1	CRUMBLER: A Tool for the Prediction of Ancestry in Cattle
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# 23 Abstract

#### 24 Background

25 In many beef and some dairy production systems, crossbreeding is used to take advantage of breed complementarity and heterosis. Admixed animals are frequently 26 27 identified by their coat color and body conformation phenotypes, however, without 28 pedigree information it is not possible to identify the expected breed composition of an 29 admixed animal and in the presence of selection, the actual composition may differ from 30 expectation. As the roles of DNA and genotype data become more pervasive in animal 31 agriculture, a systematic method for estimating the breed composition (the proportions 32 of an animal's genome originating from ancestral pure breeds) has utility for a variety of 33 downstream analyses including the estimation of genomic breeding values for crossbred animals, the estimation of quantitative trait locus effects, and heterosis and 34 heterosis retention in advanced generation composite animals. Currently, there is no 35 36 automated or semi-automated ancestry estimation platform for cattle and the objective 37 of this study was to evaluate the utility of extant public software for ancestry estimation and determine the effects of reference population size and composition and number of 38 39 utilized single nucleotide polymorphism loci on ancestry estimation. We also sought to develop an analysis pipeline that would simplify this process for members of the 40 livestock genomics research community. 41 42 Results We developed and tested a tool, "CRUMBLER", to estimate the global ancestry of cattle 43

44 using ADMIXTURE and SNPweights based on a defined reference panel.

45 CRUMBLER, was developed and evaluated in cattle, but is a species agnostic pipeline

46	that facilitates the streamlined estimation of breed composition for individuals with
47	potentially complex ancestries using publicly available global ancestry software and a
48	specified reference population SNP dataset. We developed the reference panel from a
49	large cattle genotype data set and breed association pedigree information using
50	iterative analyses to identify purebred individuals that were representative of each
51	breed. We also evaluated the numbers of markers necessary for breed composition
52	estimation and simulated genotypes for advanced generation composite animals to
53	evaluate the precision of the developed tool.
54	Conclusion
55	The developed CRUMBLER pipeline extracts a specified subset of genotypes that is
56	common to all current commercially available genotyping platforms, processes these
57	into the file formats required for the analysis software, and predicts admixture
58	proportions using the specified reference population allele frequencies.
59	
60	Background
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62	Estimation of the breed composition of individuals with complex ancestries has utility for

Estimation of the breed composition of individuals with complex ancestries has utility for estimating breed direct and heterosis effects as well as for the estimation of the additive genetic merit of these individuals. It also has value for identifying the breed composition of training populations used for genomic selection and hence the identification of target breeds in which the developed prediction equations may have some relevance. Visual classification of cattle based on breed characteristics suffers from similar problems as the self-identification of ethnicity in humans [1], as most breed characteristics are

69 determined by alleles at relatively few loci. For example, recent extensive crossing with 70 Angus cattle in the U.S. produces a black hided animal which masks all other solid coat colors found in other breeds and requires only a single dominant allele at the MC1R 71 72 locus. As a consequence, black-hided cattle have a "cryptic" population structure [1,2] 73 and the visual classification of black-hided animals for branded beef programs can 74 result in the marketing of animals with vastly different Angus genome content. 75 In the U.S. and many other countries, the breed of an animal is associated with its being 76 77 registered with a breed association which requires that both parents of the animal be identified and also registered with the association. For the previous 50 years, 78 79 parentage has been validated by each breed association using blood or, more recently, 80 DNA typing. Many breed associations have closed herdbooks which means, in theory, 81 that the pedigrees of all animals can be traced back to the animals that founded the 82 breed's herdbook. Other breed associations have open herdbooks, which means that 83 crossbred animals can be registered with the breed if they have been graded up by 84 crossbreeding to purebred status with the expectation that a certain percentage of their 85 genome (e.g., 15/16ths) originates from the respective breed based upon pedigree records and parentage validation. Pedigree errors that occurred prior to, or that were 86 not identified following the implementation of blood typing and DNA testing, lead to 87 88 admixed animals being incorrectly classified as fullblood and incorrectly identified admixture proportions in purebred animals. The effects of recombination, random 89 90 assortment of chromosomes into gametes and selection can also lead to considerable 91 variation in the extent of identity by descent between relatives separated by more than a

92 single meiosis and can also lead to admixture proportions that differ substantially from
93 expectation based on pedigree.

94

95 Crossbreeding is extensively used in commercial beef production and in other livestock species production systems to capitalize on the effects of breed complementarity and 96 97 heterosis resulting in herds of females that may have very complex ancestries that frequently use fullblood or purebred bulls sourced from registered breeders. Changes in 98 the decision as to which breed of bull to use can result in large changes in admixture 99 100 proportions of replacement cows and marketed steers between years and large 101 differences can occur between herds for the same reason. When commercially sourced 102 animals are used to generate resource populations to study the genomics of 103 economically important traits such as feed conversion efficiency [3,4] or bovine 104 respiratory disease [5], the presence of extensive admixture in the phenotyped and 105 genotyped animals may impact the GWAA [3,4] and leads to the training of genomic 106 prediction models in populations for which the breed composition is not understood. As 107 a consequence, the utility of these models in other industry populations, including the 108 registered breeds in which the majority of genetic improvement is generated is also not 109 understood.

110

As the number of genotyped beef animals has increased, the need to classify the breed composition of these animals has necessitated the development of a precise and accurate method for estimating breed composition in cattle based on single nucleotide polymorphism (SNP) data. Iterative ancestry estimation analyses performed using

115 different software input parameters may identify those that cause output sensitivity and 116 can lead to an interpretation of population structure that is close to the truth [6]. We 117 developed the CRUMBLER analysis pipeline to streamline the genomic estimation of 118 breed composition of crossbred cattle using high-density SNP genotype data, publicly 119 available software, and a reference panel containing genotypes for members of cattle breeds that are numerically important in North America. The CRUMBLER pipeline is 120 121 species agnostic and could be adapted for breed composition estimation in other 122 species. CRUMBLER and the reference panel data are available on GitHub 123 (https://github.com/tamarcrum/CRUMBLER). This pipeline tool is released under the GNU General Public License. 124 125 **Materials and Methods** 126 127 128 Genotype data 129 From among the numerically most important cattle breeds in North America, in terms of 130 their annual numbers of animal registrations, a list was compiled to define the target 131 breeds for reference panel development. Composite breeds, such as Brangus and 132 Braford, were not included in this list due to lack of available genotype data, but the 133 progenitor Angus, Hereford and Brahman breeds were included. Breeds such as 134 N'Dama, representing African taurine, and Nelore and Brahman, representing Bos 135 taurus indicus cattle, were included. We also initially included breeds that were likely to be involved in early crossbreeding of cattle in the U.S. (Texas Longhorn). 136

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138 From the 170,544 cattle with high-density SNP genotypes stored within the University of 139 Missouri Animal Genomics genotype database, we extracted genotypes for 48,776 140 animals identified as being registered with one of the numerically important U.S. Breed 141 Associations or belonging to other world breeds. Pedigree data were also obtained for 142 these animals from each of the Breed Associations, where available (Table 1). These 143 individuals had been genotyped using at least one of 9 different genotyping platforms 144 currently used internationally to genotype cattle including the GeneSeek (Lincoln, NE) 145 GGP-90KT, GGP-F250, GGP-HDV3, GGP-LDV1, GGP-LDV3, and GGP-LDV4 assays, the Illumina (San Diego, CA) BovineHD and BovineSNP50 assays, and the Zoetis 146 147 (Kalamazoo, MI) i50K assay. The numbers of variants gueried by each assay and the 148 number of individuals genotyped using each platform are shown in Table 2.

149

# 150 Marker set determination

To maximize the utility of the developed breed assignment tool, we identified the 151 152 intersection set of SNP markers located on the bovine assays for which we had 153 available genotype data (Table 2). However, during the process of identifying the 154 animals that would define the breed reference panel, only 16 individuals had been denotyped using the GGP-LDV4 (n=2) and GGP-LDV3 (n=14) assays and no animals 155 156 had been genotyped using the GGP-LDV1 assay. To retain as many SNP markers as 157 possible for subsequent analysis, we identified the intersection of markers present on 158 the GGP-90KT, GGP-F250, GGP-HDV3, GGP-LDV3, GGP-LDV4, BovineHD, 159 BovineSNP50 and i50K assays. This intersection set included 6,799 SNP markers 160 (BC7K). The intersection of the markers representing 5 assays (GGP-90KT, GGP-F250, GGP-HDV3, BovineHD, and BovineSNP50) was 13,291 markers (BC13K). By 161

- removing only the 16 individuals from the breed reference panel that had been
- 163 genotyped on the GGP-LDV3 and GGP-LDV4 assays, we were able to compare
- ancestry predictions using two marker set densities (BC13K and BC7K).
- 165
- 166 **Pipeline**
- 167 The developed CRUMBLER pipeline integrates the tools and the computational
- 168 efficiency of publicly available software, PLINK [7,8], EIGENSOFT [9,10] and
- 169 SNPweights [11] to generate ancestry estimates (Fig. 1). The pipeline integrates the
- 170 often cumbersome processes of data reformatting and sequentially processing the data
- 171 using analytical tools to generate ancestry proportions for targeted individuals based on
- a curated breed reference panel.
- 173

# 174 **PLINK**

175 PLINK PED formatted genotypes are required as input to the pipeline. PLINK

(v1.90b3.31) was used for data filtering and formatting. Genotypes can arise from anyof the common bovine genotyping platforms (Table 2), provided that a PLINK

178 compatible MAP file is provided for each assay and data produced using only a single

179 genotyping assay is included in each PED file. The pipeline utilizes the PLINK marker

180 filtering tool (--extract) to extract the user-specified marker subset for ancestry analysis.

- 181 For analyses of animals genotyped on different genotyping platforms, the marker list
- 182 representing the intersection of the platforms can be provided to extract the markers
- that are common to all assays. The pipeline allows multiple input genotype files and

uses the PLINK merge genotype files tool (--merge) to combine genotypes into a singlefile for downstream analysis.

186

# 187 EIGENSOFT

188 The EIGENSOFT convert package is used to convert all genotypes from PLINK PED

189 format into EIGENSTRAT format which is required by the SNPweights software. To

190 process the reference panel data, principal component analysis using EIGENSOFT

smartpca is used to generate the eigenvalues and eigenvectors that are required to

192 calculate SNP weights using SNPweights. However, the smartpca package included in

193 EIGENSOFT versions beyond 5.0.2 is not compatible with SNPweights. SNPweights

requires an input variable, *"trace*", to be located in the log file output from the smartpca

analysis. For versions of EIGENSOFT beyond 5.0.2, the source code can be edited to

196 ensure that the log file output is compatible with the SNPweights software (See

197 Supplementary Information).

198

# 199 SNPweights

SNPweights implements an ancestry inference model based on genome-wide SNP weights computed using genotype data for an external panel of reference individuals. To obtain SNP weights, the matrix ( $g_{ij}$ ) of reference panel genotypes for SNP i=1, ..., M and individual j=1, ..., N is normalized by subtracting the mean  $\mu_i = N^{-1} \sum_j g_{ij}$  and dividing by the standard deviation [ $p_i(1-p_i)$ ]<sup>0.5</sup> for each SNP, where  $p_i = \mu_i/2$ , to improve the results of the subsequent PCA analysis from which a kinship matrix is generated [15]. A principal component decomposition is then used to generate the eigenvalues

207 and corresponding eigenvectors of the kinship matrix [11]. The SNP weights file only 208 needs to be recalculated if the reference panel is changed. EIGENSTRAT formatted 209 target animal genotypes are input into SNPweights, along with the precomputed 210 reference panel SNP weights. The SNP weights are then applied to the target 211 individuals to estimate their ancestry proportions [11]. 212 213 **Reference panel development** 214 The definition of a set of reference individuals that define the genotype frequencies at 215 each SNP variant for each reference breed is technically demanding, but vitally 216 important to the process of defining ancestry. This process assumes that selection has 217 not operated to change gene frequencies between target and reference population 218 animals, and that each population is sufficiently large that drift has not impacted allele 219 frequencies. It also assumes that migration between different countries does not 220 influence population allele frequencies when registered animals are imported or 221 exported. FastSTRUCTURE [12] analysis and iterations of animal filtering using 222 SNPweights was performed using the genotypes of candidate reference panel 223 individuals to remove individuals with significant evidence of admixture from the 224 reference breed panel. An overview of the processes and iterations of filtering conducted in the development of this reference panel set is shown in Fig. S1 and Table 225 226 1.

227

228 FastSTRUCTURE analysis to identify candidate reference panel individuals

229 Genotype data for 48,776 individuals produced by one of 8 different genotyping assays 230 were available for fastSTRUCTURE analysis (Table 1) [12]. We initially performed 231 focused fastSTRUCTURE analyses using small numbers of reference breeds including 232 Angus and Simmental, Angus and Gelbvieh, Angus and Limousin, Angus and Red 233 Angus, Red Angus, Hereford, Shorthorn and Salers, Red Angus, Hereford and 234 Shorthorn, and N'Dama, Nelore and Brahman (Figs. S2-S8). Individuals possessing an 235 ancestry assignment of at least 97% to their designated breed were retained for 236 subsequent analysis (see Supplementary Methods and Table 1). Following filtering 237 based on fastSTRUCTURE breed assignment, 17,852 individuals representing 19 of the 238 original breeds remained for further analysis (Supplementary Methods and Figs. S2-239 S8). All of the Salers animals were removed in this filtering analysis which is consistent 240 with previous work that found that Salers and Limousin were very similar [4]. Variation in 241 reference population sample sizes has been shown to substantially influence the 242 estimation of the number of ancestral populations (K) in ancestry analyses [6,13,14]. To 243 minimize this effect and produce similar sample sizes for each of the reference breeds, 244 we randomly sampled 200 individuals from each reference breed for which at least 200 245 individuals remained after filtering on an ancestry assignment of at least 97%, otherwise 246 all remaining individuals were included for the breed (Table 1). Following 247 fastSTRUCTURE analysis using K=19 after removal of Salers and using the BC7K 248 marker set, Texas Longhorn was also removed from the reference panel breed list due 249 to the inability to distinguish Texas Longhorn as a distinct population (Figure 2). 250 Further, due to the known common ancestry [15] and similarity between Nelore and 251 Brahman (Figure 2), the breeds were combined to represent *Bos taurus indicus*.

252

# 253 SNPweights analyses to refine and validate reference panel members

254 Random sampling of reference breed individuals was performed to create sample sets 255 containing  $\leq$ n individuals per breed, for n = 50, 100, 150 and 200 individuals (Figs. 3 a-b and Figs. S9-S10). Sampling was performed such that if a reference breed had ≥n 256 candidates then n individuals were randomly sampled, otherwise, all available 257 258 individuals were sampled. An analysis was performed using the BC7K marker set. 259 SNPweights was used to assign reference breed ancestries to the same sample of individuals that was used to produce the SNP weights for each of the four samples of 260 individuals (Figs. 3 a-b and Figs. S9-S10). In the self-assignment analyses conducted 261 262 using the reference breed sample sets of ≤100 individuals per breed and ≤50 individuals 263 per breed, 7 individuals were removed due to their estimated breed ancestry being 264 ≤60% to their registry breed (Holstein n=3, Jersey n=1, Japanese Black n=3) (Figs. 3 a-265 b).

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# 267 Breeds with open herdbooks

For the Gelbvieh, Limousin, Shorthorn, Simmental, and Braunvieh breeds that have open U.S. herdbook registries, fullblood or 100% ancestry individuals were identified based on pedigree data obtained from the respective breed associations (Table 1). The term "fullblood" is used to identify cattle for which every ancestor is registered in the herdbook and can be traced back to the breed founders. The term "purebred" refers to animals that have been graded up via crossbreeding to purebred status. Charolais also has an open herdbook registry in the U.S., however, access to Full French imported

275 Charolais breed members was limited. As a result, all Charolais individuals identified as 276 purebred in the association registry were retained for downstream analysis, however, 277 these individuals could contain up to 1/32 introgression from another breed. A random 278 sample of 200 individuals was taken for each breed with more than 200 identified 279 fullblood individuals, otherwise all animals were sampled. Individuals previously 280 included in the candidate reference panel following preliminary fastSTRUCTURE filtering for the open herd book breeds were removed and replaced with the fullblood 281 282 individuals. 283 Additional reference panel filtering using SNPweights 284 285 After filtering animals identified to not be fullblood based on their pedigree information, 286 we randomly sampled <50 individuals per reference breed and utilized SNPweights to

estimate weights for each sample and also to estimate breed ancestries for members of the same sample that was used to generate the SNP weights. Based on these analyses, we created 5 overlapping reference breed sets, each containing individuals with  $\geq$ 90%,  $\geq$ 85%,  $\geq$ 80%,  $\geq$ 75%, or  $\geq$ 70% ancestry assignment to their registry breeds (Table 3).

292

# 293 Simulated Genotypes

Using the phased BC7K genotypes for the final reference population of 803 individuals
(3 Nelore genotyped with the BovineHD assay were removed because they were
determined to cause problems for the phasing software), we simulated genotypes for
803 individuals each generation (N = 1, 3, 5 and 10) by randomly sampling two

298 individuals as parents from generation N-1 and using a Poisson distribution to sample at 299 random a single recombinant chromosome from each parent. The number of 300 recombination events for each sampled chromosome was sampled from a Poisson 301 distribution with mean equal to chromosome length in Mb/100 (i.e. 1.58 Morgans for 302 chromosome 1). Simulated genotypes were produced for individuals 1 generation 303 removed from the fullblood/purebred reference population animals (i.e., 50% breed A 304 and 50% breed B), 3, 5, and 10, generations, respectively, to evaluate the ability of 305 CRUMBLER to detect large through to small admixture proportions in animals with 306 increasing numbers of breeds represented in their ancestry. Breed composition 307 estimates for these animals were obtained by tracing the breed of origin of every allele 308 present in each generation N animal. For each marker, we attributed the genomic 309 fragment from the center points of the intervals on each side of each marker to the 310 breed of origin of the two alleles at each marker and summed these across all loci. 311 Finally, we normalized these sums by dividing by the autosomal genome size using UMD3.1 coordinates. 312

313

# 314 **Results and Discussion**

315

The concept of breed and breed membership is man-made and does not inherently exist in nature. Moreover, the formation of breeds of cattle is very recent, as cattle domestication began about 10,000 years ago but the formation of herdbooks has occurred only during the last 200-250 years [16]. Nevertheless, the effects of drift and human selection over the last 200 years have caused sufficient divergence among

321 breeds that breed differences are identifiable at the molecular level. Such signals are 322 essential for breed ancestry analyses to be effective in modern admixed animals. 323 Previous work on assigning breed composition in admixed cattle utilized 50K genotype 324 data and a reference panel of 16 breeds, with the basis for reference panel inclusion 325 being breed association registration [17]. However, the continual evolution of 326 genotyping assays has led to content changes resulting in only a relatively small 327 proportion of markers in common among assays. Consequently, there is a need to 328 evaluate whether these markers are sufficient for breed content estimation, leading to 329 their conservation in the design of future assays. Furthermore the development of an 330 analytical pipeline based on these markers would simplify analysis for end-users and 331 the use of a single reference panel would allow the direct comparison of results 332 between applications.

333

## 334 **Reference panel development**

335 Previously developed cattle reference panels have relied on pedigree accuracy and 336 breed association registration for their definition [17]. Conversely, we used an iterative 337 approach for reference population curation that was able to validate the accuracy of the 338 pedigree information used to identify candidates. FastSTRUCTURE analyses 339 performed using the candidate individuals for each of the initial 19 reference breeds 340 suggested population subdivision in both the Hereford and Simmental (Figure 2). 341 Pedigree analysis for the Herefords within each subpopulation indicated that the 342 subpopulations comprised animals from the highly inbred USDA Miles City Line 1 343 Hereford population (L1) and other individuals representing broader U.S. Hereford

344 pedigrees. The Miles City L1 Hereford cattle were derived from two bulls, both sired by 345 Advance Domino 13 (AHA registration number 1668403) and 50 Hereford foundation 346 cows. Since the founding of the L1 Herefords, the migration of germplasm has been 347 unidirectional from L1 into the broader U.S. industry, as the L1 population has been 348 closed since its founding [18]. However, the L1 Herefords have profoundly influenced 349 the U.S. Hereford population. L1 Herefords do not segregate for recessive dwarfism, 350 which has been a threat to Hereford breeders since the 1950s, and this has led to L1 351 cattle becoming popular in the process of purging herds of the defect [19]. In 1980, the 352 average proportion of U.S. registered Herefords influenced by L1 genetics was 23%. 353 By 2008, this proportion had increased to 81% [18]. 354 355 The detected subpopulation division within the Simmental breed (Figure 2) represents 356 the differentiation between purebred and fullblood animals. For example, progeny of a 357 popular fullblood Simmental sire are present in both subpopulations, however, in one 358 subpopulation the family members are all fullblood and in the other they are all purebred or percentage Simmental animals. This result supports the need to identify fullblood 359 360 animals as reference panel breed representatives for breeds with open herdbooks. 361 Reference population sample size 362 363 By randomly sampling individuals from the candidate reference breed set and using

364 SNPweights to assign these individuals to reference populations, we found that

reference panel breed sample sizes of  $\leq$ 50 or  $\leq$ 100 individuals appeared to capture the

366 diversity within each breed and appropriately determined the ancestry of the tested

individuals (Fig. 3 a-b). For each breed, the percent ancestry predicted for the tested 367 368 reference samples was, on average, 3.86% higher when the SNP weights were 369 estimated using  $\leq$ 50 individuals per breed than when  $\leq$ 100 individuals per breed were 370 used (Table 4). This reflects the increased homogeneity of individuals within each 371 breed and a greater genetic distance between individuals from different breeds as 372 smaller samples of individuals from each breed are used to define the reference panel. 373 Further, due to limitations in the number of genotyped individuals for some breeds 374 (Table 1), as the sample size was increased globally, imbalances were created between 375 the reference panel breed sample sizes which impacted breed composition estimation 376 (Fig. S9-S10). It has previously been shown that the power to detect population 377 structure improves as the reference population sample sizes become more similar 378 [6,14].

379

#### 380 <u>Marker density</u>

381 After the replacement of reference breed individuals with those identified to be fullblood 382 based on pedigree analysis for the open herdbook Gelbvieh, Simmental, Limousin, 383 Braunvieh, Shorthorn, and Charolais breeds, additional self-assignment analyses were 384 conducted to evaluate the effects of marker set size on ancestry prediction. Breed 385 reference panels were again constructed by randomly sampling ≤50 individuals per 386 breed and SNP weights were calculated using both the BC13K markers and BC7K 387 markers. The estimated SNP weights were then used to self-assign ancestry to 388 members of the reference panel animals representing the reference breed set. The 389 ancestry predictions for the reference breed individuals using either the BC7K (Fig. 4a;

390	Fig. S11) or BC13K (Fig. 4b; Fig. S12) marker sets indicate that use of the BC13K
391	marker set did not significantly impact the ancestry predictions. Consequently, the use
392	of the 6,799 markers common to the 8 commercially available genotyping platforms
393	appears to be sufficient to assign breed ancestry for the majority of animals produced in
394	the U.S. The CRUMBLER pipeline can accommodate samples genotyped using
395	alternative assays, however, the produced breed composition estimates will be based
396	on the intersection of markers on the assay and the BC7K marker set.
397	
398	Assignment thresholds
399	We next examined the effects of reference breed homogeneity on ancestry assignment
400	by identifying reference panel members that had been assigned to their breed of
401	registry using SNPweights with probabilities of ancestry of $\geq$ 90%, $\geq$ 85%, $\geq$ 80%, $\geq$ 75%,
402	and $\geq$ 70%, respectively (Table 3). From these individuals, reference breed panels were
403	obtained by randomly sampling ≤50 individuals per breed, until each individual was
404	represented in at least one sample set. SNP weights were then estimated using the
405	BC7K marker set and ancestry was assigned for these individuals using SNPweights
406	(Figs. 5-6 and Figs. S13-S15). Limiting the reference breed panel members to those
407	individuals with $\ge$ 90% ancestry assigned to their breed of registry produced a reference
408	panel that did not represent the extent of diversity within each of the breeds (Fig. 5). On
409	the other hand, using an ancestry assignment of ≥85% clearly captured greater diversity
410	within each breed (Fig. 6) and maximized the self-assignment of ancestry to the breed
411	of registration (Table 5).

# 413 Reference panel definition

To examine whether the specific individuals represented in the reference panel sample influenced the self-assignment of ancestry to the sampled individuals, a second sample of  $\leq$ 50 distinct individuals per breed was obtained from the individuals with  $\geq$ 85% assignment to their breed of registration and analyzed with SNPweights (Fig. 7). Fig. 7 indicates that the ability to predict ancestry was not influenced by the specific individuals sampled from the set of animals with  $\geq$ 85% ancestry to their breed of registration.

421 Additionally, Figs. 6 and 7 suggest that the use of a reference breed panel constructed 422 by the random sampling of  $\leq$ 50 individuals per breed from individuals with  $\geq$ 85% self-423 assigned ancestry to their breed of registration maintained sufficient within-breed 424 diversity to accurately estimate the ancestry of target individuals. However, these 425 figures also reveal small amounts of apparent introgression from other reference panel 426 breeds within each of the breeds. This does not appear to be an issue of marker 427 resolution since the analyses performed with the BC7K and BC13K marker sets generated similar results (Fig. 4). We conclude that these apparent introgressions are 428 429 either due to a lack of power to discriminate among breeds using the common markers 430 designed onto commercial genotyping platforms, or represent the presence of common 431 ancestry among the breeds prior to the formation of breed herdbooks ~200 years ago. 432 Molecular evidence for this shared ancestry exists, for example, Hereford and Angus 433 cattle share the *Celtic* polled allele [20] and the segmental duplication responsible for 434 the white anterior, ventral and dorsal coat color pattern occurs only in Hereford and

435 Simmental cattle and their crosses [21]. These data clearly indicate that crossbreeding
436 was widespread prior to the formal conceptualization of breeds.

437

#### 438 **Reference panel validation**

To evaluate the ability of the selected reference breed panel to identify breed

440 composition, an analysis was conducted for all 170,544 samples in the database which

required 60 processor minutes (Fig 6-7). We extracted animals with pedigree

information including fullblood and purebred animals registered with open herdbook

443 breed associations and 2,243 crossbred animals with varying degrees of admixture.

444 Considering the amount of available data, the number of pedigreed admixed animals

445 was very limited and the purebred animals all had similar expected admixture

446 proportions. Consequently, we next simulated genotypes for animals by assuming the

random mating of members of the reference breed panel for 1, 3, 5 and 10 generations

448 assuming non-overlapping generations to generate generations of animals with different

449 numbers of breeds and breed proportions represented in their genomes.

450

## 451 Registered fullblood animals

For the Gelbvieh, Limousin, Shorthorn, Simmental, and Braunvieh breeds that have
open herdbook registries, fullblood or 100% ancestry individuals were identified based

454 on pedigree data obtained from the respective breed associations (Table 1).

455 CRUMBLER estimates were obtained for these fullblood individuals and the distribution

456 of estimates by breed are in Fig. 8. For all breeds except Charolais, >50% of the

457 individuals had CRUMBLER estimated percentages of ≥80% to their respective breeds.

Average percentage estimates for fullblood Gelbvieh, Limousin, Shorthorn, Simmental, and Braunvieh individuals were 76%, 78%, 83%, 79%, and 85%, respectively (Fig. 8b). However, the number of genotyped imported Full French Charolais animals was limited and so we also analyzed all purebred Charolais individuals which could contain up to 1/32<sup>nd</sup> of their genome introgressed from another breed. The average Charolais breed assignment was 72% and the distribution of estimates was more variable than for the fullblood animals from the other breeds (Fig. 8b).

465

#### 466 <u>Pedigreed crossbred animals</u>

467 Based on pedigree, 2,005 individuals were identified as being primarily Hereford but with varying degrees of Red Angus, Salers, Angus or unknown other breed influence. 468 469 The analysis results agreed with the pedigree data (Fig. 9a) To investigate the 470 correlations between pedigree and CRUMBLER estimated breed proportions, we 471 removed proportions for breeds that were less than 3% and normalized the remaining 472 values. CRUMBLER estimates were then correlated with the pedigree predicted estimates of the proportion of Hereford in these individuals (Fig. 9c). CRUMBLER 473 474 tended to underestimate the Hereford proportion as the pedigree estimated Hereford 475 proportion tended to 100%.

476

The remaining 238 crossbred individuals were commercial, advanced generation
animals with an expected 50% Angus and 50% Simmental ancestry based on pedigree
data. Results of the CRUMBLER analysis again support the pedigree data (Fig. 10).
The presence of Red Angus ancestry in these animals reveals the inability of the

analysis to fully differentiate between Angus and Red Angus, which only diverged in the
U.S. in 1954, and also the influence of Red Angus in the U.S. Simmental breed (Fig.
S16).

484

#### 485 <u>Simulated genotypes</u>

Genomes were simulated using the phased genotypes for 803 individuals from the 486 reference breed panel to contain varying breed numbers and admixture proportions 487 after 1, 3, 5, and 10 generations of random mating with nonoverlapping generations. In 488 489 generation 1, the admixed individuals were  $F_1$  individuals with a 50:50 autosomal 490 genome composition unless both parents were randomly sampled from the same breed. 491 CRUMBLER estimates of breed composition using the simulated genotypes were 492 strongly correlated with the simulated compositions, especially for generations 1 and 3 493 (Fig 11). As the number of generations increased, the number of breeds represented in 494 the simulated genomes tended to increase and the proportion of the genome originating 495 from any one breed tended to decrease and the correlation between the simulated proportions and CRUMBLER estimates also decreased. Nevertheless, by generation 10 496 497 44% of animals had their genome proportions estimated with a correlation of at least 498 70%. In the U.S. commercial crossbreeding does not usually involve the use of more than 3-4 breeds of cattle and while the number of generations of crossbreeding may 499 500 very well be 10 or perhaps more, many generations will involve the mating of animals 501 with similar genome ancestries and the proportions for each breed will be much greater 502 than present in the generation 10 animals in Fig 11. Consequently, the achieved 503 accuracies are likely to be closer to the generation 3 or 5 results where 99% and 68% of

animals, respectively, had their genome proportions estimated with a correlation ofgreater than 80%.

506

#### 507 Advanced generation composite animals

508 The ancestry model assumes that neither drift or selection has acted to alter the allele 509 frequencies from those created by the initial admixture proportions. We examined 510 CRUMBLER estimates of breed composition for advanced generation members of the 511 Brangus (n=11,362), Beefmaster (n=3,832) and Santa Gertrudis (n=2,010) composite 512 breeds where selection has had the opportunity to change breed composition from 513 expectations at breed formation. Brangus individuals are expected to be % Angus and 514 % Brahman, Beefmaster individuals ¼ Hereford, ¼ Shorthorn and ½ Brahman, and 515 Santa Gertrudis % Shorthorn and % Brahman, respectively. These breeds use mating 516 strategies that produce individuals that are expected to possess these proportions for 517 registration within each of the respective breed's herdbook. However, registerable 518 animals are ultimately advanced generation composites and so drift, meiotic sampling of 519 parental chromosomes and selection are all expected to create individual variation in 520 these ancestry proportions. CRUMBLER results for these advanced generation 521 composites, also known as the American breeds, are shown in Figure 12. Table 6 522 contains the average breed proportion estimates assigned to each of these breeds by 523 CRUMBLER and their standard deviations across the animals analyzed for each breed. 524 In every instance, CRUMBLER underestimates the expected proportions for each of the 525 American breed populations, however, the ancestral breeds clearly dominate the 526 assignments (Table 6). Interestingly, on average, CRUMBLER estimated proportions of

527 Holstein ancestry for advanced generation Beefmaster and Brangus animals (Figure 12 528 and Table 6). These American breeds do not contain any Holstein introgression and 529 they do not contain ancestry from a "Ghost Population", a population that is not present 530 in the reference set, which would lead to a breed assignment to a reference breed that it 531 most closely resembled [6]. We speculate that this effect is caused by selection 532 creating a deviation in allele frequencies from those found in the founder breeds which 533 the model explains by an introgression from a distantly related breed, in this case, 534 Holstein. Stratifying these genotyped animals according to the number of generations 535 from foundation fullblood animals and examining the extent of estimated Holstein 536 introgression, which would be expected to increase with generation number, would 537 enable this to be tested, but we did not have access to the necessary data. However, 538 this hypothesis is supported by the fact that the Santa Gertrudis had the least estimated 539 Holstein introgression and the breed has published estimates of additive genetic merit 540 for many fewer years than the Beefmaster or Brangus.

541

#### 542 Admixture

We also tested the ADMIXTURE software [22] for ancestry estimation and integration into the CRUMBLER pipeline using the same reference breed panel that was developed for use with SNPweights. ADMIXTURE uses maximum likelihood estimation to fit the same statistical model as STRUCTURE, however, STRUCTURE does not allow the specification of individuals of known descent to be used as a reference panel [22]. ADMIXTURE allows a supervised analysis, in which the user can specify a reference set of individuals, by specifying the "--supervised" flag and requires an additional file

with a ".pop" suffix to specify the genotypes of the reference population individuals [22].
Unlike SNPweights, the reference population individuals' genotypes must be provided in
a genotype file for each analysis.

553

554 We first conducted an ADMIXTURE analysis in which we self-assigned ancestry for the 555 animals in the reference breed set formed with  $\leq$ 50 individuals per breed from the 556 individuals that had ≥85% assignment to the breed of registration (Fig. 13). The results 557 shown in Fig. 13 are similar to those in Fig. 6 for the same reference panel, albeit with 558 perhaps less evidence of background introgression. We next conducted an analysis 559 using the reference panel used in Fig. 13 merged with data for the 2,005 high 560 percentage crossbred Herefords animals. The results shown in Fig. 14, reveal a 561 significant change in the ancestry proportions estimated for the reference panel 562 Guernsey, Gelbvieh and Romagnola individuals between the two analyses which used exactly the same reference panel, but differed only in the number of individuals for 563 564 which ancestry was to be estimated. This suggests that ADMIXTURE may use the 565 target individuals to update information provided by the reference panel individuals 566 specified in the ".pop" file. Consequently, the ADMIXTURE estimated ancestry proportions appear to be context dependent and may vary based on the other 567 individuals included in the analysis. 568

569

570 Moreover, the order in which the target individuals appear in the genotype input file also 571 appears to affect ADMIXTURE estimates of ancestry proportions for the target 572 individuals. Fig. 15 shows the results of an ADMIXTURE analysis in which the target

573 individuals were identical to those shown in Fig. 14, but for which the order of the 574 reference individuals and the 2,005 Hereford crossbred individuals was reversed in the input files. In Fig. 14, the reference individuals appear before the 2,005 Hereford 575 576 crossbred individuals in the input file, whereas in Fig. 15, the 2,005 Hereford crossbred 577 individuals appeared before the reference individuals in the input file. The results reveal 578 a significant change in ancestry proportions for Guernsey and Gelbvieh, but the 579 Romagnola now appear to be non-admixed. Finally, we performed an ADMIXTURE 580 analysis for these animals in which the order of animals in the input genotype file was 581 completely randomized (Fig. 16). Following analysis, the individuals were sorted to 582 generate Fig. 16. Again, the ancestry proportions for the Guernsey, Gelbvieh and Romagnola individuals suggest these breeds to be admixed. 583

584

585 STRUCTURE and ADMIXTURE are widely used for characterizing admixed populations 586 [6], however, we have not found any reports in the literature that indicate that the 587 software is sensitive to the input order of individuals. However, we suspect that the 588 majority of users would have no need or motivation to run the software with permuted 589 data input files. Nevertheless, because of these inconsistencies between results, we 590 chose to not use ADMIXTURE for ancestry estimation within the CRUMBLER pipeline. 591

# 592 Broader application using additional commercially available assays

593 To broaden the spectrum of data from different commercially available assays that can 594 be evaluated, an additional intersection of markers was obtained using 11 commercially 595 available bovine assays including the GGP-90KT, GGP-F250, GGP-HDV3, GGP-LDV3,

596 GGP-LDV4, BovineHD, BovineSNP50, i50K, Irish Cattle Breeding Federation (Cork, 597 Ireland) IDBv3, and GeneSeek (Lincoln, NE) BOVG50v1 assays. The intersection SNP set included 6.363 SNPs (BC6K). A SNPweights self-assignment analysis using the 598 599 reference set of individuals with ≥85% assignment to their breed of registration was 600 conducted to assess the effects of the reduction in number of markers used for ancestry 601 assignment. The ancestry proportions assigned based on the BC6K marker set (Fig. 17) did not differ appreciably from those obtained using the BC7K marker set (Fig. 6). 602 603 This result indicates the utility of CRUMBLER and the reference panel breed set across 604 the spectrum of commercially available genotyping platforms.

605

# 606 **Conclusions**

607 The determination of a set of reference population breeds and individuals that define 608 allele and genotype frequencies at each variant for each of the breeds is arguably the 609 most important, yet technically difficult step in the process of ancestry estimation. We 610 employed several iterations of filtering to remove recently admixed individuals and 611 identify a relatively homogeneous set of individuals that nevertheless represented the 612 variation that might be expected among individuals within a breed. Once determined, 613 the reference panel genotype data need only be processed once to obtain SNP weights 614 removing the need to share genotype data for reference individuals in subsequent 615 studies [11]. The upfront development of an external reference breed panel capitalizes 616 on the rich ancestry information available in large available datasets, and relatedness, 617 variation in sample sizes and diversity among the target individuals does not affect the inference of ancestry [11]. 618

620	In cattle, the visual evaluation of breed characteristics is a poor method for evaluating
621	the ancestry of individuals. Breed association pedigrees can be used to estimate
622	expected breed compositions, however, the random assortment of chromosomes into
623	gametes and selection can lead to ancestry proportions that differ from those expected
624	based upon pedigree. Moreover, the vast majority of commercial beef cattle in the U.S.
625	have no or very limited pedigree information and since these animals are frequently
626	used for genomic research [3–5], there is a need for a tool that can routinely provide
627	ancestry estimates for downstream use in GWAA or other genetic studies.
628	
629	We tested ADMIXTURE and SNPweights and found that results from ADMIXTURE
630	appear to depend on the ancestry and order of appearance of individuals within the
631	genotype input file. We therefore developed an analysis pipeline, CRUMBLER, based
632	upon PLINK, EIGENSOFT and SNPweights to automate the process of ancestry
633	estimation. The developed bovine pipeline utilizes the 6,799 SNPs present on 8
634	commercially utilized bovine SNP genotyping assays and results using these SNPs are
635	consistent with results obtained when 13,291 SNPs were used. From an available
636	48,776 genotyped individuals, we also developed a reference panel of 806 individuals
637	sampled from 17 breeds to have $\leq$ 50 individuals per breed that had $\geq$ 85% assignment
638	to their breed of registration. This panel appears to allow the robust estimation of the
639	ancestry of advanced generation admixed animals, however, all breeds share some
640	common ancestry which predates the recent development of breed association
641	herdbooks [16,23].

- 643 CRUMBLER is not limited to application in cattle and with the provision of suitable
- 644 reference breed allele frequencies can be applied to other species for ancestry
- 645 estimation. CRUMBLER pipeline scripts and reference panel breed SNP weights are
- 646 available on GitHub (https://github.com/tamarcrum/CRUMBLER).

# 647 Additional files

648	Supplementary Information (PDF). This file contains the source code changes in
649	SMARTPCA within versions of EIGENSOFT beyond 5.0.2 to enable compatibility with
650	SNPweights.
651	
652	Supplementary Methods (PDF). This file describes the preliminary fastSTRUCTURE
653	analyses conducted on subsamples of breeds in the development of the reference
654	breed panel.
655	
656	Supplementary Figures (PDF). This file contains Supplementary Figures S1-S16.
657	
658	Fig. S1 An overview of the processes and iterations of filtering conducted in the
659	development of the reference panel.
660	
661	Fig. S2 Preliminary FastSTRUCTURE analysis of candidate Angus and Simmental
662	reference population animals.
663	
664	Fig. S3 Preliminary fastSTRUCTURE analysis of candidate Angus and Gelbvieh
665	reference population animals.
666	
667	Fig. S4 Preliminary fastSTRUCTURE analysis of candidate Angus and Limousin
668	reference population animals.

669

- **Fig. S5 Preliminary fastSTRUCTURE analysis of candidate Angus and Red Angus**
- 671 reference population animals.
- 672
- 673 Fig. S6 Preliminary fastSTRUCTURE analysis of candidate Red Angus, Hereford,
- 674 Shorthorn and Salers reference population animals.
- 675
- 676 Fig. S7 Preliminary fastSTRUCTURE analysis of candidate Red Angus, Hereford
- and Shorthorn reference population animals.
- 678
- **Fig. S8 Preliminary fastSTRUCTURE analysis of candidate N'Dama, Nelore and**
- 680 Brahman reference population animals.
- 681
- **Fig. S9 SNPweights self-assignment analysis for the reference sample set**
- 683 containing ≤200 individuals per breed analyzed using the BC7K marker set.
- 684
- **Fig. S10 SNPweights self-assignment analysis for the reference sample set**
- 686 containing ≤150 individuals per breed analyzed using the BC7K marker set.
- 687
- Fig. S11 SNPweights self-assignment analysis for the reference sample set
   containing ≤50 individuals per breed analyzed using the BC7K marker set.

690

Fig. S12 SNPweights self-assignment analysis for the reference sample sets
 containing ≤50 individuals per breed analyzed using the BC13K marker set.

Fig. S13 SNPweights self-assignment analysis for the reference sample set with

693

694

- ≥80% ancestry to breed of registry and ≤50 individuals per breed using the BC7K 695 696 marker set. 697 Fig. S14 SNPweights self-assignment analysis for reference sample set with  $\geq$ 75% 698 699 ancestry to breed of registry and ≤50 individuals per breed using the BC7K 700 marker set. 701 702 Fig. S15 SNPweights self-assignment analysis for the reference sample set with 703 ≥70% ancestry to breed of registry and ≤50 individuals per breed using the BC7K 704 marker set. 705 706 Fig. S16 SNPweights self-assignment analyses using a reference panel with ≤50 707 individuals per breed and sampling from the individuals with ≥85% assignment to 708 their breed of registry but with (a) Red Angus or (b) Angus excluded from the 709 reference panel. 710 Authors' contributions 711 712 TC conceived the study and managed the project. TC, RS, JD, and JT contributed to 713 defining the research questions and analytical approaches and interpretation of the
- results. TC programmed the CRUMBLER pipeline and carried out the data analyses.
- TC and JT drafted the manuscript. LR provided the Nelore samples but did not have

- involvement in the scientific direction. All authors read and approved the final
- 717 manuscript.
- 718
- 719 Competing interests
- 720 The authors declare that they have no competing interests.
- 721
- 722 Availability of data and materials
- 723 Project Name: CRUMBLER
- 724 Project Home Page: <u>https://github.com/tamarcrum/CRUMBLER</u>
- 725 Programming Language: Python
- 726 Other Requirements: PLINK, EIGENSOFT, and SNPweights
- 727 License: GNU GPL
- 728
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- 736 26760.
- 737
- 738 Consent for Publication

739 Not applicable.

740

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### Table 1. Genotype data for 48,776 registered individuals from 20 breeds were

#### 811 used to establish the reference population.

Breed	No. Registered Individuals	No. FullBlood Individuals <sup>a</sup>	No. Individuals Assigned to Breed <sup>b</sup>	Sampled Individuals <sup>c</sup>	No. Individual After Pedigre and SNPweights <sup>(</sup>
Angus	5552	5552	485	200	200
Hereford	969	969	348	200	200
Limousin	2734	321	367	200	200
Charolais	1542	1489	1542	200	200
Simmental	15858	337	1583	200	196
Japanese Black	97	97	97	97	94
Braunvieh	148	69	148	148	69
Gelbvieh	12835	51	6000	200	51
Romagnola	37	37	37	37	37
Salers	68	68	0	0	0
Texas Longhorn	45	45	45	0	0
Shorthorn	291	178	166	166	178
Red Angus	1377	1377	124	124	124
Holstein	5816	5816	5816	200	197
Jersey	119	119	119	119	118
Brown Swiss	92	92	92	92	90
Guernsey	30	30	30	30	30
N'Dama	98	98	59	59	59
Brahman	127	127	86	86	50
Nelore	941	941	708	200	50
Total	48776	17813	17852	2558	2143

- <sup>a</sup>Number of registered animals determined by pedigree analysis to be fullblood for breed
- 814 associations with open herdbooks.
- <sup>b</sup>Number of registered animals assigned to their identified breed with P≥0.97 by
- 816 fastSTRUCTURE in preliminary analyses and retained for subsequent analyses.
- <sup>c</sup>A random sample of 200 individuals was obtained for breeds with >200 individuals after
- fastSTRUCTURE analysis and all individuals were sampled for breeds with ≤200 per breed and
- the data were again analyzed by fastSTRUCTURE with K=19 after removal of the Salers.
- <sup>d</sup>Animals that were determined to not be fullblood by pedigree analysis and animals
- assigned with  $P \le 0.60$  by SNP weights to their breed of registry were removed.

### Table 2. The number of variants queried by each assay and the number of

824 individuals from the 20 reference breeds genotyped using each assay.

825

Assay	No. of Variants	No. of Registered Individuals
BovineSNP50	58336	20485
BovineHD	777962	2303
GGP-F250	227234	3068
GGP-90KT	76999	4407
GGP-LDV3	26504	6065
GGP-HDV3	139977	3630
GGP-LDV4	30105	8653
GGP-LDV1	8762	165
Zoetis i50K	59825	0
ICBF IDBv3	53450	0
BOVGv1	47843	0
Total		48776

## Table 3. Number of individuals for each reference breed assigned to their breed of registration by minimum ancestry threshold.

829

	Breed Assignment Probability						
Breed	≥90%	≥85%	≥80%	≥75%	≥70%		
Angus	51	136	184	199	200		
Hereford	58	136	184	200	200		
Limousin	93	127	144	162	173		
Charolais	52	92	119	132	147		
Simmental	21	43	81	103	121		
Japanese Black	52	73	78	83	86		
Braunvieh	37	57	63	65	68		
Gelbvieh	23	31	39	43	43		
Romagnola	10	25	32	36	37		
Shorthorn	34	98	159	170	177		
Red Angus	48	88	110	120	123		
Holstein	39	119	172	193	196		
Jersey	52	77	91	108	116		
Brown Swiss	38	64	73	82	86		
Guernsey	12	22	29	30	30		
N'Dama	27	45	59	59	59		
Brahman	15	40	50	50	50		
Nelore	32	50	50	50	50		
Total	694	1323	1717	1885	1962		

# Table 4. Ancestry proportion statistics for the self-assignment of reference panel members from samples of ≤50 or ≤100 individuals from the candidate reference breed individuals.

834

Breed	Min % (≤50)	Avg % (≤50)	Max % (≤50)	Min % (≤100)	Avg % (≤100)	Max % (≤100)
Angus	86.22	90.40	95.54	78.49	87.05	94.13
Hereford	79.75	90.08	95.05	73.41	87.39	96.81
Limousin	69.52	88.53	98.16	18.36	86.40	98.81
Charolais	78.14	90.19	99.82	48.93	77.46	93.96
Simmental	81.06	90.37	97.66	61.36	73.05	88.11
Japanese Black	81.44	90.00	97.07	24.51	86.50	98.95
Braunvieh	71.59	89.46	98.61	65.46	88.36	98.70
Gelbvieh	73.03	76.27	81.63	60.92	74.59	80.33
Romagnola	75.05	87.18	96.66	74.79	85.99	95.12
Shorthorn	84.42	88.69	94.54	70.71	85.27	96.35
Red Angus	79.00	89.60	96.33	68.07	86.83	97.38
Holstein	85.82	90.30	97.51	62.95	86.97	97.81
Jersey	78.55	89.28	95.93	61.23	86.54	97.18
Brown Swiss	80.10	89.22	96.40	61.68	86.02	98.42
Guernsey	79.53	89.19	95.85	77.40	88.31	94.36
N'Dama	80.67	89.25	96.90	78.91	87.78	95.67
Bos taurus indicus	87.83	91.91	97.75	81.43	89.79	97.60

# Table 5. Average predicted ancestry and variance in predicted ancestry for candidate reference breed individuals when filtered on minimum predicted

#### 837 candidate reference breed individuals when filtered of 838 ancestry.

839

Breed	Avg % (70%)	Var (70%)	Avg % (75%)	Var (75%)	Avg % (80%)	Var (80%)	Avg % (85%)	Var (85%)	Avg % (90%)	Var (90%)
Angus	86.50	0.21	87.95	0.19	87.33	0.22	88.86	0.13	72.34	0.97
Hereford	86.99	0.22	87.09	0.23	87.48	0.19	88.25	0.13	84.62	0.43
Limousin	86.77	0.55	89.03	0.44	87.92	0.38	88.48	0.43	80.62	1.19
Charolais	80.18	2.16	85.03	1.77	86.28	0.99	88.56	0.52	81.54	0.76
Simmental	72.73	0.89	78.45	0.58	83.81	0.36	89.65	0.15	87.82	0.50
Japanese Black	87.85	0.52	88.04	0.39	88.46	0.27	88.74	0.21	80.06	0.61
Braunvieh	87.01	0.37	87.84	0.36	87.33	0.38	88.71	0.21	80.47	1.24
Gelbvieh	86.68	0.41	87.10	0.43	87.52	0.34	88.43	0.34	83.31	1.25
Romagnola	86.16	0.33	86.37	0.32	87.16	0.32	86.22	0.29	86.38	1.16
Shorthorn	85.97	0.26	87.03	0.22	86.80	0.14	87.38	0.07	83.00	0.70
Red Angus	86.41	0.53	87.08	0.48	87.40	0.35	87.46	0.23	23.37	0.66
Holstein	86.44	0.27	87.82	0.21	87.54	0.13	88.77	0.12	79.71	0.61
Jersey	87.01	0.46	86.93	0.44	87.86	0.24	87.98	0.27	80.52	0.71
Brown Swiss	86.22	0.47	86.73	0.51	88.24	0.26	88.11	0.20	82.23	0.70
Guernsey	86.46	0.23	87.64	0.19	87.50	0.25	88.02	0.51	80.43	2.36
N'Dama	87.76	0.19	87.91	0.21	87.89	0.15	89.25	0.17	86.40	0.52
Bos taurus indicus	87.68	0.07	88.24	0.09	87.55	0.11	88.53	0.09	84.89	0.38
Average	85.58	0.48	86.84	0.41	87.30	0.30	88.32	0.24	78.69	0.87

840

### 842 Table 6. Average breed ancestry percentages assigned to American Breed

### 843 individuals.

844

Breed	Avg. Ancestry Beefmaster % (± st. dev)	Avg. Ancestry Brangus % (± st. dev)	Avg. Ancestry Santa Gertrudis % (± st. dev)
Angus	3.29 (± 4.27)	32.15 (± 8.96)	4.90 (± 4.48)
Hereford	16.13 (± 2.83)	2.03 (± 2.93)	2.50 (± 4.05)
Limousin	1.40 (± 2.28)	1.73 (± 2.56)	1.29 (± 2.19)
Charolais	6.89 (± 3.97)	2.07 (± 3.79)	5.26 (± 3.42)
Simmental	2.65 (± 3.12)	1.16 (± 2.92)	0.40 (± 1.40)
Japanese Black	0.53 (± 3.46)	0.10 (± 0.63)	0.22 (± 0.89)
Braunvieh	0.63 (± 1.64)	0.33 (±1.29)	0.59 (± 1.63)
Gelbvieh	3.19 (± 3.30)	3.14 (± 3.67)	2.59 (± 3.20)
Romagnola	1.05 (± 1.94)	0.54 (± 1.39)	0.68 (± 1.57)
Shorthorn	15.36 (± 4.72)	5.86 (± 3.42)	37.71 (± 5.46)
Red Angus	3.66 (± 3.57)	13.60 (± 3.95)	1.18 (± 3.46)
Holstein	6.22 (± 6.73)	4.53 (± 4.82)	0.89 (± 2.83)
Jersey	0.73 (± 1.65)	0.52 (± 1.37)	0.26 (± 1.08)
Brown Swiss	1.05 (± 2.14)	1.28 (± 2.26)	0.73 (± 1.81)
Guernsey	1.53 (± 2.20)	0.17 (± 0.81)	1.50 (± 2.14)
N'Dama	0.52 (± 1.35)	0.19 (± 0.87)	0.16 (± 0.76)
Bos taurus indicus	27.32 (± 4.84)	23.09 (± 6.73)	30.50 (± 4.52)

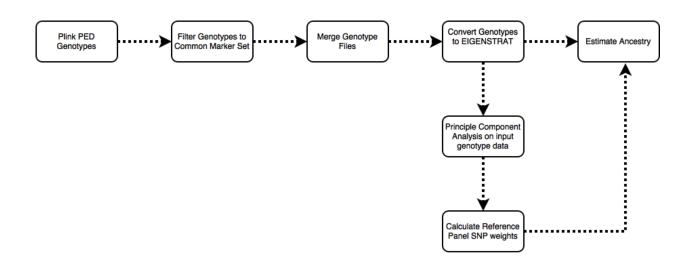
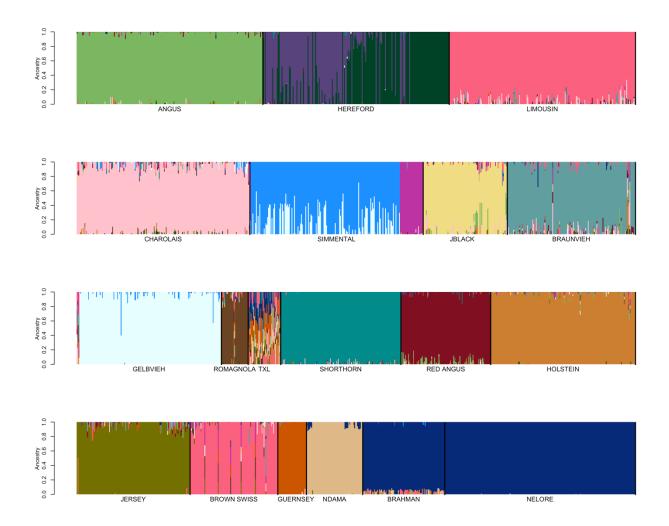
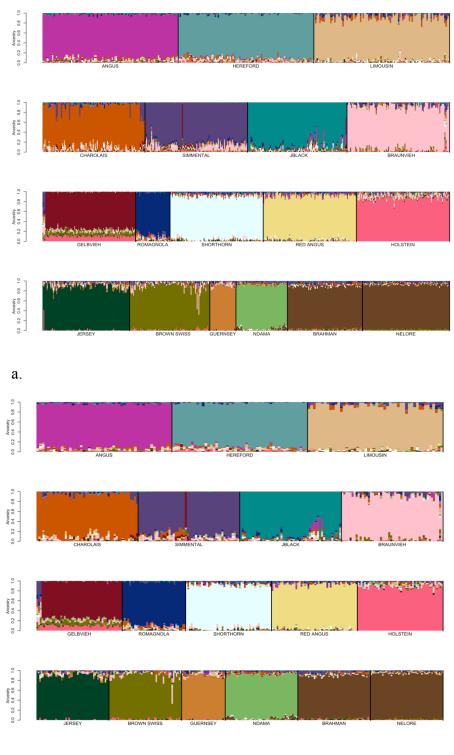


Fig. 1 Flow diagram of the breed composition pipeline.

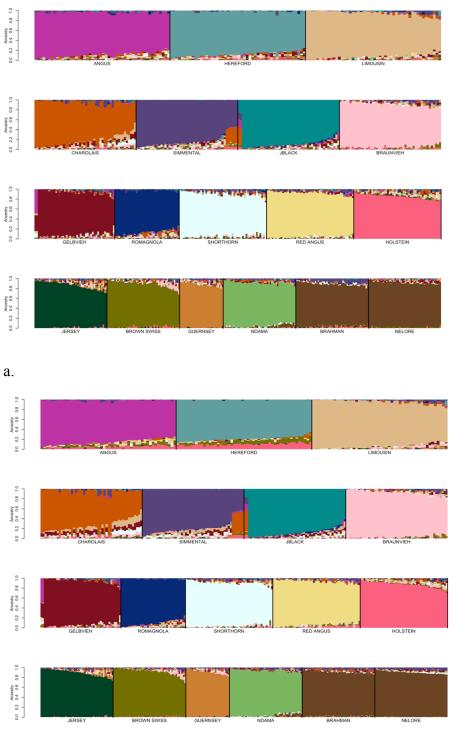


**Fig. 2** FastSTRUCTURE results for a random sample of  $\leq 200$  individuals per breed from the pool of 17,852 potential reference individuals at K=19. Breed identification is shown below each colored block and each animal is represented as a vertical line within the block.



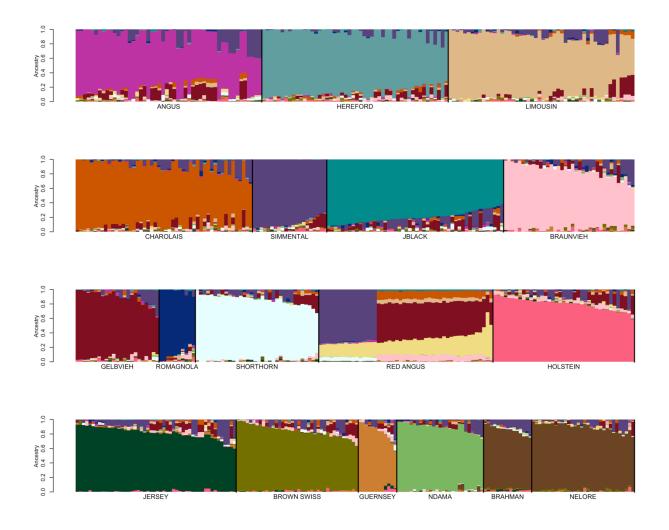
b.

**Fig. 3** SNPweights self-assignment analysis results for reference panel sample sets consisting of: (a)  $\leq 100$  individuals per breed, or (b)  $\leq 50$  individuals per breed. Seven individuals were filtered for  $\leq 60\%$  ancestry to their breed of registry (Holstein n=3, Jersey n=1, Japanese Black n=3).



b.

**Fig. 4** SNPweights self-assignment of ancestry for candidate reference breed individuals following evaluation of open herdbook breeds using: (a) the BC7K, or (b) the BC13K marker panels. Reference breed panels were constructed by random sampling  $\leq$ 50 individuals per breed and SNP weights were estimated using the BC7K and BC13K marker sets.



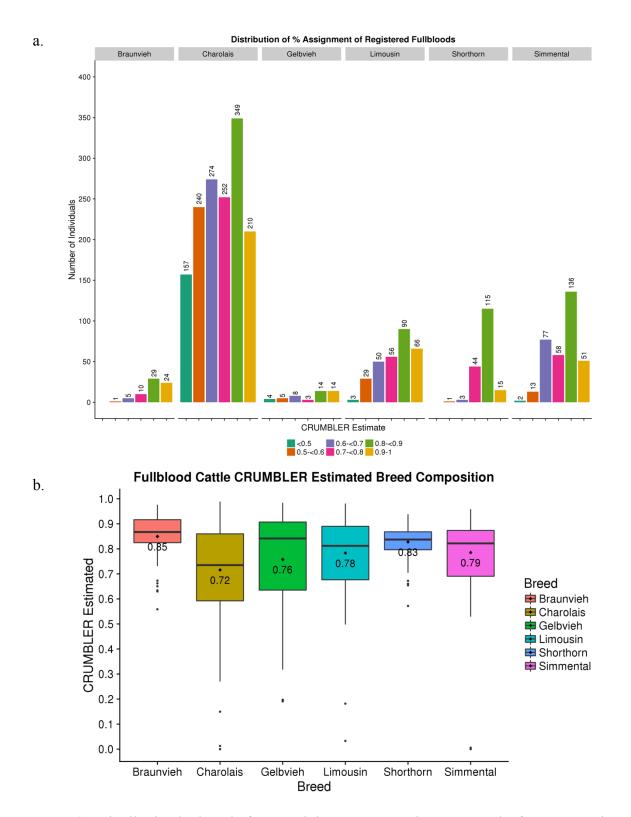
**Fig. 5** Reference breed panel constructed by the random sampling of  $\leq$ 50 individuals per breed from individuals with  $\geq$ 90% ancestry was self-assigned to reference breed ancestry using the BC7K marker set.



**Fig. 6** Reference breed panel constructed by the random sampling of  $\leq$ 50 individuals per breed from individuals with  $\geq$ 85% ancestry was self-assigned to reference breed ancestry using the BC7K marker set.

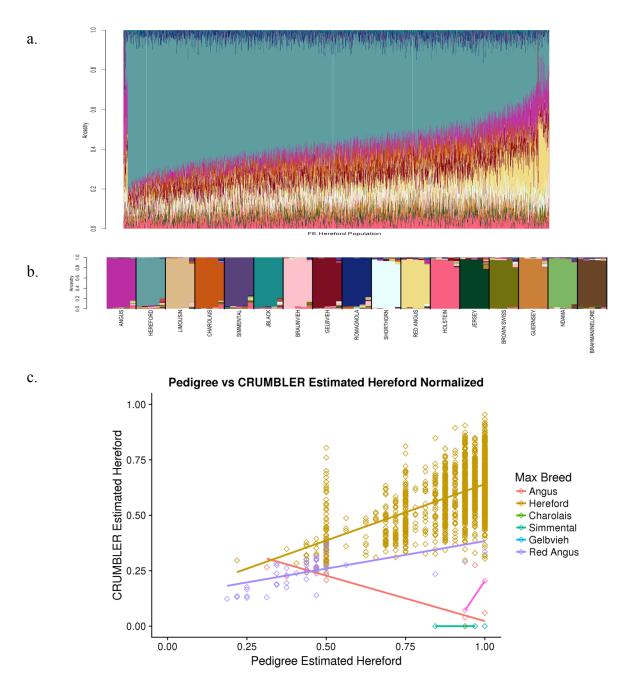


Fig. 7 Reference breed panel constructed by the independent random sampling of a second sample of  $\leq$ 50 individuals per breed from individuals with  $\geq$ 85% ancestry after eliminating individuals represented in the first sample was self-assigned to reference breed ancestry using the BC7K marker set.

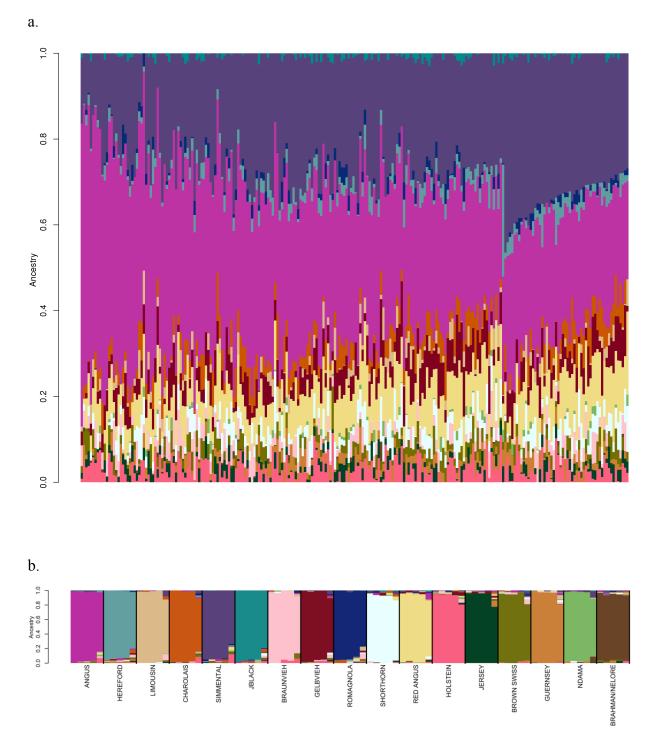


**Fig. 8** (a) Distribution by breed of SNPweights ancestry assignment results for 2,408 registered fullblood animals from open herd book breeds. (b) Pictorial representation of CRUMBLER estimates for 2,408 registered fullblood animals from open herd book breeds.

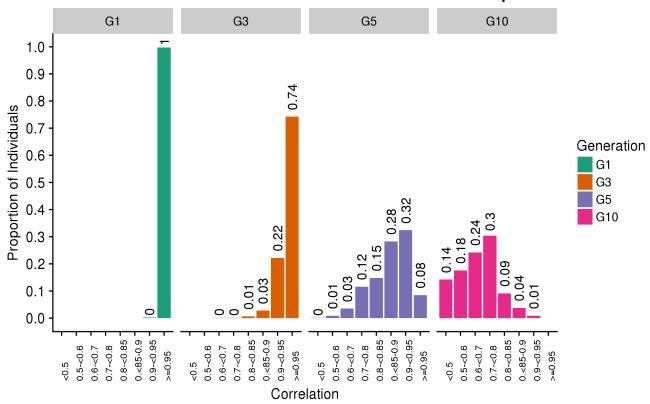
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**Fig. 9** (a) SNPweights ancestry results for 2,005 crossbred Hereford individuals with *a-priori* breed composition estimates determined by pedigree. (b) Breed assignment reference breed key. (c) Hereford SNPweights estimated proportions using CRUMBLER are plotted against the pedigree estimates. Data point color indicates the breed for which SNPweights assigned the highest proportion for each individual.

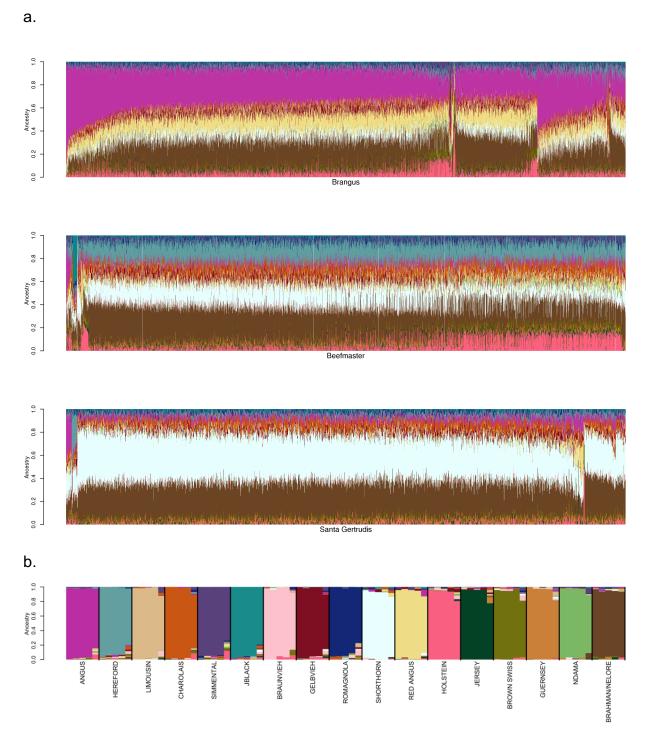


**Fig. 10** (a) SNPweights ancestry results for 238 crossbred individuals with *a-priori* breed composition estimates of 50% Angus and 50% Simmental based on a reference panel with  $\leq$ 50 individuals per breed sampled from individuals with  $\geq$ 85% assignment to their breed of registry. (b) Breed assignment for the crossbred individuals can be determined using this reference breed key.

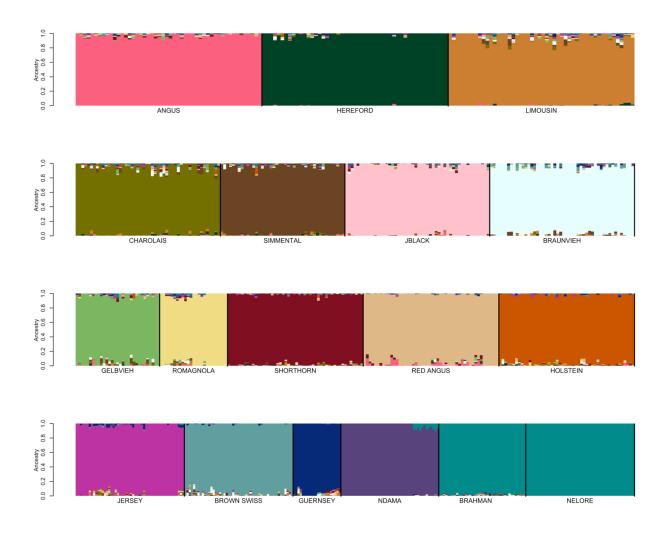


### **Correlations between CRUMBLER and Simulated Breed Proportions**

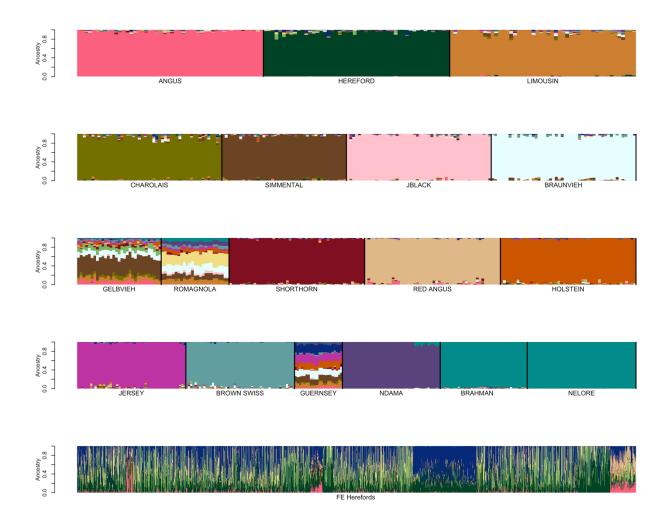
**Fig. 11** Genotypes were simulated for the indicated number of generations of random mating, with generation 1 (G1) animals being 50:50 proportion except when two parents from the same breed were mated. SNPweights results were obtained using CRUMBLER pipeline parameters correlations between these estimates and the known simulated breed compositions were produced and the proportion of individuals within each correlation class is indicated.



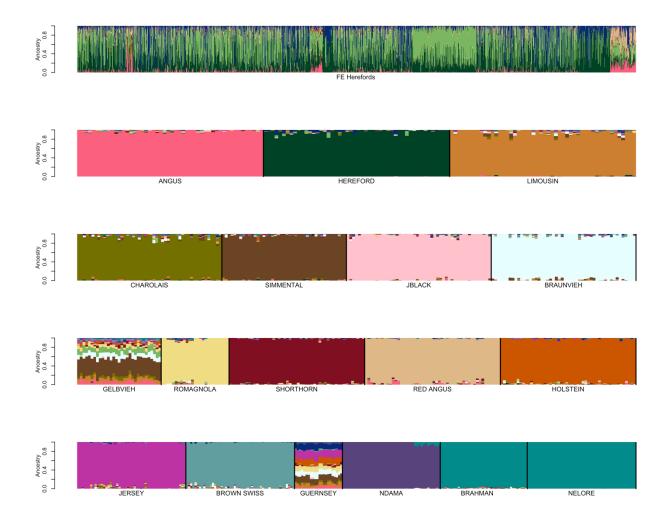
**Fig. 12** (a) SNPweights ancestry results using CRUMBLER pipeline for 11,362 Brangus, 3,832 Beefmaster, and 2,010 Santa Gertrudis individuals. (b) Breed assignment for these advanced generation composite animals can be determined using this reference breed key.



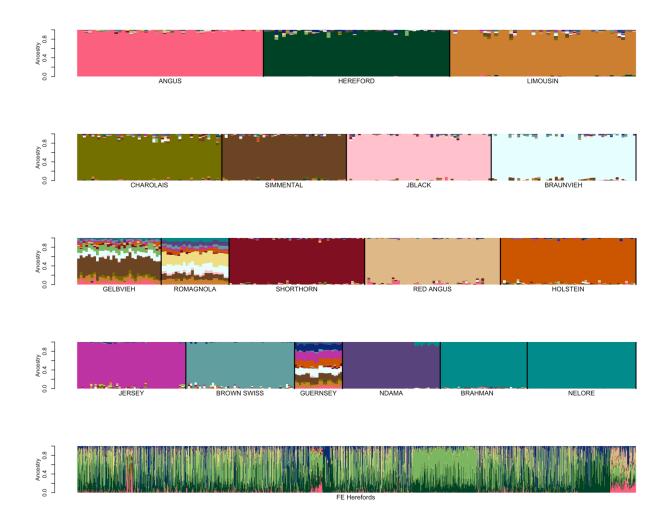
**Fig. 13** Self-assignment of ancestry for the animals in the reference breed set formed with  $\leq$ 50 individuals per breed from the individuals that had  $\geq$ 85% assignment to their breed of registration using ADMIXTURE.



**Fig. 14** ADMIXTURE analysis conducted using the same data as shown in Figure 13 (first four rows), merged with an additional 2,005 high percentage crossbred Hereford target individuals (last row). Here, the 2,005 Hereford crossbred individuals appear after the reference individuals in the input genotype file.



**Fig. 15** ADMIXTURE analysis conducted using the same data as shown in Fig. 14. Here, the 2,005 Hereford crossbred individuals appear before the reference individuals in the input genotype file. The first row represents the 2005 Hereford crossbred samples. Rows 2 to 5 show the reference panel individuals.



**Fig. 16** ADMIXTURE analysis conducted using the same data as shown in Figs. 14 and 15, but with the order of the individuals in the input genotype file randomized. The animals were sorted following analyses to generate this figure where the first four rows represent the reference panel individuals, the fifth row shows the 2,005 Hereford crossbred animals.



Fig. 17 Reference breed panel constructed by the random sampling of  $\leq$ 50 individuals per breed from individuals with  $\geq$ 85% ancestry was self-assigned to reference breed ancestry using the BC6K marker set.