a pair of individuals is  
 574 considered unrelated when in fact they are related to some  
 575 extent. In this latter case, the type II error was 8%, i.e. the  
 576 overlapping area to the left of the critical value for the UR  
 577 vs. HS test. The pairs with LR greater than the critical point  
 578 were CE7–CE22 (0.1316), CE5–CE13 (0.1543), CE8–  
 579 CE23 (0.1701) and CE21–CE24 (0.3727). The last pair's  
 580 LR value is a logic result, since it was discovered that CE21  
 581 is the mother of CE24, with an expected relatedness  
 582 coefficient of 0.5.

583 When we account for the presence of null alleles, the  
 584 critical values decreased from 0.126 to 0.088 for the UR–  
 585 HS, and from 0.216 to 0.189 in the UR–FS case.  
 586 Considering the new critical value (0.088), the probability  
 587 of type II error increased (14.4%), as well as the number of  
 588 putatively related pairs in the elite population. Two  
 589 additional pairs were detected: CE17–CE20 (0.0902) and  
 590 CE3–CE14 (0.0965).

591 All other relatedness coefficients had critical values  
 592 above that for LR and therefore were less stringent in  
 593 detecting related pairs of individuals.



**Fig. 2** The plotted values are the density distributions obtained from Monte Carlo simulations based on 10,000 replicas, excluding null alleles. In the *x-axis* the relatedness range and in the *y-axis* the density values. The overlapping distributions from *left to right* represent UR,

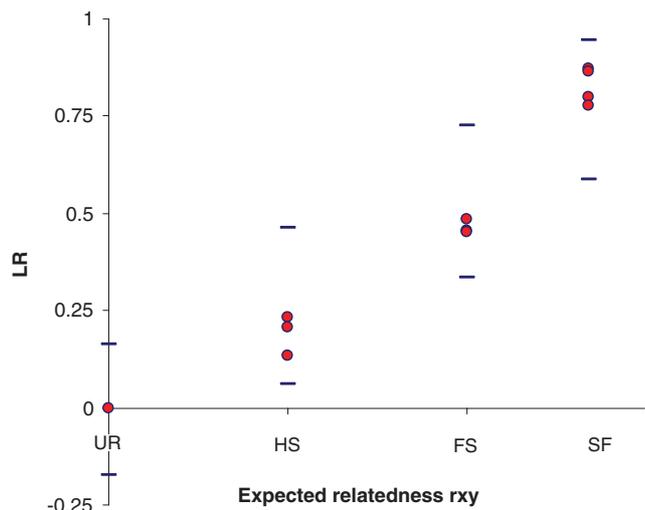
HS, FS and SF for the different relatedness/coancestry estimators: Li et al. (1993) (L), Ritland (1996) (R), Queller and Goodnight (1989) (Q), and Lynch and Ritland (1999) (LR)

594 **4 Discussion**

595 4.1 SSR markers' informativeness

596 The average expected heterozygosity reported in the  
 597 literature for *E. globulus*, using SSR markers, is similar  
 598 to the value we obtained in the current study (~0.85).  
 599 However, reported  $H_o$  is generally lower than our  
 600 observed value (0.73): 0.66 (Steane et al. 2001) and 0.62

(Jones et al. 2002). The fact that we used an artificial 601  
 population could explain, at least partly, the higher levels 602  
 for  $H_o$  found in our study. In an Australian breeding 603  
 population (140 individuals), Jones et al. (2006) obtained 604  
 $H_e=0.82$  and  $H_o=0.71$ , with  $H_o$  being lower in the 605  
 corresponding native populations that they studied 606  
 (0.66). Astorga et al. (2004) detected similar values in *E.* 607  
*globulus* using 26 SSR markers with trees selected in 608  
 progeny trials:  $H_e=0.80$  and  $H_o=0.70$ . Finally, in other 609



**Fig. 3** LR relatedness coefficient pairwise values based on real data (filled circles) framed by the exact percentiles at 2.5% and 97.5% (between dashes) from the simulated data, as in the Lynch and Ritland plot from Fig. 1, in the different relatedness groups. The reference population was used to estimate the unrelated pairs pairwise LR

610 studies using microsatellites in *E. grandis* and *E. urophylla*,  
 611 the average observed heterozygosity was much smaller than  
 612 the expected one ( $H_o \approx 0.56-0.62$  and  $H_e \approx 0.86-0.82$ )  
 613 (Brondani et al. 1998, 2002).

614 In terms of the amount of expected heterozygosity,  
 615 Blouin et al. (1996) concluded that 10 loci with  $H_e = 0.75$   
 616 would accurately discriminate more than 90% of the FS  
 617 from UR individuals, but 14 loci would be required to  
 618 achieve the same level of discrimination between FS and  
 619 HS. In this context, the circumstances of the present study  
 620 are seemingly far more promising, as only one marker out  
 621 of 16 had  $H_e < 0.75$ .

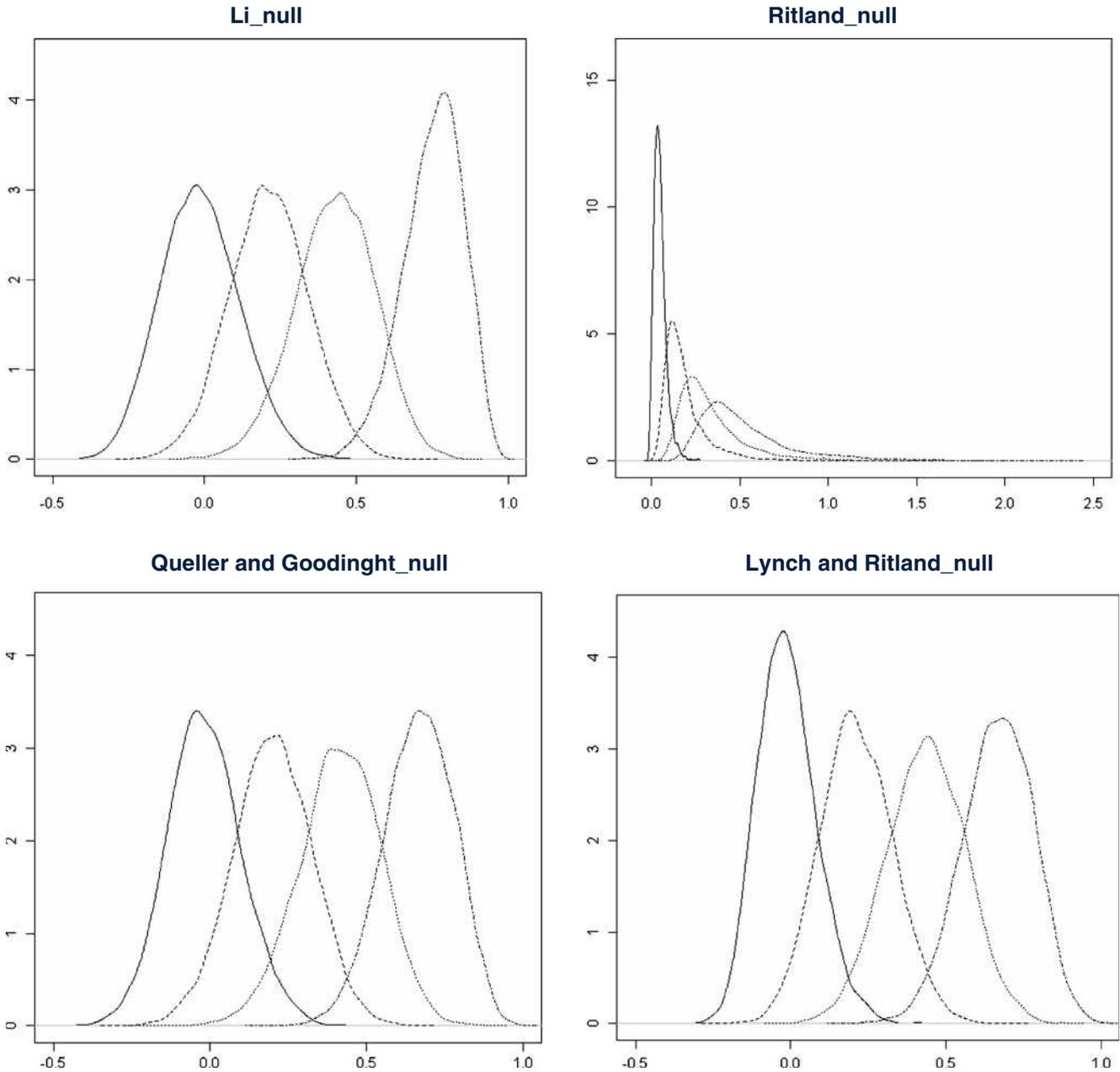
622 However, besides expected heterozygosity, other factors  
 623 play a role in the quality of relatedness discrimination, like  
 624 the number of available SSR loci, the number of segregat-  
 625 ing alleles and their spectra of frequencies. Different  
 626 relatedness estimators respond differently to the available  
 627 sample (Milligan 2003), making prospective studies inval-  
 628 uable. Ideally, marker locus should have a large number of  
 629 alleles with even allelic frequencies. For instance,  
 630 EMBRA23 showed the highest  $D$ , or discrimination power,  
 631 as well as one of the flattest allele frequency distributions.  
 632 Other less informative loci brought, however, additional  
 633 precision to the multilocus estimates of relatedness.  
 634 Dropping the less polymorphic loci, for example, if  
 635 suspected of hosting null alleles, as advised by Dakin and  
 636 Avise (2004), could increase the estimator's sampling  
 637 variance. It is expected (Milligan 2003) that the standard  
 638 error of the estimator declines with the number of loci.  
 639 Furthermore, some of the less polymorphic markers with  
 640 uneven allele distributions have rare alleles, which are  
 641 important to discriminate some genotypes.

#### 4.2 Relatedness coefficient selection

642

643 Marker-based relatedness estimates typically show a large  
 644 error of inference (Ritland 1996; Lynch and Ritland 1999).  
 645 One of the sources of variation comes from the  
 646 recombination and segregation of polymorphic markers  
 647 (Blouin 2003). However, there are differences between  
 648 relatedness estimators, and these are usually dependent on  
 649 the characteristics of the sample, such as allele frequency  
 650 spectra, number of alleles per locus and the actual range of  
 651 pedigree relatedness to be estimated. Van de Castele et al.  
 652 (2001) suggested the use of prospective studies to  
 653 evaluate different estimators in the context of the target  
 654 population, for instance, by the use of Monte Carlo  
 655 simulations with actual data. Other studies of this kind  
 656 used the allele frequencies obtained from real data to  
 657 simulate gene pools from which to draw pairs of related  
 658 individuals (e.g. Blouin et al. 1996; Lynch and Ritland  
 659 1999; Van de Castele et al. 2001; Milligan 2003). In our  
 660 study, we used the real genotypes of the reference  
 661 population as a source of virtual gametes from which to  
 662 obtain pairs of related and unrelated individuals in silico.  
 663 The advantage of our approach is to be closer to the actual  
 664 genotypic arrangements, when selecting the best fitted  
 665 estimator for a particular population, and to take into  
 666 account any deviation due to linkage disequilibrium  
 667 between markers. Such deviations from equilibrium are  
 668 common in breeding populations, which are usually  
 669 artificial composites of genotypes coming from different  
 670 origins.

671 The simulation approach allowed us to select LR as the  
 672 relatedness estimator best fitted for fingerprinting the  
 673 population under study. LR was unbiased, more accurate,  
 674 with lower percentage of overlapping values between  
 675 relatedness groups and smaller exact confidence percen-  
 676 tiles. Moreover, it demonstrated smaller impact when null  
 677 alleles were present, except in the case of higher relatedness  
 678 values. These features are important because they  
 679 improve the ability to identify, with statistical confidence,  
 680 unrelated from related individuals. Thomas (2005) refers  
 681 that the regression-based relatedness estimator of Lynch  
 682 and Ritland (1999) (our LR) shows the most desirable  
 683 properties over the widest range of marker data. In  
 684 agreement with Van de Castele et al. (2001), the author  
 685 adds that, ideally, simulations should be used to check  
 686 whether this holds true for the particular population under  
 687 study. Csillery et al. (2006) studied natural outbred popula-  
 688 tions that were less related than half-sibs and, in agreement  
 689 with our findings, concluded that the Q estimator had  
 690 smaller sampling variances in high relationship categories  
 691 while LR was better in the low relationship categories.  
 692 Furthermore, Blouin et al. (1996), in their study on  
 693 misclassification in sheep, found that for all populations



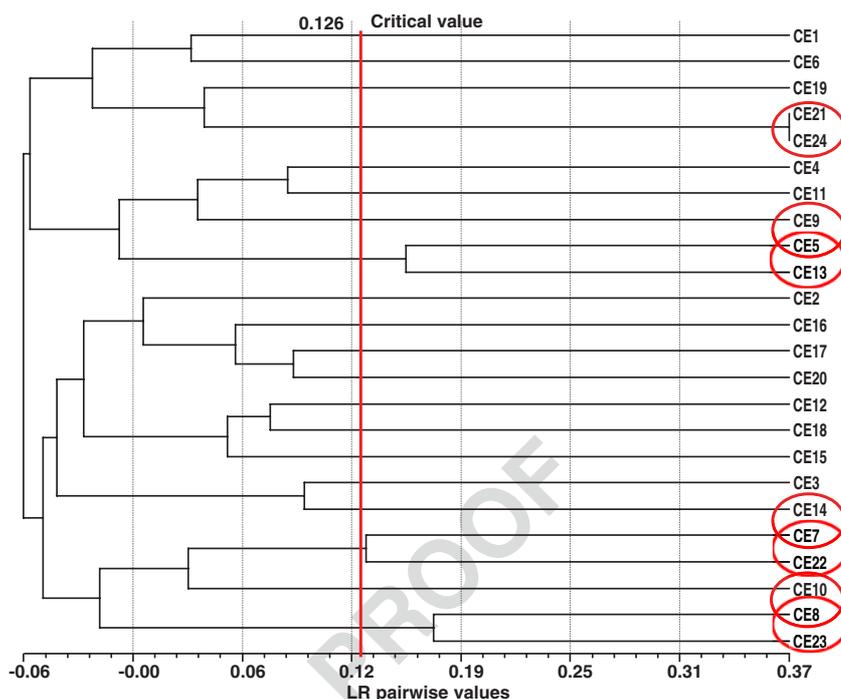
**Fig. 4** The plotted values are the density distributions obtained from Monte Carlo simulations based on 10,000 replicas, accounting for the presence of null alleles. In the *x-axis* the relatedness range and in the *y-axis* the density values. The overlapping distributions from *left to*

*right* represent UR, HS, FS and SF for the different relatedness/coancestry estimators: Li et al. (1993) (L), Ritland (1996) (R), Queller and Goodnight (1989) (Q) and Lynch and Ritland (1999) (LR)

694 studied, the misclassification rate was lowest with the LR  
 695 estimator. They demonstrated that the highest proportion of  
 696 the relatedness variance was explained with LR, reflecting  
 697 the fact that this estimator had the smallest sampling  
 698 variance for the UR or low-related pairs, which are more  
 699 common in outbred populations (Csillery et al. 2006). In our  
 700 study, we wanted to discriminate the unrelated from the  
 701 related individuals and therefore needed a coefficient with  
 702 higher precision for the low-related pairs of individuals.

703 The results from our study also confirmed those  
 704 presented by Ritland and Travis (2004), where the LR  
 705 estimator showed lower error variances compared with R,  
 706 except for the class of unrelated individuals. Indeed, we  
 707 found that the exact confidence percentiles of R increased  
 708 rapidly with the expected values of coancestry, making it  
 709 unsuitable for assigning a relatedness group for most of the  
 710 observed *r*-values (Fig. 1). Milligan (2003) points out that  
 711 the R estimator performs less well than other estimators,

**Fig. 5** Elite clones' relatedness dendrogram (UPGMA) built with the Lynch and Ritland (1999) pairwise relatedness estimator matrix. The *x*-axis represents the LR coefficient similarity distances, the labels in the right part of the figure, from CE1 to CE24, are the elite clones' codes. The vertical dotted lines represent relatedness values intervals. The vertical straight line corresponds to the threshold (critical value=0.126) to distinguish UR from HS. The four pairs of individuals that were found to be related to a certain extend were included inside circles



712 especially under conditions of high relatedness and less  
 713 polymorphic markers. In the same paper, Milligan shows  
 714 that estimators of relatedness are often skewed, Q and R in  
 715 particular, but in opposite directions. This was confirmed in  
 716 our study, though Q was only slightly skewed to the right  
 717 for high relatedness distributions (Fig. 4). This skewness  
 718 may have significant impacts on the use of these estimators,  
 719 as suggested by Milligan (2003), because means and modes  
 720 do not match.

#### 721 4.3 Validation with individuals of known pedigree

722 After selecting the most suitable estimator, LR pairwise  
 723 relatedness values were computed in groups of individuals  
 724 with known pedigree (UR, HS, FS and SF), for validation.  
 725 All families' *r*-values were within the simulated exact  
 726 percentiles at 2.5% and 97.5% for each relatedness group  
 727 (Fig. 3). The slight departures of observed *r*-values from  
 728 expected values are not easily explained. These departures  
 729 correspond to upward biases for SF and downward biases  
 730 for HS and FS. Asymmetries in the distribution of expected  
 731 values do not appear to be a possible cause, as distributions  
 732 for HS and FS were nearly symmetrical, while that of SF  
 733 presented less values being greater than the mode. The  
 734 relatively small number of families and their small size  
 735 could increase the sampling effects.

#### 736 4.4 Null allele impact

737 Our analyses revealed an important deficit of observed  
 738 heterozygosity for some markers, from what would be

739 expected from allelic frequencies in the reference population.  
 740 Other studies with *E. globulus* also found deficits in observed  
 741 heterozygosity (e.g. Astorga et al. 2004; Jones et al. 2006).  
 742 The presence of a relatively high percentage of null  
 743 alleles could be one of the main reasons for this. Based  
 744 in our estimations, seven out of the 16 SSR loci had null  
 745 allele's frequencies above 5%. This high number of  
 746 affected loci could be partially explained by the fact that  
 747 EMBRA SSR loci were originally developed for *E.*  
 748 *grandis* (Brondani et al. 1998). The frequency of null  
 749 alleles is expected to increase when transferring markers  
 750 between more distantly related species. Indeed, in their  
 751 study, Brondani et al. (2006) observed that the overall  
 752 occurrence of null alleles was much higher in *E. urophylla*  
 753 than in *E. grandis*, when using SSR originally developed  
 754 from *E. grandis* libraries.

755 The presence of null alleles had a negative effect in all  
 756 relatedness estimators, as expected from the literature  
 757 (Wagner et al. 2006). Our assumption was extreme in the  
 758 sense that all homozygotes were considered to be carriers of  
 759 null alleles, hence being an upper bound for the expected  
 760 effects of null alleles. Null alleles increased the variation  
 761 associated to each estimator and consequently the over-  
 762 lapping areas between neighbouring density distributions of  
 763 simulated *r*-values. This had the effect of increasing the  
 764 associated  $\alpha$  and  $\beta$  errors. Accordingly, critical values  
 765 between relatedness classes decreased with null alleles. As  
 766 a consequence, the probability of type II error and the  
 767 number of putatively related pairs detected in the elite  
 768 population increased. As a principle of precaution, and  
 769 given the likelihood of null alleles when working with  
 770

770 transferred markers from distant species, pairs detected as  
771 related, close to the critical value, should be considered  
772 related, at the risk of falling into type II errors.  
773 Nevertheless, our results show that the Lynch and  
774 Ritland (1999) relatedness estimator proved adequate for  
775 our data set, even when all the homozygotes were  
776 considered carriers of null alleles.

#### 777 4.5 Putatively related elite clones

778 Excluding the presence of null alleles, four pairs of  
779 putatively unrelated elite individuals were considered  
780 related to the level of half-sibs, based on the LR estimator.  
781 This represents a small portion (1.4%) of all the possible  
782 pairwise values (276) in the relatedness matrix. In the  
783 worst-case scenario, when all homozygotes were consid-  
784 ered carriers of a null allele, we detected two additional  
785 pairs of putatively related individuals (2.2% of the total).  
786 Despite the fact that the group of elite clones had, to our  
787 knowledge, no recent common ancestors, there might have  
788 been an influx of relatedness into the Portuguese land race  
789 (Borrhalho et al. 2007) or mislabelling in the breeding  
790 population management. Recently established plantations  
791 may have been originated from the same seed collected on  
792 a few trees, with pollination dominated by a restricted  
793 number of males. Moreover, eucalypts have a mixed  
794 mating system, and the collected open-pollinated seeds  
795 from one mother-plant may contain a mixture of selfs  
796 (and possibly other forms of inbreeding) and unrelated  
797 crosses (Eldridge et al. 1994; Jones et al. 2006; Costa e  
798 Silva et al. 2010). This would explain why some of the  
799 elite clones, selected in different plantations, could show  
800 some level of relatedness. Decisions about the elite clones  
801 to be used in future crossings schemes should take into  
802 account not only their breeding values but also their level  
803 of coancestry. The long-term effect of inbreeding depres-  
804 sion on traits related to fitness, such as survival and  
805 growth, is severe in *E. globulus* (Costa e Silva et al. 2010),  
806 neutralizing improvement efforts.

807 We present a simulation approach that allows different  
808 estimators to be evaluated in a particular context, even when a  
809 population is the result of an artificial mixture of different  
810 origins. In the absence of reliable pedigree information, LR  
811 values could be useful to avoid or limit consanguinity and to  
812 identify relatives in breeding populations. However, our goal  
813 was not simply to confirm the suitable properties of LR  
814 compared to other relatedness estimators. Indeed, some of the  
815 results could be expected given the characteristics of the  
816 population under study, notably the absence of high related-  
817 ness that could pinpoint the use of LR. Our objective was to  
818 propose a method that could be easily applied to other  
819 populations and species, confronted with the dilemma of  
820 selecting from a series of relatedness estimators.

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