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## Genetic insights into crossbred dairy cattle of Pakistan: exploring allele frequency, linkage disequilibrium, and effective population size at a genome-wide scale

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1 **Genetic Insights into Crossbred Dairy Cattle of Pakistan: Exploring Allele Frequency,**  
2 **Linkage Disequilibrium, and Effective Population Size at a Genome-Wide Scale**

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## 26 **Abstract**

27 Linkage disequilibrium (LD) affects genomic studies accuracy. High-density genotyping  
28 platforms identify SNPs across animal genomes, increasing LD evaluation resolution for  
29 accurate analysis. This study aimed to evaluate the decay and magnitude of LD in a cohort of  
30 81 crossbred dairy cattle using the GGP\_HDv3\_Ci Bead Chip. After quality control, 116,710  
31 Single Nucleotide Polymorphisms (SNPs) across 2520.241 Mb of autosomes were retained.  
32 LD extent was assessed between autosomal SNPs within a 10 Mb range using the  $r^2$  statistics.  
33 LD value declined as inter-marker distance increased. The average  $r^2$  value was 0.24 for SNP  
34 pairs <10 kb apart, decreasing to 0.13 for 50-100 kb distances. Minor allele frequency (MAF)  
35 and sample size significantly impact LD. Lower MAF thresholds result in smaller  $r^2$  values,  
36 while higher thresholds show increased  $r^2$  values. Additionally, smaller sample sizes exhibit  
37 higher average  $r^2$  values, especially for larger physical distance intervals (>50 kb) between SNP  
38 pairs. Effective population size and inbreeding coefficient were 150 and 0.028 for the present  
39 generation, indicating a decrease in genetic diversity over time. These findings imply that the  
40 utilization of high-density SNP panels and customized/breed-specific SNP panels represent a  
41 highly favorable approach for conducting Genome-Wide Association Studies (GWAS) and  
42 implementing Genomic Selection (GS) in the Bos indicus cattle breeds, whose genomes are  
43 still largely unexplored. Furthermore, it is imperative to devise a meticulous breeding strategy  
44 tailored to each herd, aiming to enhance desired traits while simultaneously preserving genetic  
45 diversity.

46 **Keywords**

47 Linkage Disequilibrium, Minor allele frequency, Effective population size, Crossbred dairy  
48 cattle, SNP Chip, Pakistan

49 **Introduction**

50 When alleles are sufficiently close together on a chromosome, they tend to be inherited together  
51 through linked inheritance rather than being passed down independently. This means that the  
52 offspring receives blocks of alleles or haplotypes from each parent, rather than individual  
53 alleles (O'Brien et al., 2014, Ardlie et al., 2002). Linkage disequilibrium (LD) arises due to  
54 the interconnection of alleles on a chromosome, which results in a certain degree of correlation  
55 among them. This phenomenon can be observed not only for nucleotides in the genome but  
56 also for different types of genetic markers, including single nucleotide polymorphisms (SNPs)  
57 (O'Brien et al., 2014). In essence, LD between molecular markers represents the extent to  
58 which the genotypes of two SNPs are correlated (Porto-Neto et al., 2014). While physical  
59 proximity plays a significant role in determining LD, it is important to acknowledge that other  
60 factors such as evolutionary processes and historical events can also affect the correlation  
61 between molecular markers. These factors encompass inbreeding, selection, population  
62 stratification, genetic drift, genetic bottleneck, effective population size, mutation,  
63 recombination rate, and migration (Karimi et al., 2015, Ardlie et al., 2002, Reich et al., 2001).

64 Comprehending the concept of LD holds paramount importance in the mapping of genes and  
65 their relevance to genomic studies. Through the analysis of LD between SNPs, researchers can  
66 obtain valuable insights into the diversity across various breeds, estimate recombination event  
67 frequencies, investigate fluctuations in effective population size across generations, and  
68 identify genomic regions suitable for enhancing economically important traits. Such

69 understanding contributes significantly to the advancement of genetic research and the targeted  
70 improvement of desired traits(O'Brien et al., 2014, Espigolan et al., 2013, McKay et al., 2007).

71 Effective population size is an important genetic parameter that estimates the effect of genetic  
72 drift in a population (Crow and Kimura, 1970). It is one of the best quantitative indicators of  
73 genetic diversity, (Makanjuola et al., 2020) that determining help determine the number of  
74 independent chromosome segments which is required for genomic predictions (Mrode et al.,  
75 2019). Estimating the effective population size is valuable not only from an evolutionary  
76 standpoint but also for enhancing models used in the mapping of genes related to quantitative  
77 traits (Li and Kim, 2015).

78 The decreasing cost of conducting high-throughput genotyping assays has opened up new  
79 possibilities for conducting large-scale genomic studies. The effectiveness and precision of  
80 these genomic investigations are greatly influenced by the extent and structure of LD observed  
81 between SNPs throughout the genome. As LD patterns determine the level of correlation  
82 between markers, understanding LD is crucial for maximizing the utility and accuracy of  
83 GWAS and GS approaches (Goddard and Hayes, 2012). Investigations have been carried out  
84 to examine the LD between markers within the genomes of diverse taurine and indicine cattle  
85 breeds. (Espigolan et al., 2013, Makina and Taylor, 2015). The findings of their study showed  
86 that moderate LD with a value of  $r^2 = 0.20$  was observable in distances of less than 100  
87 kilobases. This suggests that a set of 50,000 SNPs is sufficient to capture most of the LD  
88 information needed for conducting GWAS in taurine breeds (McKay et al., 2007, Espigolan et  
89 al., 2013). In contrast, the researchers observed a lower extent of LD ( $r^2 = 0.20$  to 0.34) within  
90 indicine cattle at distances less than 30 kilobases. This suggests that a higher-density SNP chip  
91 would be necessary to capture the LD information required for conducting genomic studies in  
92 these cattle (Makina and Taylor, 2015). The diminished LD extent observed in indicine cattle

93 breeds can be attributed to a potential ascertainment bias inherent in the SNP chips utilized for  
94 genotyping.

95 The practice of crossbreeding in dairy cows has been identified as a highly effective approach  
96 for enhancing livestock productivity, reproductive efficiency, and sustainability (Leroy et al.,  
97 2016, Mbole-Kariuki et al., 2014, Bebe et al., 2003). In a single lactation, the crossbred  
98 offspring of Sahiwal(*Bos indicus*) and HF(*Bos taurus*) cows have the ability to produce  
99 approximately 4,000 liters of milk containing 4% fat (Kumar et al., 2018). Crossbreeding  
100 Sahiwal and HF cows result in offsprings that benefit from hybrid vigor, which leads to  
101 improved health traits and increased productivity. This is due to the combination of the high  
102 milk yield of HF cows and the adaptability and heat tolerance of Sahiwal cows, resulting in  
103 offsprings that are well-suited to local conditions and have improved milk yield.

104 In a recent study, admixture patterns and signature of selection for the same samples were  
105 studied (Unpublished data). However, the investigation of genome-wide LD and its pattern  
106 using this specific chip remains unexplored. The prediction accuracy from genomic selection  
107 (GS) is affected by marker density, minor allele frequency (MAF), and genetic architecture of  
108 the target trait (Zhang et al., 2019). Also, the accuracy of the genomic prediction depends on  
109 the amount of genetic variation explained by the markers resulting from the LD between the  
110 marker and QTL (Goddard, 2009). Therefore, this study examines the distribution of allelic  
111 frequencies, determines the level of LD (measured using  $r^2$ ), and estimates the effective  
112 population size in the population of crossbred dairy cattle, which have a major impact on the  
113 accuracy of GS in this admixed population. This study will provide valuable insights for  
114 estimating marker density in genomic studies of crossbred dairy cattle.

## 115 **Materials and methods**

### 116 **Ethics statement:**

117 To ensure the ethical and humane treatment of animals, the study described in this research  
118 paper was approved by the institutional review committee. During blood collection, a  
119 professional veterinarian was there to ensure minimal distress and harm to the animals. Before  
120 collecting any samples, the researchers met with the owners of the farm where the animals  
121 were housed to explain the purpose of the study and obtain informed consent verbally.

### 122 **Animal sample and genotype quality control**

123 The sample size for this study consisted of 81 crossbred cattle from the Military Farm located  
124 in Renala Khurd near Okara, Punjab. These animals were selected based on having varying  
125 percentages of HF and Sahiwal genetics from different lactations. Due to the nature of  
126 crossbreeding, the breed composition varies from individual to individual due to variations in  
127 Sahiwal and HF inheritance. For instance, some crossbreds have an approx. 50% inheritance  
128 from both HF and Sahiwal, while others have 31/32 parts of HF inheritance the remaining  
129 being Sahiwal. Blood sampling was carried out in different visits to cattle farms during 2021  
130 and 2022.

131 DNA was extracted from the blood samples using the FavorPrep™ Blood Genomic DNA  
132 Extraction Mini Kit, following the manufacturer's guidelines. The quality and quantity of the  
133 DNA were evaluated using different methods, including a NanoDrop spectrophotometer,  
134 agarose gel electrophoresis, and a Qubit spectrophotometer. The extracted DNA was genotyped  
135 using the GGP\_HDv3\_C (GeneSeek® Genomic Profiler™) and commercially available  
136 services at GeneSeek (Neogen Corporation, Lincoln, NE, United States). The genotypes were  
137 identified and analyzed using the Genome Studio software from Illumina, Inc. The analysis  
138 was based on the bovine genome assembly, ARS-UCD1.2.

### 139 **Quality control (QC):**

140 After the genotyping process, the initial raw data comprised 139,376 SNPs for the crossbred  
141 individuals. Quality control measures were applied using the PLINK v1.9 software, (Slifer,  
142 2018) which involved removing SNPs that had a call rate of less than 95%, minor allele  
143 frequency (MAF) of less than 0.02, and a Hardy-Weinberg equilibrium (HWE) of less than  
144  $10E^{-05}$ . For subsequent analysis, only autosomal SNPs were considered.

#### 145 **Marker Statistics:**

146 The R software was employed to estimate multiple characteristics of the autosomes. These  
147 included the length of each chromosome in megabases (Mb), the count of markers on each  
148 autosome, the longest and shortest intervals between SNPs, and the average interval between  
149 SNPs across all autosomes (Team, 2020).

#### 150 **Minor allele frequency (MAF):**

151 To calculate the MAF of autosomal SNPs, default settings in PLINK v1.9 software were used  
152 with the command "--file data --freq" (Slifer, 2018). The distribution of allele frequencies  
153 across various chromosomes was analyzed using the R software. Additionally, a plot was  
154 generated to visualize the proportion of SNPs falling within different frequency categories,  
155 namely 0.02-0.10, 0.10-0.20, 0.20-0.30, 0.30-0.40, and 0.40-0.50 (Team, 2020).

#### 156 **Inbreeding Coefficient (F) and Effective Population Size (Ne):**

157 To estimate F, the expected and observed homozygote differences were used with PLINK v1.9  
158 software (Slifer, 2018) using the formula  $F_i = (O_i - E_i) / L_i - E_i$ . In this equation,  $F_i$  is the  
159 estimated inbreeding coefficient of the  $i^{\text{th}}$  animal,  $O_i$  represents the number of observed  
160 homozygous loci,  $E_i$  represents the count of expected homozygous loci, while  $L_i$  represents  
161 the count of genotyped autosomal loci. The calculation was performed using PLINK v1.9  
162 software (Slifer, 2018).



163 To estimate the effective population size ( $N_e$ ), the SNeP tool was utilized, leveraging the  
164 relationship between  $N_e$ , linkage disequilibrium (represented by  $r^2$ ), and recombination rate ( $c$ )  
165 (Barbato et al., 2015). This is given by:

$$166 \quad N_T(t) = 1 / \{4f(C_t)\} * [1 / \{E(r_{adj}^2) C_t\} - \alpha] \quad (\text{Corbin et al., 2012})$$

167 In the provided equation:  $N_T(t)$  represents the estimated effective population size  $t$  generations  
168 ago in the past,  $C_t$  denotes the recombination rate  $t$  generations ago in the past,  $r_{adj}^2$  signifies  
169 the adjusted LD estimation, accounting for sampling bias,  $f$  is mapping function and  $\alpha$   
170 represents a constant value.

### 171 **Linkage Disequilibrium (LD):**

172 The assessment of LD was carried out using the square of the correlation coefficient between  
173 two loci, represented as  $r^2$ . This metric is regarded as robust and unaffected by fluctuations in  
174 allele frequency and population size (Zhao et al., 2007). The estimation of  $r^2$  plays a crucial  
175 role in determining the number of loci needed for conducting GWAS and quantitative trait loci  
176 (QTL) mapping. This measure helps to assess the extent of LD between markers and assists in  
177 designing the appropriate sample size and marker density for such studies (Makina and Taylor,  
178 2015). The equation for estimating LD using the  $r^2$  value is expressed as follows:

$$179 \quad D = (p_{Ai}A_i)(p_{Bj}B_j) - (p_{Ai}B_j)(p_{Bj}A_i)$$

$$180 \quad r^2 = D^2 / p_{Ai}(1-p_{Ai}) p_{Bj} (1-p_{Bj})$$

181 In this context, the frequency of the  $i^{\text{th}}$  allele at locus A is denoted as  $p_{Ai}$ , while the frequency  
182 of the  $j^{\text{th}}$  allele at locus B is represented as  $p_{Bj}$ . Additionally, the frequency of the haplotype  
183  $A_iB_j$  in the population is denoted as  $p_{A_iB_j}$ .

184 The MapThin v1.11 was used to thin the map files, selecting 20 SNPs per  $10^6$  bp positions to  
185 minimize false positive results and increase the efficiency of the analysis (Howey and Cordell,

186 2011). The PLINK v1.9 software was used with the default command “--ld-snp-list mysnp1ist  
187 --ld-window-kb 186000 --ld-window 99999 --ld-window r<sup>2</sup> 0” to estimate the r<sup>2</sup> between all  
188 pairs of SNPs on autosomes as the length of the longest chromosomes (chr1) is around 186kb  
189 (Slifer, 2018).

190 To verify the occurrence of free recombination at a physical distance greater than 10 Mb, two  
191 types of analyses were conducted on our dataset: one without considering a 10 Mb window,  
192 and the other with considering a 10 Mb window (Zhao et al., 2014).

193 1. To analyze the decay of LD value, the genomic regions were divided into eight categories  
194 based on a range of 20Mb each, namely 0-20 Mb, 20-40 Mb, 40-60 Mb, 60-80 Mb, 80-100  
195 Mb, 100-120 Mb, 120-140 Mb, and 140-160 Mb. The LD value was then calculated for all  
196 possible regions within each category.

197 2. By taking into account a maximum distance of 10 Mb between SNP pairs, the LD decay  
198 was calculated for all possible SNP pairs across the autosomes. The trend in Linkage  
199 Disequilibrium (LD) decay for crossbred individuals was plotted across the entire first 10  
200 megabases (MB) of the genome. This analysis likely provides insights into how LD  
201 changes over increasing physical distances within this specific genomic region for  
202 crossbred animals.

203 The calculated LD decay was then categorized into eight intervals based on distance ranges.  
204 These intervals included: 0-10 kb, 10-25 kb, 25-50 kb, 50-100 kb, 100-500 kb, 0.5-1 Mb, 1-5  
205 Mb, and 5-10 Mb. This categorization allows for a comprehensive assessment of LD decay  
206 patterns across varying distances, providing valuable insights into the dynamics of LD in the  
207 autosomal genome and plotted against distance range.

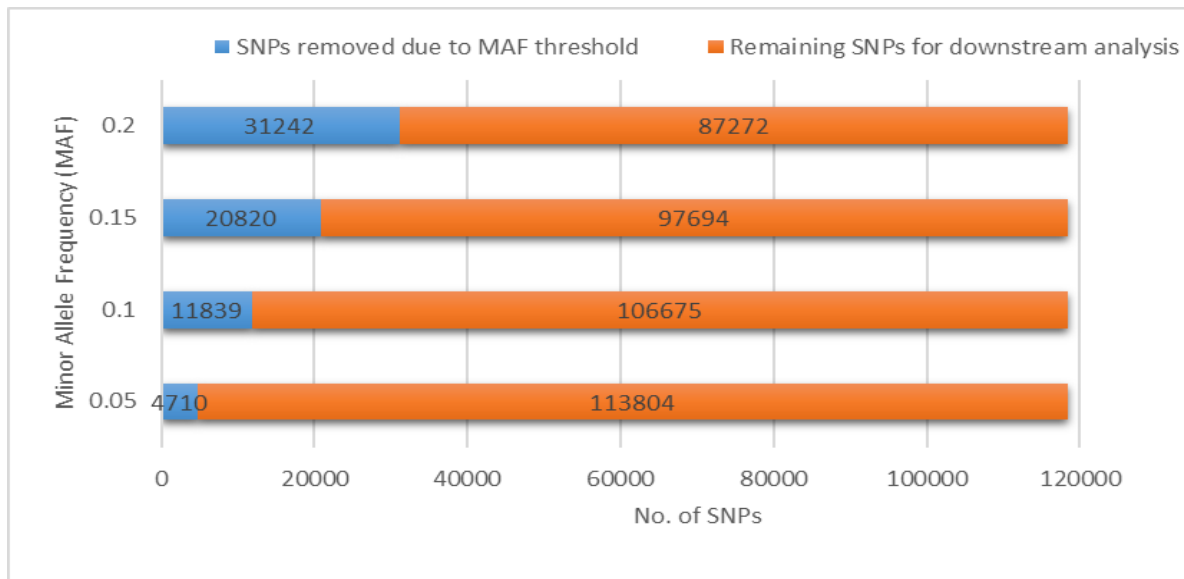
208 **Minor Allele Frequency and Sample Size Impact:**

209 To assess the impact of minor allelic frequency (MAF) and sample size on LD, the analysis  
210 was extended. For a physical distance of 10 Mb, LD was computed using four distinct MAF  
211 thresholds (0.05, 0.10, 0.15, and 0.2). Furthermore, seven random subsets of the population  
212 were selected with different sample sizes (N=10, 20, 30, 40, 50, 60, and 70) to investigate the  
213 impact of sample size on r<sup>2</sup>-based LD. The extent of LD was assessed for each subset, and the  
214 impact of sample size and MAF on LD (r<sup>2</sup>) was also depicted through plotting.

## 215 **RESULTS**

### 216 **Quality control:**

217 Table 1 summarizes the quality control results for different MAF thresholds. For example, for  
218 a 0.02 MAF threshold, 1804 SNPs were removed due to an MAF less than 0.02; 216 SNPs  
219 were removed based on Hardy-Weinberg Equilibrium (HWE); and 1111 SNPs were excluded  
220 due to a call rate threshold criterion. Therefore, a total of 116,710 autosomal SNPs with a  
221 genotypic rate of 0.99 were available for downstream analysis. These steps were repeated for  
222 different MAF values. All the remaining parameters were the same therefore the effect of  
223 different maf values on the final number of SNPs left for downstream analysis is depicted in  
224 Figure 1.



225

226 *Figure 1 Effect of different MAF thresholds on the total no. of SNPs left for downstream analysis*

227

228 **Marker statistics:**

229 The quality control process resulted in a total of 2520.241 Mb of retained SNPs across the  
 230 genome of crossbred dairy cattle, with an average chromosome length of 86.90 Mb. The longest  
 231 chromosome was BTA1, with a length of 158.8551 Mb, while the shortest was BTA25, with a  
 232 length of 42.85 Mb. The number of SNPs on each chromosome exhibited a proportional  
 233 relationship with the length of the respective chromosome. Notably, the highest number of  
 234 SNPs was observed on BTA1 (7078), while the lowest number was recorded on BTA25 (1945).  
 235 On average, the distance between adjacent SNPs was approximately 21.70 kb. The longest  
 236 distance between SNPs was observed on BTA5 (612 kb), and the longest distance between  
 237 SNPs on the same chromosome was found on BTA5 (3882 kb). Conversely, the mean shortest  
 238 distance between SNPs was 0.16 kb, with the shortest distance occurring on BTA18 (0.002 kb).  
 239 Descriptive statistics for each autosome's SNP markers are provided in Table 2.

240 *Table 1 Snapshot of the SNP markers studied and their minor allele frequency (MAF) across*  
 241 *the autosomal chromosomes (BTA)*

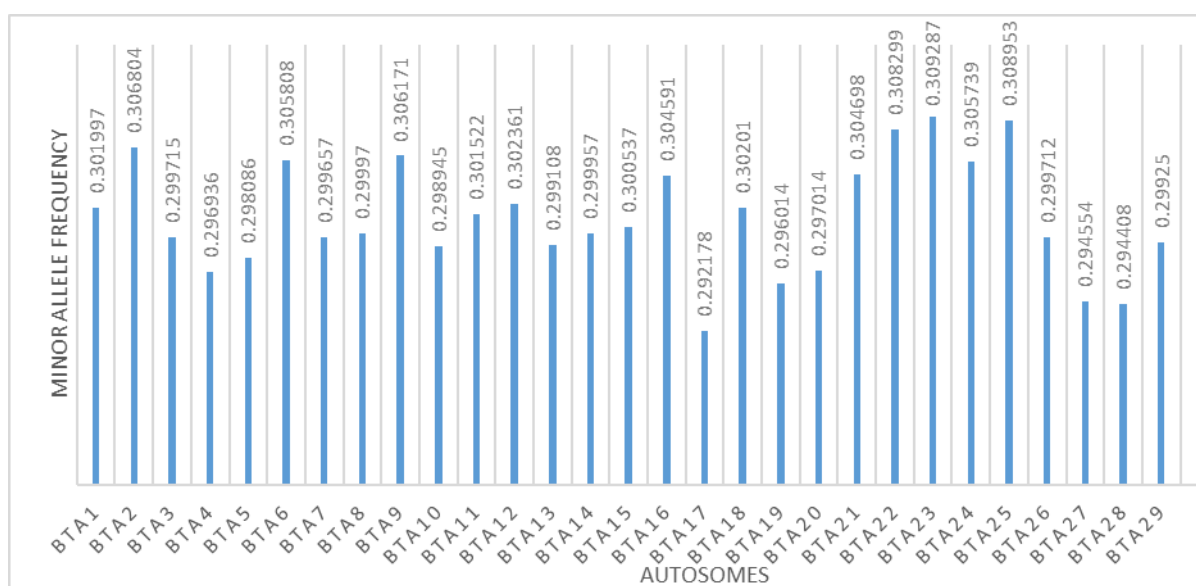
Chromosome no	Length (Mb)	Number of SNPs	Longest SNP Interval (kb)	Shortest SNP Interval (kb)	Average SNP Interval $\pm$ SD (kb)
BTA1	158.8551	7078	561.588	0.066	22.444 $\pm$ 17.782
BTA2	136.7696	6284	206	0.075	21.759 $\pm$ 15.989
BTA3	123.149	5659	1745.571	0.007	21.759 $\pm$ 28.315
BTA4	120.6419	5379	211.953	0.163	22.429 $\pm$ 16.104
BTA5	125.0587	5899	3882.807	0.007	21.198 $\pm$ 53.387
BTA6	122.5097	6562	1919.865	0.005	18.667 $\pm$ 32.844
BTA7	112.6101	5585	1146.872	0.003	20.165 $\pm$ 23.583
BTA8	113.6262	5004	446.389	0.084	22.707 $\pm$ 19.746
BTA9	105.689	4785	135.389	0.247	22.089 $\pm$ 15.86
BTA10	104.2536	4703	395.732	0.274	22.167 $\pm$ 18.657
BTA11	107.283	4814	145.246	0.178	22.282 $\pm$ 16.311
BTA12	91.13102	4043	895.952	0.102	22.539 $\pm$ 31.517
BTA13	84.22998	3733	373.764	0.038	22.561 $\pm$ 19.002
BTA14	84.62824	4612	525.259	0.211	18.225 $\pm$ 20.71
BTA15	85.27231	3835	226.131	0.092	22.222 $\pm$ 16.271
BTA16	81.68807	3636	772.05	0.568	22.463 $\pm$ 21.368
BTA17	75.13293	3338	509.683	0.193	22.508 $\pm$ 20.518
BTA18	65.9992	2960	248.273	0.002	22.289 $\pm$ 18.395

BTA19	64.04478	2844	180.7	0.239	22.465±15.837
BTA20	71.97177	3688	192.949	0.042	19.5±16.124
BTA21	71.5735	3192	524.177	0.047	22.41±19.349
BTA22	61.3782	2762	355.005	0.246	22.218±21.218
BTA23	52.46563	2390	358.949	0.129	21.955±17.689
BTA24	62.6437	3236	152.828	0.011	19.084±15.509
BTA25	42.85112	1945	136.474	0.185	22.018±14.725
BTA26	51.68014	2358	394.35	0.281	21.87±17.185
BTA27	45.38817	2037	597.764	0.592	22.284±23.675
BTA28	46.22406	2045	128.661	0.036	22.612±15.776
BTA29	51.49248	2277	394.565	0.613	22.576±18.563

242

243 **Minor Allele Frequency (MAF):**

244 The mean MAF observed across all autosomes was recorded as 0.30. Figure 2 provides a visual  
 245 representation of the distribution of MAF on all autosomes.

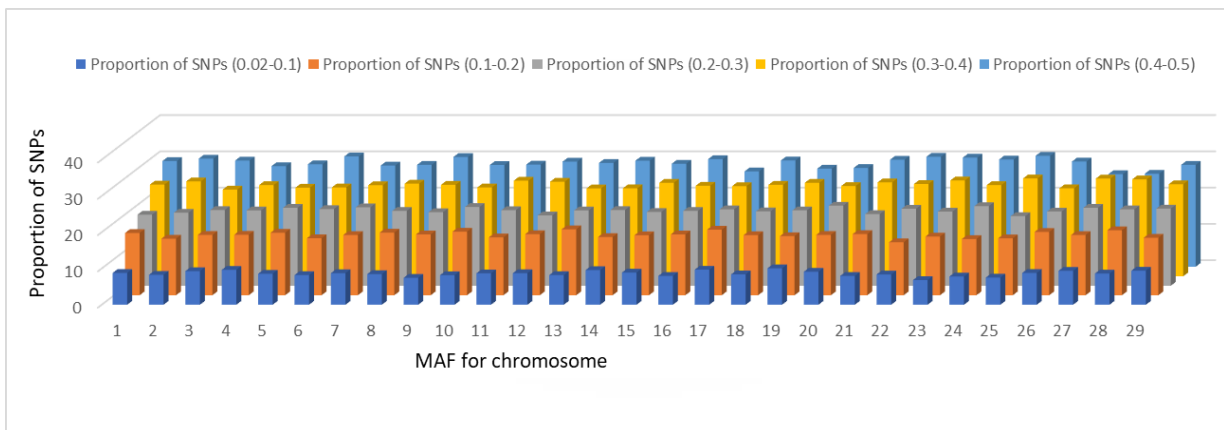


246

247 *Figure 2 Minor Allele Frequency (MAF) in all autosomes*

248 Similarly, the distribution of MAF indicated that a significant percentage of SNPs exhibited  
 249 elevated MAF values (Figure 3). Specifically, around 54% of the SNPs were categorized in the  
 250 last two MAF groups ( $MAF \geq 0.3$ ), while a lower percentage of SNPs fell into the initial  
 251 categories. On average, around 25.20% of the SNPs displayed an MAF value lower than 0.2.  
 252 This distribution highlights the predominance of SNPs with higher MAF values in the analyzed  
 253 dataset.

254 It is noteworthy that all autosomes exhibited a similar trend, with a greater percentage of SNPs  
 255 falling into the last two groups ( $MAF \geq 0.3$ ). However, BTA25, BTA6, BTA22, BTA9, and  
 256 BTA23 had a higher percentage of SNPs in the last category ( $MAF \geq 0.4$ ). Among the  
 257 chromosomes, BTA19 (10.04%), BTA17 (9.67%), BTA4 (9.61%), and BTA14 (9.54%) had a  
 258 higher percentage of SNPs with MAF values between 0.02 and 0.1.



259  
 260 *Figure 3 Proportion of SNPs categorized by minor allele frequencies (MAF) across autosomal*  
 261 *chromosomes*

262 **Inbreeding Coefficient (F) and Effective Population Size (Ne):**

263 The average value of F was estimated to be 0.028, indicating that the risk of negative impacts  
 264 due to inbreeding depression can be considered insignificant at this level of inbreeding.

265 The  $N_e$  of the crossbred dairy cattle was estimated throughout the past 1000 generations based  
 266 on the average  $r^2$  values, as presented in Table 2. The results showed a declining trend in  $N_e$ ,  
 267 which decreased from 2775 (995 generations ago) to 150 (13 generations ago). This suggests  
 268 that the crossbred dairy cattle population has experienced a decrease in genetic diversity over  
 269 time.

270 *Table 2 Effective Population Size ( $N_e$ ) across generations determined through linkage*  
 271 *disequilibrium ( $r^2$ )*

Generations Ago	$N_e$	Distance	$r^2$	$r^2$ (SD)
13	150	3748832	0.042443	0.058646
15	165	3272844	0.044289	0.061595
17	183	2843931	0.045914	0.064077
20	203	2459746	0.047784	0.066845
23	226	2116420	0.049734	0.070699
27	252	1811032	0.05185	0.074908
32	286	1541094	0.053603	0.077165
38	328	1303393	0.055299	0.080254
45	377	1095203	0.057112	0.082466
54	435	914086	0.059203	0.084556
65	508	757766	0.061023	0.088151
80	598	623567	0.062809	0.090512
98	705	509487	0.065115	0.093385
120	827	413344	0.068169	0.097614
150	969	333170	0.071866	0.102766
187	1130	267075	0.076524	0.11055



234	1306	213281	0.082388	0.117489
293	1489	170160	0.089823	0.126196
366	1666	136285	0.09919	0.138301
454	1842	110080	0.109739	0.150293
553	1993	90367	0.121873	0.162818
658	2185	75961	0.130922	0.171969
759	2349	65842	0.139131	0.178594
847	2461	59027	0.146845	0.185381
914	2542	54693	0.152421	0.19237
958	2567	52141	0.157367	0.196599
983	2694	50818	0.154391	0.189964
995	2775	50240	0.152043	0.192054

272

273 **Extent of LD across the genome**

274 Without considering the window, we obtained a total of 47,054,338 possible pairs in the whole  
 275 dataset, with a mean  $r^2$  value of 0.020025 (Table 4). While a total of 9,115,588 combination  
 276 pairs across the autosomes were analyzed to estimate LD for SNP pairs with a physical distance  
 277 of  $\leq 10$  Mb. The mean  $r^2$  value for markers at a 10 Mb distance was determined to be 0.128.

278 Table 4 provides the mean LD ( $r^2$ ) values for different intervals of physical distance.

279 *Table 3 Statistical summary of linkage disequilibrium ( $r^2$ ) over the entire genome and up to 10*  
 280 *MB SNP distance*

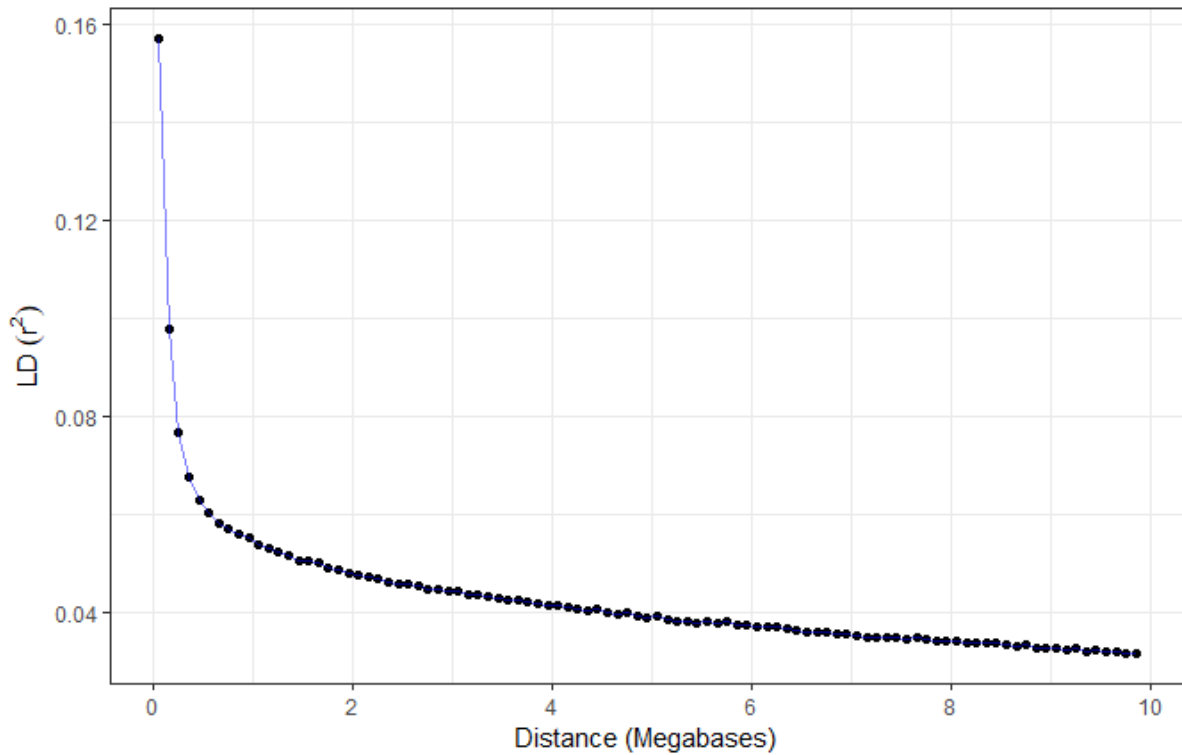
Entire genome			Upto 10 Mb distance between SNP pairs		
Distance (Mb)	No of SNP pairs	Mean $r^2$	Distance	No of SNP pairs	Mean $r^2$

0-20	17129667	0.0358	0-10 kb	171	0.243576
20-40	12674399	0.0212	10-25 kb	1970	0.242189
40-60	8343391	0.0182	25-50 kb	22927	0.182909
60-80	4946708	0.0173	50-100 kb	48204	0.141243
80-100	2610172	0.0169	100-500 kb	387883	0.076373
100-120	1004252	0.0167	0.5-1 Mb	481614	0.057482
120-140	279260	0.0165	1-5 Mb	3745729	0.0451343
140-160	66489	0.0176	5-10 Mb	4427090	0.035091

281

282 Table 4 shows that considering a 10 Mb window is important because there is an inverse  
283 relationship between LD ( $r^2$ ) and the distance between SNP pairs. The mean  $r^2$  values are higher  
284 when the SNP pair distance is smaller, i.e., between 0-10 kb, and decrease from 0-10 kb to 5-  
285 10 Mb. Therefore, it is suggested that SNP pairs within a distance of 10 Mb should be explored  
286 further.

287 The level of Linkage Disequilibrium (LD) decay, about the distance between pairs of Single  
288 Nucleotide Polymorphisms (SNPs), is depicted in Figure 4 for all autosomes. Notably, higher  
289 levels of LD were predominantly observed at shorter distances between SNP pairs, highlighting  
290 the rapid decay of LD as the physical distance between SNPs increases.



291

292 *Figure 4 Average linkage disequilibrium (LD) decay in relation to the SNP pair distance*

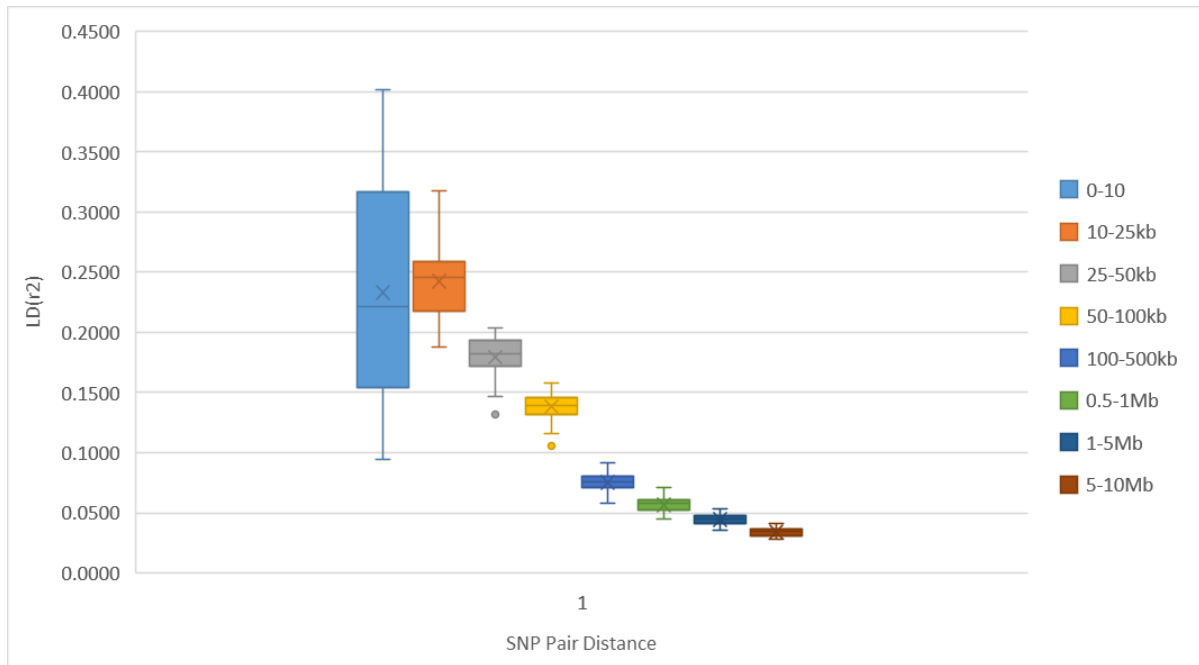
293

294 The level of LD measured by  $r^2$  varied across each chromosome, and was dependent on the  
 295 physical distance between genetic markers. To explore the relationship, the mean  $r^2$  was  
 296 computed for various physical distance intervals of markers across each chromosome.  
 297 Chromosomes BTA22, BTA19, BTA18, and BTA7 exhibited higher levels of LD. When  
 298 considering markers separated by <10 kb, the average  $r^2$  was found to be 0.2332, which  
 299 decreased to 0.1792 for markers with distances between 25-50 kb. The average  $r^2$  continued to  
 300 decline with increasing distance, reaching a final value of 0.0344 for the 5-10 Mb category.  
 301 These results indicate that the mean  $r^2$  values decrease as the physical distance between markers  
 302 increases, demonstrating a decline in LD with increasing genetic distance (Figure 4).

303

304

305 The average  $r^2$  values showed a significant difference across various autosomes, especially for  
 306 SNP distances less than 10kb. On the other hand, for SNP distances greater than 100kb, lower  
 307 mean  $r^2$  values with relatively little variation across different autosomes were observed (Fig 6).



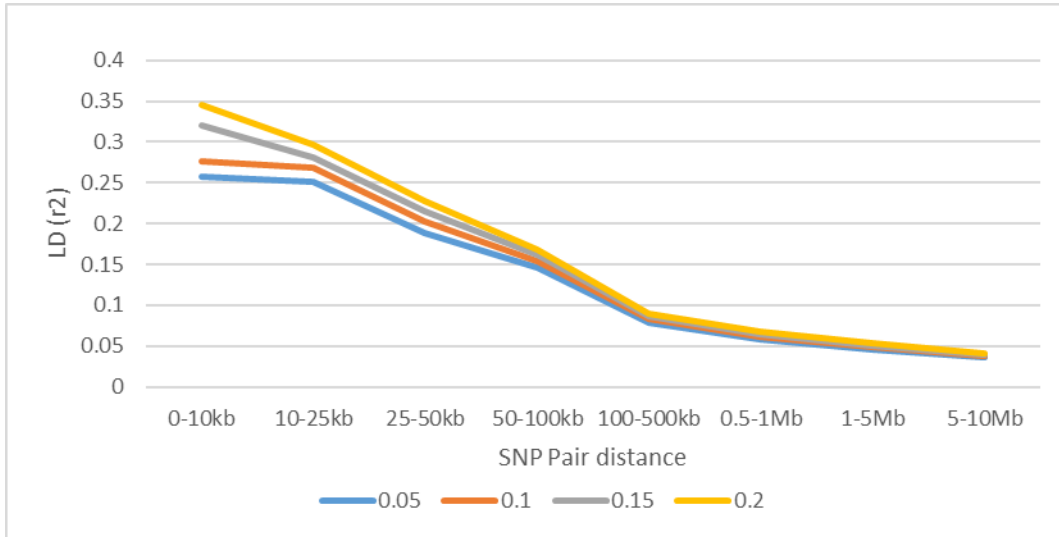
308  
 309 *Figure 5 Box Plot of mean  $r^2$  and SNP Pair distance up to 10 Mb for all 29 autosomes*

310 **Minor Allele Frequency (MAF) and Linkage Disequilibrium (LD) estimates**

311 The impact of MAF on the magnitude of LD was examined by employing four threshold levels:  
 312 0.05, 0.10, 0.15, and 0.20. This analysis focused on SNP pairs with 10 Mb physical distances  
 313 (Fig 3). The findings revealed a notable influence of the MAF threshold on the average  $r^2$ ,  
 314 especially in the case of shorter distances between SNPs. A decrease in the  $r^2$  value between  
 315 SNP pairs was observed when the MAF threshold was set to a lower value (0.05), while a  
 316 substantial increase in the  $r^2$  value was noted at higher thresholds of MAF. The mean  $r^2$  values  
 317 ranged from 0.03 to 0.25 for  $MAF > 0.05$ , 0.03 to 0.27 for  $MAF > 0.10$ , 0.03 to 0.32 for  $MAF$   
 318  $> 0.15$ , and 0.04 to 0.34 for  $MAF > 0.20$ . These results indicated that the MAF threshold has a  
 319 considerable effect on the LD extent between SNPs, with higher MAF thresholds resulting in  
 320 stronger LD.

321

322

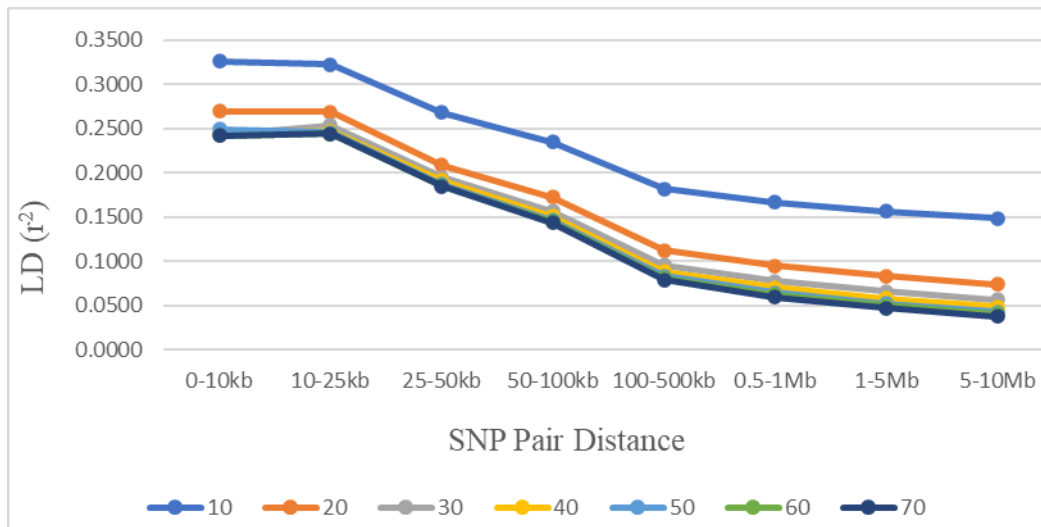


323

324 *Figure 6 Effect of Minor Allele Frequency (MAF) on Linkage Disequilibrium Extent*

325 **Sample size and LD estimates**

326 To study the effect of sample size, random samples of sizes 10, 20, 30, 40, 50, 60, and 70 were  
327 selected from the total population for analysis. A noteworthy finding of this study is that the  
328 average  $r^2$  increased for smaller sample sizes, particularly when the physical distance intervals  
329 between SNP pairs exceeded 50 kb (Figure 4). These results suggest that a larger sample size  
330 (at least 40 animals) is needed for an accurate estimation of  $r^2$ .



331

332 *Figure 7 Effect of different sample size on mean  $r^2$  estimates*

333 **Discussion**

334 Following rigorous quality control measures, a final set of 116,710 autosomal SNPs were  
 335 retained for analysis. These SNPs spanned a genomic region of 2520.241 Mb in crossbred dairy  
 336 cattle. The average MAF was found to be 0.30, aligning with previously reported MAF values  
 337 observed in diverse cattle breeds (Makina and Taylor, 2015). These findings align with previous  
 338 studies on other taurine breeds of cattle (O'Brien et al., 2014, Matukumalli et al., 2009, McKay  
 339 et al., 2007). However, the average MAF values observed in this study were notably higher  
 340 compared to indicine breeds of cattle, which typically exhibit MAF values ranging from 0.19-  
 341 to 0.20 (O'Brien et al., 2014, Espigolan et al., 2013, Silva et al., 2010). In contrast to taurine  
 342 cattle, indicine breeds typically display a distinct pattern in MAF levels, characterized by a  
 343 greater representation of alleles with lower frequencies (< 0.2)(O'Brien et al., 2014, Gibbs et  
 344 al., 2009, Villa-Angulo et al., 2009). The variation mentioned above could be ascribed to the  
 345 increased genetic diversity identified in indicine breeds (Murray et al., 2010, Gibbs et al.,  
 346 2009). As there are few such reports on crossbred cattle, especially with *Bos Indicus* and *Bos*  
 347 *taurus* crossbreds, this may serve as a positive contribution and important reference for the  
 348 future studies of native breeds. Furthermore, the commercially available SNP panel used in this

349 study predominantly utilized sequence data from *Bos taurus* breeds. Thus, it may lead to the  
350 ascertainment bias leading to a greater proportion of SNPs with low MAF in indicine breeds  
351 of cattle.

352 The distribution of MAF has a direct impact on the extent of LD, as a lower MAF can result in  
353 a greater difference in allelic pair frequencies, leading to an underestimation of LD (Wray,  
354 2005). To examine the effect of MAF on LD, four different MAF thresholds were selected. The  
355 results indicated that higher thresholds of MAF ( $>0.20$ ) were associated with higher average  
356 LD ( $r^2$ ) between SNPs, particularly at shorter distances(O'Brien et al., 2014, Sargolzaei et al.,  
357 2008, Uimari et al., 2005). At a lower MAF threshold (e.g., 0.05), there might be the inclusion  
358 of rare variants in the analysis. Rare variants may behave differently in terms of LD leading to  
359 the observed decrease in  $r^2$  as they are less likely to be in strong linkage with other variants.  
360 Although, it has been established till now that the  $r^2$  method is less affected by the sample size  
361 it may also be a contributing factor to this finding indicating that SNP chips with a higher  
362 density of SNPs and studies on larger populations may be preferable for genomic studies in  
363 native cattle breeds of Pakistan.

364 The estimation of LD between SNP pairs was conducted using the correlation ( $r^2$ ) method,  
365 which is known to be less affected by MAF (Ardlie et al., 2002) and small sample size (Zhao  
366 et al., 2014). To assess the decay of LD, the physical distance between markers was divided  
367 into distinct intervals. The findings demonstrated a swift decrease in  $r^2$  beyond a threshold of  
368 100 kb. Furthermore,  $r^2$  declined from 0.24 to 0.17 when considering marker distances of 10  
369 kb and 50 kb, respectively. For inter-marker distances of up to 25 kb, the average  $r^2$  value was  
370 0.24, which is comparatively lower than previous LD estimates, documented for taurine breeds  
371 such as Angus (0.46) and Hereford (0.49), as well as indicine breeds like Brahman (0.25) and  
372 Nellore (0.27) cattle(Porto-Neto et al., 2014, Espigolan et al., 2013, Lu et al., 2012). The results

373 showed higher mean  $r^2$  values for BTA22, BTA19, BTA18, and BTA7, while lower mean  $r^2$   
374 values were observed for BTA27, BTA21, BTA9, and BTA26.

375 LD ( $r^2$ ) values that surpass 0.3 are deemed valuable for dependable association studies and  
376 precise genomic predictions (Ardlie et al., 2002, Meuwissen et al., 2001, Kruglyak, 1999). In  
377 this study, regions up to 10 kb on BTA5, BTA7, BTA13, BTA18, BTA22, BTA26, and BTA27  
378 exhibited  $r^2$  values larger than 0.3. On the other hand, BTA19 showed a slower decay in LD,  
379 achieving the same level of  $r^2$  up to a distance of 25 kb. These findings deviate from the average  
380 LD levels documented in other taurine breeds such as Angus, Holstein, Brown Swiss, and  
381 Fleckvieh reach an average  $r^2$  value of 0.3 at distances ranging from 40 to 50 kb (O'Brien et  
382 al., 2014). These results align with the findings observed in indicine breeds such as Gyr and  
383 Nelore, which exhibit a more rapid decline in LD, reaching a similar  $r^2$  value at distances of  
384 approximately 20 kb. Similar outcomes have been observed in other taurine breeds, where  $r^2$   
385 values remained comparable for distances equal to or less than 30 kb (Larmer et al., 2014,  
386 Bolormaa et al., 2011). Nevertheless, no correlation was identified between chromosomal size  
387 and  $r^2$  estimates (Bohmanova et al., 2010).

388 The LD decay analysis within a range of up to 10 megabases (MB), employing 10-kilobase  
389 (kb) windows, is presented in Figure 4 for crossbred individuals. This analysis revealed a  
390 pronounced decline in LD at shorter distances between pairs of SNPs. This behavior is likely  
391 attributed to the relatively low number of SNP pair comparisons available at these close  
392 distances.

393 These findings suggest that, when utilizing the set of SNPs contained in the GGPHDv3-C chip,  
394 there may not be consistent LD levels expected for genomic distances less than 10MB.  
395 Importantly, these results align with those reported by (O'Brien et al., 2014) in their LD analysis  
396 conducted across different taurine and indicine breeds.



397 To examine the influence of sample size on the extent of LD, various sample sizes were  
398 employed in the computation of  $r^2$  values as it is previously reported that a small sample size  
399 may lead to overestimation of LD (Yan et al., 2009, Khatkar et al., 2008). In the present  
400 investigation, a sample size of 40 cattle did not influence  $r^2$ , which aligns with previous findings  
401 (Bohmanova et al., 2010, Singh et al., 2021). However, various other studies have reported  
402 different threshold limits for sample size. For example, Zhu et al. (2013) suggested a minimum  
403 sample size of 100. In the case of Holstein cattle a minimum sample size of 400 is necessary  
404 for reliable LD decay analysis (Khatkar et al., 2008). Human studies have indicated even higher  
405 sample sizes (Chen et al., 2006). The minimum threshold for sample sizes appears to be around  
406 75, as  $r^2$  accuracy is significantly compromised below this value (Khatkar et al., 2008).  
407 Similarly, another study suggested a minimum sample size of 55 (Bohmanova et al., 2010).

408 Previous studies have consistently emphasized the significance of employing a larger number  
409 of SNPs to adequately cover the genome in genomic evaluations, especially when analyzing  
410 data from crossbreds and indicine breeds (Makina and Taylor, 2015, Espigolan et al., 2013).  
411 The findings from our study support this notion, that a higher density SNP array provides more  
412 information and enhances the reliability of GWAS and GS in crossbred dairy cattle populations.  
413 These results are consistent with other studies that have also emphasized the benefits of  
414 utilizing a higher SNP density for such analyses (Singh et al., 2021).

415 To gain a better understanding of the population diversity and structure, we estimated  $F$  and  
416  $N_e$ . Our study revealed an inbreeding coefficient of 0.028. This finding is comparable to  
417 previously reported inbreeding coefficients of 3%, 4%, and 6% in the Vrindavani crossbred  
418 cattle population of India (Chhotaray et al., 2021, Singh et al., 2021, Elavarasan et al., 2023).  
419 The Karan Fries crossbred cattle of Karnal exhibited an inbreeding coefficient of 3.68%  
420 (Mumtaz et al., 2021). In the case of Sahiwal cattle, one of the 11 breeds studied by Bang et al.  
421 (2022), the inbreeding coefficient was 0.9%. In Tharparker cattle, different methods were

422 employed to estimate genomic inbreeding coefficients, resulting in values of 0.0589 (FROH),  
423 0.0215 (FHOM), 0.0532 (FGRM), and 0.0160 (FUNI) (Saravanan et al., 2022). Another study  
424 was conducted on Holstein, Montebeliarde, and Normande breeds, an inbreeding coefficient of  
425 4.5-5% (Dezetter et al., 2015). For pure African taurine (Baoulé) and its crossbreeds with  
426 indicine Zebu cattle, genomic inbreeding coefficients ranged from 0 to 4% (Ouédraogo et al.,  
427 2021). Among nine breeds, the mean genomic inbreeding estimates were highest for Jersey  
428 (0.173) and lowest for Hereford (0.051) (Kelleher et al., 2017). Lower inbreeding was observed  
429 in six Columbian cattle breeds, ranging from 0.5 to 4.5% (Martinez et al., 2023). In a study of  
430 171 cattle groups conducted by Tian et al. (2023), the average inbreeding coefficient ranged  
431 from 0.22 to 0.05.

432 In our study, we observed a decrease in effective population size ( $N_e$ ) over multiple generations  
433 in crossbred dairy cattle. The estimated  $N_e$  in our population was 150, and a decreasing trend  
434 in  $N_e$  was observed specifically 13 generations ago. When the effective population size ( $N_e$ )  
435 decreases, the genetic diversity available for selection in genomic breeding is constrained. This  
436 reduction in diversity limits the number of allelic variants that can be considered. Additionally,  
437 increased inbreeding resulting from a smaller  $N_e$  compromises fitness and undermines the  
438 accuracy of predictions due to the correlation of genetic variants. Moreover, the limited genetic  
439 contributions and heightened genetic drift further hinder the effectiveness of GS. When  
440 comparing our findings to previous studies, a range of 33-153  $N_e$  was observed in different  
441 studies on dairy cattle (Doekes et al., 2018, Rodríguez-Ramilo et al., 2015, Stachowicz et al.,  
442 2011). Effective population sizes for European taurine breeds ranged from 98 to 152, with  
443 Brown Swiss exhibiting the lowest value (98), and Limousine and Piedmontese showing the  
444 highest values (138 and 144, respectively). African taurine breeds recorded a range of 120 to  
445 175 for  $N_e$ . Among indicine cattle breeds, Gir had the highest  $N_e$  estimate (180), while  
446 Tharparker had the lowest (63) (Barbato et al., 2020). In the context of buffalo breeds, both

447 purebred and crossbred populations demonstrated a decreasing trend in recent  $N_e$ , with  
448 estimated values closer to 387 and 113, respectively, 13 generations ago. This suggests that  
449 these animals have undergone strong selection or genetic drift, resulting in a decline in  
450 population size (Deng et al., 2019).

#### 451 **Conclusion**

452 This study aimed to assess the level of LD between markers in crossbred dairy cattle from  
453 Pakistan using the GGP\_HDv3\_C (GeneSeek® Genomic Profiler™) SNP panel. The average  
454 estimated value of  $r^2$  was 0.24, which was lower compared to both indicine and taurine breeds.  
455 This suggests that a denser SNP panel is necessary to obtain more precise and accurate results  
456 in whole genome association studies for crossbred dairy cattle.

457 Additionally, the study observed a declining trend in the estimates of effective population size  
458 ( $N_e$ ) in the population. This indicates the need for a well-designed breeding plan that can  
459 maintain a sufficiently large  $N_e$  to mitigate the negative effects of genetic drift and inbreeding.  
460 Conducting studies on a larger population using a high-density array of SNPs would provide  
461 more comprehensive and reliable information regarding the extent of LD and the effective  
462 population size in crossbred dairy cattle of Pakistan.

#### 463 **List of Abbreviations:**

464 MAF: Minor Allele Frequency

465 LD: Linkage Disequilibrium

466  $N_e$ : Effective Population Size

467 SNP: Single Nucleotide Polymorphism

468 GWAS: Genome-Wide Association Study

469 r<sup>2</sup>: Correlation coefficient

470 **Declarations:**

471 **Ethics statement:**

472 To ensure the ethical and humane treatment of animals, the study described in this research  
473 paper was approved by the Research Ethics Committee of the National Institute for  
474 Biotechnology and Genetic Engineering (NIBGE), Faisalabad, Pakistan on 10-06-2020.  
475 During blood collection, a professional veterinarian was there to ensure minimal distress and  
476 harm to the animals. Before collecting any samples, the researchers met with the owners of the  
477 farm where the animals were housed to explain the purpose of the study and obtain informed  
478 consent verbally.

479 **Availability of data and materials:**

480 All the necessary files are provided with the paper.

481 **Competing interests:**

482 The authors declare that they have no competing interests

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487 improvement in dairy-related traits”.

488 **Author Contributions**

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501 Shahid Mansoor, Imran Amin.

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