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SELECTION INDICES FOR EARLY SELECTION IN DUAL-PURPOSE MERINO PRECOZ SHEEP UNDER LOW-INPUT CONDITIONS

Felipe Lembeye[1]*, Giorgio Castellaro[2a] and Héctor Uribe[2b]

[1] Departamento de Ciencias Animales, Facultad de Agronomía y Sistemas Naturales, Pontificia Universidad Católica de Chile, Santiago, Chile
https://orcid.org/0000-0001-5912-4524

[2a] Departamento de Producción Animal, Facultad de Ciencias Agronómicas, Universidad de Chile, Santiago, Chile
https://orcid.org/0000-0003-0106-560X

[2b] Departamento de Producción Animal, Facultad de Ciencias Agronómicas, Universidad de Chile, Santiago, Chile

* Corresponding author: flembeye@uc.cl

ABSTRACT

In central Chile's low-input drylands, sheep breeding is challenged by early selection at weaning, often without pedigree records, and limited resources. These constraints reduce genetic progress, as farmers rely on visual selection. Nevertheless, selection indices provide an alternative for more efficient and accurate genetic improvement of dual-purpose breeds such as Merino Precoz (MP) sheep. This study aimed to estimate regression coefficients and relative contributions (RC) of key traits within several selection indices to optimize breeding objectives and estimate genetic progress in MP sheep. Five indices were simulated under three economic scenarios based on the relative price of fibre diameter (FD) to greasy fleece weight (GFW), integrating pre-weaning and maternal data. The breeding objective included GFW, FD, number of lambs weaned (NLW), weaning weight (WW) and adult weight (AW). Results showed that WW consistently had the greatest RC (8.74–8.82%), while NLW contributed less (4.18–4.22%), and excluding NLW notably increased index accuracy (0.47–0.49 vs. 0.35). Wool traits gained importance as the economic value of FD increased, although WW remained the most influential trait across indices. Expected annual genetic gains ranged from 0.014 to 0.025 kg for GFW, -0.044 to 0.022 μm for FD, 0.279 to 0.300 kg for WW, and 0.525 to 0.621 kg for AW. These findings suggest that excluding NLW from the breeding objective improves accuracy and increases the predicted response for several production traits under low-input systems, while dam live-weight records provide little improvement in accuracy. The coefficients presented in this study are valuable for farmers practicing early selection at weaning, enabling more efficient genetic improvement of wool and meat traits under resource-limited conditions.

Keywords: selection index, genetic gain, relative contribution, Merino Precoz, dual-purpose sheep.

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INTRODUCTION

Sheep production can be improved through environmental management or genetic programs, with genetic improvement offering permanent and cumulative benefits (Conington et al., 2001; Ramos et al., 2025). However, genetic programs remain limited, particularly in developing countries, where sheep farming occurs on marginal lands and farmers tend to prioritize cost reduction over genetic progress. Nevertheless, the global trend toward intensification and specialization highlights an increasing demand for genetic improvement programs (Mueller et al., 2015).

In Chile, selection is primarily based on visual assessment, resulting, in theory, in low genetic gains. Importing germplasm from countries such as Australia and New Zealand is an alternative, but it faces challenges related to costs, availability, and export policies (Mueller, 2006). For the implementation of genetic selection programs, Hazel (1943) introduced selection indices that optimize the selection of breeding animals by correlating selection criteria (traits recorded as predictors) with breeding objectives (traits of interest for improvement). In selection programs, after characterizing the production system, the next step is to define the breeding goal and the economically important traits that influence this goal (breeding objective), while selection criteria –measurable traits that form the index– are used to assess an individual's breeding value (Mueller et al., 2015). According to Hazel (1943), these traits are weighted (regression factors) to maximize the correlation between the breeding objective and the selection criteria.

Several simulation studies have explored ways to enhance genetic gain through selection indices (Safari et al., 2006; Valera et al., 2009; Lembeye et al., 2014; Alvarez et al., 2014; Guo et al., 2025). For a dual-purpose sheep breed such as Merino Precoz (MP), Lembeye et al. (2014) compared several indices and found that daily growth rate (GR) from birth to weaning contributed most significantly to the breeding goal. However, key traits valued by farmers, such as weaning weight (WW) and the number of lambs weaned (NLW), were omitted. Additionally, the indices calculated by Lembeye et al. (2014) relied solely on an animal's own performance for breeding traits (wool and growth traits), which is a limitation because most commercial farmers select replacements animals at weaning, before wool and reproductive traits can be measured.

Recently, Lembeye and Castellaro (2025) refined the breeding objective for the MP breed, incorporating greasy fleece weight (GFW), fibre diameter (FD), NLW, WW, and adult weight (AW; ewe´s weight at 18 months of age). NLW is particularly relevant but challenging to improve due to its low heritability (0.03-0.07; Nel et al., 2021) and record-keeping limitations, which lead to genetic inaccuracies (Zhang and Amer, 2021; Ramos et al., 2025), although there is evidence that efforts to improve NLW are worthwhile (Nel et al., 2021). Regarding AW, there is a discrepancy as to whether this trait should increase (Álvarez et al., 2014; Mueller and Aranguren, 2022) or decrease (Conington et al., 2004; Bohan, 2019). For sheep farming on Mediterranean dryland grasslands in central Chile, it seems appropriate to reduce ewe weight at maturity, since heavier ewes affect forage availability, stocking rate, and farm structure (Lembeye and Castellaro, 2025).

In modern genetic programs, instead of the selection indices developed by Hazel (1943), a more refined methodology for estimating breeding values (EBVs) of candidates is BLUP (best linear unbiased predictor; Henderson, 1950), as it accounts for genetic relationships and offers greater flexibility, provides more accurate predictions, allows comparison of lambs born in different years and flocks, and facilitates the monitoring of genetic progress in the evaluated population (Mueller et al., 2016a). However, the selection indices based on accumulated phenotypic information developed by Hazel (1943) serve as an alternative when BLUP-EBV is unavailable in low-input systems (because BLUP requires pedigree information, which is not readily available). They are still used to design breeding programs, estimate genetic gain and selection accuracy, and support decision-making regarding which traits and measurements should be included in an index, as well as the relative importance of each trait (Conington et al., 2001; Guo et al., 2025). Furthermore, in Australia, the genetic evaluation system MERINOSELECT provides selection indices with different emphasis on wool traits even for dual-purpose Merino (Sheep and Genetics, 2019). Therefore, by determining appropriate indices and economic values, selection decisions can be made efficiently based on readily available measurements, facilitating immediate selection (Alvarez et al., 2014; Mueller et al., 2021). This study evaluates genetic responses to selection indices that integrate pre-weaning performance alongside maternal data, aiming to enhance genetic progress under extensive management conditions in central Chile using selection index theory and providing a practical approach for low-input sheep production systems where pedigree records are unviable.

MATERIALS AND METHODS

This study was conducted using information from the MP flock belonging to the Rinconada de Maipú Experimental Station of the Faculty of Agricultural Sciences of the University of Chile, located in the commune of Maipú, Metropolitan Region, Chile (33°31′ S, 70°50′ W; 470 m.a.s.l.). In the design of the selection scheme for the MP population, selection index theory (Hazel, 1943) was used to investigate a breeding objective composed of the following traits: GFW, FD, WW, NLW and AW. Dam´s GFW (one record), dam´s FD (one record), dam´s staple length (SL; one record), lamb's birth weight (BW), lamb´s growth rate (GR, from birth to weaning), lamb´s WW (weight at four months of age), dam´s NLW (one record) and dam´s AW (one record; weight at 18 months old) were the traits used as predictors (criteria) and, hence, included in the index. Repeated records were not considered in the analyses. For the wool traits, the records corresponded to the first shearing. Genetic parameters for fleece traits and for the relationships between these traits and live weight (heritabilities, correlations and variances) were obtained from the literature review conducted by Safari et al. (2005) for dual-purpose breeds (Table 1), while phenotypic parameters among BW, WW and GR corresponded to the flock. According to Safari et al. (2006) and Mueller et al. (2015), using parameters obtained from data from other populations would not be a limitation in this type of study if the breeds and production systems are similar to those of the population in which the selection will be applied. Because Safari et al. (2005) reported broadly consistent estimates for major wool and growth traits across sheep populations, these parameters were considered suitable for comparing alternative selection indices in MP sheep, while acknowledging that population-specific differences may affect the magnitude of the predicted responses.

Population structure

The study considered two selection pathways under natural mating. The herd consisted of 400 breeding ewes, with rams representing 4% of the ewe population. Selection pressure was 40% in ewes and 2.5% in rams. Taking into account a 5% annual loss due to mortality and culling, the theoretical age structure of the herd was calculated as follows: 22.0% 2-year-olds, 21% 3-year-olds, 20% 4-year-olds, 19% 5-year-olds, and 18% 6-year-olds. The age structure for rams was 35% 2-year-olds, 33% 3-year-olds, and 32% 4-year-olds. Based on this age structure, and considering a fertility rate of 91%, a prolificacy rate of 135%, and a survival rate from birth to first mating of 90% (representing the performance of the MP flock during 2008–2024), the population size available for selection was 221 animals in each pathways. Consequently, 88 female lambs and 6 male lambs were selected. Selection intensities and generation intervals calculated for the herd's age structure in both the ewe and ram pathways are presented in Table 2.

Selection index

The selection index (*I*) is a method for predicting the breeding objective (*H*), in which several valuable traits are selected simultaneously, such as $I = H$. These expressions can be represented as follows (Cameron, 1997):

$$I = \sum_{i=1}^{m} b_i x_i = x'b = H = \sum_{i=1}^{n} v_i g_i = g'v$$

where x' is a row vector of known and adjusted phenotypic values of the measured traits, *b* is

Table 1. Heritability (on the diagonal), genetic correlations (below the diagonal), and phenotypic correlations (above the diagonal) among traits.

	GFW	FD	SL	BW	GR	WW	NLW	AW
GFW	0.38	0.31	0.32	0.24	0.25	0.25	0.00	0.37
FD	0.36	0.57	0.19	-0.05	0.05	0.05	0.00	0.13
SL	0.44	0.19	0.48	0.00	0.01	0.01	0.00	0.1
BW	0.21	0.18	0.05	0.19	0.13	0.16	0.09	0.26
GR	0.24	0.05	0.17	0.27	0.17	0.90	0.06	0.34
WW	0.24	0.05	0.17	0.47	0.79	0.18	0.06	0.56
NLW	-0.10	0.00	-0.45	0.12	0.29	0.29	0.05	-0.02
AW	0.22	0.15	0.01	0.22	0.78	0.75	0.27	0.31

GFW: greasy fleece weight; FD: fibre diameter; SL: staple length; BW: birth weight; GR: growth rate from birth to weaning; WW: weaning weight at 120 d; NLW: number of lambs weaned; and AW: adult weight at 18 months of age.

Table 2. Population size, number selected, proportion selected, and selection intensity for the selection scheme Merino Precoz sheep breed at the Rinconada de Maipú Experimental Station.

Pathway	Population	Number selected	Proportion selected	Intensity of selection	Generation interval
Rams	221	6	0.027	2.37	3.38
Ewes	221	88	0.398	0.97	3.90

a column vector of weight coefficients to be estimated, g' is a row vector of unknown true breeding values of the n traits included in H, and v is a column vector of the corresponding n known relative economic values. These values were reported by Lembeye and Castellaro (2025) as follows: US$5.42 (GFW); US$-0.59, US$-1.18, and US$-2.35 for a proportion representing 3.5%, 7% and 14% of the GFW price, respectively; US$151.1 (NLW); US$4.93 (WW); and US$-0.09 (AW). Economic weights were standardized by expressing all values relative to the economic value of FD.

The vector b was estimated using the following equation:

$$b = P^{-1}Gv$$

where G is the genetic (co)variance matrix, p^{-1} is the inverse phenotypic (co)variances matrix, and v and b are the vectors defined previously for H and I, respectively.

Matrix P is an $m \times m$ matrix of phenotypic covariances among the measured traits; in this case, P has a dimension of 8 × 8; G is a $m \times m$ matrix of genetic covariances between the measured traits and the traits included in H. The dimension of this matrix is 8 × 5.

Accuracy of the index

The correlation between the selection index (I), and the true breeding value (H) provides a measure of accuracy and is calculated as follows:

$$r_{IH} = \sqrt{\frac{b'Pb}{v'Cv}}$$

where C is a $n \times n$ matrix of genetic covariances between the goal traits (a 5 × 5 matrix), and b and p were previously defined.

The dimension of the matrices indicated above corresponds to index 1. Since genetic improvement for NLW is difficult and limited (Zhang and Amer, 2021), a second index was proposed that excludes NLW from H (index 2). Although NLW is the most economically important trait in the breeding objective, its expression occurs later in life than the age at which replacements are selected. Because this study aimed to develop selection indices applicable to commercial low-input production systems, where reproductive records are often unavailable, an alternative breeding objective excluding NLW was evaluated. Under this assumption, P, G and C were reduced to 7 × 7, 7 × 4 and 4 × 4 matrices, respectively.

Considering that recording GFW requires more effort during shearing, a third index was proposed (index 3), discarding GFW as a selection criterion but retaining it as a goal trait. In this case, the dimension of matrices P and G were reduced to 6 × 6 and 6 × 4 dimension, respectively, while C maintained the same structure as in index 2. A fourth and fifth index were proposed similarly to indices 2 and 3, respectively, but with the inclusion of dam's records for BW, GR and WW. For clarity, the breeding objective traits and selection criteria considered in each index are summarized in Table 3.

The formulas used to calculate the elements of matrices P and G, and C, were derived using the methodology described by Cameron (1997). Genetic covariances were obtained from the corresponding variances and genetic correlations, and maternal genetic effects were not explicitly considered. All calculations were performed using PROC IML in SAS (SAS Institute Inc., Cary, NC, USA), and all phenotypic covariance matrices were verified to be positive definite by evaluating their eigenvalues prior to matrix inversion and index calculation.

Calculation of genetic gain

The expected correlated response in each trait was calculated using the following equation:

$$\Delta R_j = i\frac{b'G_j}{\sqrt{b'Pb}}$$

where ΔR_j is the correlated response for trait j in the selection objective, G_j is the j^{th} column of the genetic (co)variance matrix G, and i is the

Table 3. Breeding objective traits (*H*) and selection criteria (*I*) considered in the five selection indices evaluated in Merino Precoz sheep at the Rinconada de Maipú Experimental Station.

Index	Breeding objective (H)	Selection criteria (I)
1	GFW, FD, WW, NLW, AW	GFW d, FD d, SL d, BW, GR, WW, NLW d, AW d
2	GFW, FD, WW, AW	GFW d, FD d, SL d, BW, GR, WW, AW d
3	GFW, FD, WW, AW	FD d, SL d, BW, GR, WW, AW d
4	GFW, FD, WW, AW	GFW d, FD d, SL d, BW, GR, WW, AW d, BW d, GR d, WW d
5	GFW, FD, WW, AW	FD d, SL d, BW, GR, WW, AW d, BW d, GR d, WW d

GFW: greasy fleece weight; FD: fibre diameter; SL: staple length; BW: birth weight; GR: growth rate from birth to weaning; WW: weaning weight at 120 d; NLW: number of lambs weaned, AW: adult weight at 18 months;
d: record of the candidate's dam.

selection intensity of the index. Matrix *P* and row vector b' were as previously defined.

As the breeding scheme involves two pathways with different selection intensities, the annual genetic gain (ΔG_j) for each trait was estimated as the sum of the responses from both pathways, as follows:

$$\Delta G_j = \frac{i_e\left[\frac{b'G_j}{\sqrt{b'Pb}}\right] + i_r\left[\frac{b'G_j}{\sqrt{b'Pb}}\right]}{L_e + L_r}$$

where ΔG_j is the annual correlated response for the j[th] trait, i_e and i_r are the selection intensities for the ewe and ram pathways, respectively, and L_e and L_r are the generation intervals for both the ewe and the ewe and the ram pathways, respectively (Guo et al., 2025).

Expected monetary return

The expected monetary return, or economic-genetic gain, of the aggregate genotype (ΔH) resulting from the use of *I* was determined as follows:

$$\Delta H = \sum_{i}^{n} \Delta G_j \times v_i$$

where ΔH is the annual genetic gain of the aggregate genotype resulting from the use of the selection index, which considers the sum of the correlated responses (ΔG) achieved for each trait included in *H*, multiplied by its corresponding economic value v_i).

Contribution of each trait to the selection index

The contribution of each trait in the index to *H* was calculated by measuring the reduction in the accuracy of *I*, which is the correlation between the true breeding value and *I*, after each trait was individually excluded. This was calculated using the following equation (Cameron, 1997):

$$\frac{\overset{*}{r}_{IH}}{r_{IH}} = 1 - \sqrt{1 - \frac{b_j^2}{b'PbP_{jj}^{-1}}}$$

where $\overset{*}{r}_{IH}$ is the accuracy of *I* after the j[th] trait was omitted, b_j^2 is the square of the j[th] element of the regression vector, and P_{jj}^{-1} is the j[th] diagonal element of the inverted matrix *P*

RESULTS

Tables 4 and 5 present the regression coefficients and their respective contributions for each trait in the selection criteria across the five proposed indices. These regression coefficients serve as useful indicators for farmers seeking to align their breeding decisions with specific genetic improvement objectives. Regarding FD, the negative regression coefficients indicate that a reduction in this trait constitutes a desirable genetic improvement, as evidences by the negative values for FD across the proposed indices. By contrast, AW did not result in a negative regression coefficient, despite efforts to reduce it given its negative economic value (Table 4).

In index 1, WW exhibited the highest contribution to the index, with an 8.74-8.82% decrease in the efficiency of *I* when WW was excluded (Table 5). The contribution of WW was greater than that of NLW, despite the latter trait constituting more than 50% of the breeding goal. The contribution of WW increased in the other indices, being greatest in index 3 when FD was valued at 7% of the GFW price (17.42%). The contribution of wool traits was generally low compared with live weight traits, particularly when FD represented 3.5-7% of the wool values.

As presented in Table 6, indices 2-5 achieved higher accuracy than index 1 (0.47-0.491 vs. 0.35). However, a greater ΔH is expected for index 1 compared with the other four indices (4.22-1.06

Table 4. Regression coefficients (b′) for each trait in the index for a breeding objective including GFW, FD, WW, NLW and AW, and considering three breeding purposes of the wool (3.5%, 7% and 14%).

	Index 1			Index 2			Index 3			Index 4			Index 5		
b'	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%
GFW d	0.5474	0.2795	0.1463	1.4548	0.7332	0.3741				1.1835	0.6141	0.3297			
FD d	-0.0167	-0.1517	-0.2185	-0.3152	-0.3010	-0.2934	-0.2187	-0.2523	-0.2686	-0.2779	-0.2854	-0.2887	-0.1981	-0.2440	-0.2665
SL d	-0.1726	-0.0861	-0.0430	0.0355	0.0180	0.0092	0.0469	0.0237	0.0121	0.0409	0.0205	0.0104	0.0500	0.0253	0.0129
BW	3.2006	1.5355	0.7084	2.2117	1.0411	0.4601	2.2252	1.0479	0.4636	2.1533	1.0168	0.4530	2.1544	1.0173	0.4533
GR	-0.0652	-0.0329	-0.0168	-0.0934	-0.0470	-0.0239	-0.0936	-0.0471	-0.0239	-0.0901	-0.0455	-0.0232	-0.0914	-0.0461	-0.0236
WW	2.8328	1.4161	0.7120	2.3353	1.1674	0.5871	2.3352	1.1673	0.5870	2.2862	1.1438	0.5768	2.2972	1.1495	0.5798
NLW d	7.1254	3.5624	1.7902												
AW d	0.5089	0.2545	0.1287	0.2331	0.1166	0.0594	0.2695	0.1350	0.0688	0.1338	0.0678	0.0361	0.1650	0.0840	0.0447
BW d										0.2768	0.0795	-0.0196	0.4257	0.1568	0.0218
GR d										0.0013	0.0007	0.0006	0.0094	0.0049	0.0029
WW d										3.7763	0.1895	0.0937	0.3000	0.1500	0.0725

GFW: greasy fleece weight; FD: fibre diameter; SL: staple length; BW: birth weight; GR: growth rate from birth to weaning; WW: weaning weight at 120 d; NLW: number of lambs weaned; AW: adult weight at 18 months; d: record of the candidate´s dam.

Table 5. Relative contribution (RC, %) of each trait in the index for a breeding objective, including GFW, FD, WW, NLW and AW, and considering three breeding purposes of the wool (3.5%, 7% and 14%).

	Index 1			Index 2			Index 3			Index 4			Index 5		
RC	**3.5%**	**7%**	**14%**	**3.5%**	**7%**	**14%**	**3.5%**	**7%**	**14%**	**3.5%**	**7%**	**14%**	**3.5%**	**7%**	**14%**
GFW d	0.04	0.04	0.04	0.72	0.74	0.73				0.42	0.46	0.50			
FD d	0.00	0.16	1.28	0.46	1.69	6.30	0.24	1.28	5.68	0.34	1.44	5.77	0.18	1.13	5.25
SL d	4.52	4.54	4.46	0.51	0.53	0.53	0.98	1.01	1.02	0.65	0.66	0.65	1.06	1.09	1.09
BW	2.97	2.76	2.30	3.89	3.48	2.59	3.99	3.58	2.67	3.53	3.18	2.40	3.53	3.18	2.40
GR	0.56	0.57	0.58	3.15	3.24	3.18	3.21	3.30	3.24	2.67	2.76	2.75	2.76	2.85	2.84
WW	8.74	8.82	8.77	15.92	17.14	16.51	17.18	17.42	16.77	14.78	15.00	14.54	14.95	15.17	14.72
NLW d	4.18	4.22	4.20												
AW d	6.17	6.23	6.27	3.48	3.53	3.50	5.40	5.49	5.45	0.58	0.60	0.65	0.95	1.00	1.08
BW d										0.05	0.02	0.00	0.13	0.07	0.01
GR d										0.00	0.00	0.00	0.02	0.02	0.03
WW d										0.22	0.23	0.21	0.14	0.15	0.13

GFW: greasy fleece weight; FD: fibre diameter; SL: staple length; BW: birth weight; GR: growth rate from birth to weaning; WW: weaning weight at 120 d; NLW: number of lambs weaned; AW: adult weight at 18 months.
d: record of the candidate's dam.

vs. 2.60-0.65). Importantly, within each index, ΔH was greatest when the FD represents 3.5% of the GFW price. Additionally, the inclusion of the dam's live weight records in indices 4 and 5 produced only marginal changes in accuracy compared with indices 2 and 3, indicating a negligible contribution of these maternal records to the prediction of H.

Predicted annual genetic responses and their correlations with the traits included in H are shown in Table 7. When NLW was excluded from the indices, the expected genetic improvements ranged between 0.025 and 0.014 kg, -0.044 and 0.022 μm, and 0.279 and 0.300 kg for GFW, FD, and WW, respectively, compared with 0.008 and 0.011 kg, -0.020 and 0.019 μm, and 0.258

Table 6. Genetic merit improvement and accuracy of the index for a breeding objective including GFW, FD, WW, NLW and AW, and considering three breeding purposes of the wool (3.5%, 7% and 14%).

	Index 1			Index 2			Index 3			Index 4			Index 5		
	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%
Genetic merit improvement	4.22	2.10	1.06	2.56	1.27	0.65	2.54	1.26	0.65	2.60	1.29	0.66	2.59	1.29	0.66
Accuracy of the index	0.35	0.35	0.35	0.49	0.48	0.47	0.48	0.48	0.47	0.49	0.49	0.48	0.49	0.49	0.47

Table 7. Expected annual genetic gain for a goal including GFW, FD, WW, NLW and AW, and considering three breeding purposes of the wool (3.5%, 7% and 14%).

	Index 1			Index 2			Index 3			Index 4			Index 5		
	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%	3.5%	7%	14%
GFW (Kg)	0.011	0.010	0.008	0.025	0.023	0.018	0.020	0.018	0.014	0.024	0.022	0.018	0.021	0.019	0.014
FD (µm)	0.019	0.006	-0.020	0.021	-0.001	-0.044	0.021	-0.001	-0.044	0.021	-0.002	-0.045	0.022	-0.001	-0.044
WW (Kg)	0.264	0.263	0.258	0.292	0.290	0.279	0.295	0.293	0.282	0.297	0.295	0.283	0.300	0.298	0.287
NLW (un)	0.008	0.008	0.008												
AW (kg)	0.621	0.615	0.599	0.577	0.567	0.534	0.589	0.579	0.546	0.566	0.556	0.525	0.578	0.569	0.539

GFW: greasy fleece weight; FD: fibre diameter; SL: staple length; BW: birth weight; GR: growth rate from birth to weaning; WW: weaning weight at 120 d; NLW: number of lambs weaned; AW: adult weight at 18 months.

and 0.264 kg for the same traits in index 1. An expected increase in AW was observed across all scenarios, despite efforts to reduce it (0.534-0.621 kg); however, the smallest theoretical increase in AW resulted from the indices that include dam's selection criteria and excluded GFW as selection criteria (index 4).

DISCUSSION

The results of this study are important because it is the first study conducted to estimate regression coefficients for applying selection at weaning in the dual-purpose MP sheep breed in Chile (Table 4). The selection indices used in Australia and Argentina consider measurements at 12 months of age; however, in production systems where lambs are sold at an early age, the need to select animals earlier makes this practice difficult (Lembeye et al., 2014). Therefore, the results presented in this study are valuable for farmers who select replacement animals at an early age.

Notably, in index 1, the regression coefficient for SL in the candidate's dam was negative, likely due to the moderate genetic correlation (r_g) between SL and NLW. Consequently, when NLW was omitted from (indices 2-5), the regression coefficient for SL became positive. Across the simulations, GR displayed a negative coefficient despite its strong r_g with WW (0.79), whereas AW exhibited a positive coefficient, even though it v is negative (US$ -0.09). This discrepancy arises from the relatively high to moderate r_g between AW and other growth and wool traits (Table 1). These results are particularly relevant to Mediterranean dryland production systems, where increases in mature ewe weight may increase maintenance requirements, reduce stocking rates, and negatively affect production efficiency (Conington et al., 2001). Therefore, restricted (Cunningham et al., 1970) or desired-gain (Pesek and Baker, 1969; Li et al., 2017) selection indices could be considered to constrain AW while maintaining genetic progress in the other economically important traits.

As presented in Table 5, indices 2-5 achieved higher accuracy than index 1, likely due to the exclusion of NLW, which has low heritability and unfavourable genetic correlations (r_g) with GFW and SL, justifying the exclusion of this trait in spite of its great economic importance. However, greater index accuracy did not necessarily result in a greater ΔH. The highest ΔH was obtained with index 1, whereas excluding NLW improved the predicted response of several production traits and the accuracy of selection.

Although it could be argued that the most economically important traits, such as NLW, should be included in H, the lower accuracy of index 1 reported by Zhang and Amer (2021) suggests that this approach may not be appropriate. Furthermore, empirical evidence indicates that no genetic change is observed when selection focuses on reducing FD and increasing GFW, as in the present study (Ramos et al., 2025). Therefore, despite its high economic importance, NLW inclusion in the breeding objective may be questioned in low-input production systems where pedigree information and reproductive records are limited, because its inclusion substantially reduces selection accuracy across all the scenarios evaluated. Thus, under low-input production systems, selection accuracy may be a more relevant decision criterion than maximizing ΔH.

Previous simulation studies reported accuracy values ranging between 0.26 and 0.65, indicating moderate to low accuracy of genetic evaluation at weaning (Conington et al., 2001; Mueller et al., 2021; Guo et al., 2025). Accuracy can be enhanced by including information from parents and sib's, reaching up to 0.70 (Guo et al., 2025). However, in the present study, the inclusion of the dam's BW, pre-weaning GR, and WW records produced only negligible improvements in index accuracy. This is consistent with Hazel et al. (1994), who indicated that the benefit of incorporating additional family information depends on its contribution beyond the animal's own performance and may be limited when substantial information is already available from the candidate itself.

In Argentina, the Provino genetic evaluation system using Best Linear Predictor Unbiased Prediction (BLUP) methodology, as in this study, with records solely from the candidates' own performance, reaches 60% accuracy, while nucleus breeding programs using BLUP can attain up to 90% when pedigree (especially progeny) and production records are available (Mueller, 2000; Guo et al., 2025). In the latter scenario, the inclusion of NLW as a goal trait seems feasible and recommended (Nel et al., 2021).

Index 1 is expected to achieve a greater ΔH than the other indices (Table 6). Sivanadian and Smith (1997) explain that the inclusion of a trait in I always increases the response to selection; however, as explained in the previous paragraph, indices 2-5 may represent a better alternative under the assumptions considered in the present study. Regardless of the simulation, the highest predicted ΔH was obtained when FD contributed 3.5% to the fleece price, suggesting that reducing fleece diameter improvement is not a priority. This occurs because placing greater emphasis on FD limits the progress of live weight traits, such as WW, which is the primary trait affecting economic productivity (McManus et al., 2011; Mueller et al., 2021). In Australia, Brown et al. (2006) and Mortimer et al. (2010) suggested that maintaining FD is achievable when it represents 3.5% of the fleece price, However, due to the high economic importance of live weight traits, this was not theoretically feasible in this study. Hence, sheep farmers who have already achieved their desired fibre quality may benefit from restricted selection indices (Cunningham et al., 1970). Restriction of FD would result in a small loss in efficiency compared with the breeding goal obtained from an unrestricted selection index (Lembeye et al., 2014). In a second period (seven-years) of a genetic program in ultrafine Merino breed (Ramos et al., 2025) focused on increasing both wool and live weight while maintaining FD, fibre thickening (0.116 µm) was observed, along with increases in wool and live weight similar to those observed in this study.

The results shown in Table 7 cannot be directly compared with those of other studies because economic and marketing conditions differ across regions and countries. However, there is sufficient evidence that increases in fleece weight and reductions in FD are achievable. Mueller (2006) reported genetic progress through the use of selection indices in Merino, Corriedale, and Ideal sheep breeds, with goals similar to those of the present study (7% of GFW price). In Argentina, Mueller and Aranguren (2022) reported lower improvements (0.12-0.14 kg and -0.05 µm for WW and FD per year, respectively) compared with the results shown in Table 7 for indices 2 and 3 when the price relation between FD and GFW was 7% (8% in Mueller and Aranguren, 2022).

It is important to note that the expected response to selection presented in Table 7 may be smaller because farmers usually cull 10-20% of the candidates for phenotypic reasons that are not correlated with the goal traits. Additionally, the use of genetic parameters derived from the literature may contribute to differences between predicted and realized genetic gains if the genetic relationships among traits differ from those assumed in the present study. Support for this possibility is provided by Mueller and Bidinost (2005) and Mueller et al. (2016*b*), who aimed to reduce FD while increasing live and fleece weights. The latter study reported a 9-year genetic gain of -0.50% (-0.45 µm, FD), 0.68% (0.61 kg live weight), and 0.31% (0.37 kg fleece) per year, achieving 82–92% of the expected progress. Mueller and Bidinost (2005) reported a 90.4-94.5% of the expected genetic progress for the same traits in the Merino breed.

CONCLUSIONS

This study highlights the use of regression coefficients for selecting traits with moderate to high heritability for genetic improvement in dual-purpose sheep breeding in Chile, particularly for farmers selecting replacements animals at an early age (at weaning). While traits such as NLW have significant economic value, their inclusion in *I* may reduce accuracy due to their low heritability, making these indices more suitable for low-input sheep production systems. Additionally, the inclusion of the dam's BW, GR and WW records did not substantially improve index accuracy.

Author contributions

Conceptualization: Felipe Lembeye; methodological design: Felipe Lembeye; analysis: Felipe Lembeye; writing: Felipe Lembeye; revision and discussion: Felipe Lembeye, Giorgio Castel and Héctor Uribe; Bibliographical review: Felipe Lembeye.

LITERATURE CITED

Álvarez, J.M., J.P. Mueller, P.A. Vozzi and F. Milicevic. 2014.Objetivos de mejoramiento e índices de selección para la raza Corriedale en Argentina. XV Congreso Mundial Corriedale, 21-22 de Julio, Buenos Aires, Argentina. Comunicación Técnica INTA Bariloche Nro PA 769.

Bohan, A., L. Shalloo, P. Creighton, D. Berry, T. Boland, A.C. O' Brien, T. Pabiou, E. Wall, K. McDermott and N. McHugh. 2019. Deriving economic values for national sheep breeding objectives using a bio-economic model. Livestock Science 227: 44-54. doi.org/10.1016/j.livsci.2019.05.018

Brown, D.J., A. Ball, A.E. Huisman, A.A. Swan, K.D. Atkins, H.U. Graser, R. Banks, P. Swan and R. Woolaston. 2006. Sheep Genetics Australia: A national genetic evaluation system for Australian sheep. In Proceedings of the 8th World Congress on Genetics Applied to Livestock Production, August 13-18, Belo Horizonte, MG, Brasil.

Cameron, N. 1997. Selection indices and prediction of genetic merit in animal breeding. CAB International, Wallingford, UK.

Conington, J., S.C. Bishop, B. Grundy, A. Waterhouse and G. Simm. 2001. Multi-trait selection indexes for sustainable UK hill sheep production. Animal Science 73: 413-423. doi:10.1017/S1357729800058380

Conington, J., S.C. Bishop, A. Waterhouse and G. Simm G. 2004. A bioeconomic approach to derive economic values for pasture-based sheep in genetic improvement programs. Journal of Animal Science 82:1290-1304. https://doi.org/10.2527/2004.8251290x

Cunningham, E.P., R.A. Moen and T. Gjedrem. 1970. Restriction of selection indexes. Biometrics 26: 67-74. doi.org/10.2307/2529045

Guo, T., W. Li, C. Yuan, X. Wang, J. Liu and B. Liang. 2025. Defining multi-trait breeding objectives and selection indexes to develop more efficient breeding programs for superfine wool sheep. Animals 15: 1873. doi.org/10.3390/ani15131873

Hazel, L.N. 1943. The genetic basis for constructing selection indexes. Genetics 28: 476-490. doi: 10.1093/genetics/28.6.476

Hazel, L.N., G.E. Dickerson, A.E. Freeman. 1994. The Selection Index–Then, Now, and for the Future. Journal of Dairy Science 77: 3236-3251.

Henderson, C. 1950. Estimation of genetic parameters (abstract). Annals of Mathematical Statistics 21: 309-310.

Lembeye, F., G. Castellaro, J.C. Magofke and H. Uribe. 2014. Comparación de distintos índices y criterios de selección en ovinos Merino Precoz manejados en condiciones extensivas de la zona central de Chile. Archivos de Medicina Veterinaria 46: 389-397. doi.org/10.4067/S0301-732X2014000300007

Lembeye, F. and G. Castellaro. 2025. Developing a breeding objective for dual-purpose Merino Precoz breed in central Chile: derivation of economic weights. Chilean Journal of Agricultural & Animal Sciences 41: 209-216. doi.org/10.29393/CHJAAS41-19DEFE20019

Li, Y., H. Dungey, A. Yanchuk and L.A. Apiolaza. 2017. Improvement of non-key traits in radiata pine breeding programme when long-term economic importance is uncertain. PloS One 12: e0177806. doi: 10.1371/journal.pone.0177806

McManus, C., B. F. Pinto, R.F.S. Martins, H. Louvandini, S.R. Paiva, J.B. Neto and T.D.P. Paim. 2011. Selection objectives and criteria for sheep in Central Brazil. Revista Brasileira de Zootecnia 40(12): 2713-2720. https://doi.org/10.1590/s1516-35982011001200014

Mortimer, S.I., K.D. Atkins, S.J. Semple and N.M. Fogarty. 2010. Predicted responses in Merino sheep from selection combining visually assessed and measured traits. Animal Production Science 50: 976–982. doi.org/10.1071/AN10085

Mueller, J.P. 2000. Mejoramiento genético de las majadas patagónicas. Comunicación Técnica INTA Bariloche Nro PA 375, 16 pp.

Mueller, J.P. and F. Bidinost. 2005. Respuesta a la selección en Merino con diferentes procedimientos. Comunicación Técnica INTA Bariloche Nro PA 473, 6 pp.

Mueller, J.P. 2006. Avances en el mejoramiento genético de ovinos en la Argentina. Comunicación técnica INTA EEA Bariloche Nro PA 493, 6 pp.

Mueller J.P., B. Rischkowsky, A. Haile, J. Philipsson, O. Mwai, B. Besbes, A. Valle Zárate, M Tibbo, T. Mirkena, G. Duguma, J. Sölkner and M. Wurzinger. 2015. Community-based livestock breeding programs: essentials and examples. Journal Animal Breeding and Genetics 132: 155-168. https://doi.org/10.1111/jbg.12136

Mueller J.P., P.A.Vozzi, N. Giovannini and J.M Álvarez. 2016a. Beneficio del progreso genético en ovinos de la Argentina. Revista Argentina de Producción Animal 42: 307-316.

Mueller, J.P., N. Giovannini and F. Bidinost. 2016b. Twenty-eight years of genetic improvement in a Merino flock compared with a control flock without selection. Revista Argentina de Producción Animal 36: 63-74.

Mueller, J.P., T. Getachew, M. Rekik, B. Rischkowsky, Z. Abate, B. Wondim and A. Haile. 2021. Converting multi-trait breeding objectives into operative selection indexes to ensure genetic gains in low-input sheep and goat breeding programs. Animal 15: 100198. doi: 10.1016/j.animal.2021.100198

Mueller, J.P. and E. Aranguren. 2022. Implementación y resultados de un programa de mejora genética en ovinos. Revista de Investigaciones Agropecuarias 48(1):16-23.

Nel, C.L., A.A. Swan, K. Dzama, A.J. Scholtz and S.W.P. Cloete. 2021. Genetic parameters and trends for lamb survival following long-term divergent selection for number of lambs weaned in the Elsenburg Merino flock. Animal Production Science 61: 1965–1981. doi:10.1071/an21198

Pesek, J., and R. J. Baker. 1969. Desired improvement in relation to selection indices. Canadian Journal Plant Science 49: 803–804. doi: 10.4141/cjps69-137

Ramos, Z., D.J. Garrick, H.T. Blair, I. De Barbieri, G. Ciappesoni, F. Montossi, and P.R. Kenyon. 2025. Genetic trends for production and reproduction traits in ultrafine Merino sheep of Uruguay. Journal Animal Breeding and Genetics. doi.org/10.1111/jbg.12937. Epub ahead of print. PMID: 40116167.

Safari E., N.M. Fogarty and A.R. Gilmour. 2005. A review of genetic parameter estimates for wool, growth, meat and reproduction traits in sheep. Livestock Production Science 92: 271-289. doi.org/10.1016/j.livprodsci.2004.09.003

Safari, E., N.M. Fogarty and A.R. Gilmour. 2006. Sensitivity of response of multitrait index selection to changes in genetic correlations between production traits in sheep. Australian Journal of Experimental Agriculture 46: 283-290. doi.org/10.1071/EA04232

Sivanadian, B. and C. Smith. 1997. The effect of adding further traits in index selection. Journal of Animal Science 75: 2016-23. doi: 10.2527/1997.7582016x

Sheep Genetics. 2019. MERINOSELECT Indexes. A Ram Breeder's Guide. https://www.sheepgenetics.org.au/globalassets/sheep-genetics/resources/brochures-and-fact-sheets/19mla-breeder-merino.pdf [accessed 04 November 2025]

Valera, M., F. Arrebola, M. Juarez, A. Molina. 2009. Genetic improvement of wool production in Spanish Merino sheep: genetic parameters and simulation of selection strategies. Animal Production Science 49: 43-47. doi.org/10.1071/EA07061

Zhang, X., and P. Amer. 2021. A New selection index percent emphasis method using subindex weights and genetic evaluation accuracy. Journal of Dairy Science 104: 5827-5842. https://doi.org/10.3168/jds.2020-19547