Title: Improving the prediction of maturity from anthropometric variables using a maturity ratio.

Preferred running head: Improving prediction of maturity from anthropometry

Submission type: Original investigation

ABSTRACT

Purpose: This study aimed to improve the prediction accuracy of Age at Peak Height Velocity (APHV) from anthropometric assessment using non-linear models and a maturity ratio rather than a maturity offset.

Methods: The dataset used to develop the original prediction equations was used to test a new prediction model, utilising the maturity ratio and a polynomial prediction equation. This model was then applied to a sample of male youth academy soccer players (n = 1330) to validate the new model in youth athletes.

Results: A new equation was developed to estimate APHV more accurately than the original model (new model; Akaike Information Criterion: -6062.1, R^2 = 90.82%; original model: Akaike Information Criterion = 3048.7, R^2 = 88.88%) within a general population of boys, particularly with relatively high/low APHVs. This study has also highlighted the successful application of the new model to estimate APHV using anthropometric variables within youth athletes, thereby supporting the use of this model in sports talent identification and development.

Conclusion: This study argues that this newly developed equation becomes standard practice for the estimation of maturity from anthropometric variables in boys from both a general and athletic population.

Key Words: SPORTS, CHILDREN, ADOLESCENCE, GROWTH, PEAK HEIGHT VELOCITY

INTRODUCTION

Youth athletes are often grouped by their chronological age (CA) for training and competition purposes (1). However, large inter-individual discrepancies between the CA = years from birth) and biological age (BA = years from a maturation milestone) of individuals exist. During the period surrounding the adolescent growth spurt (±12 years in girls, ±14 years in boys) individuals' BA can differ by as much as four years (31). These differences are particularly apparent around the Age at Peak Height Velocity (APHV) and reflect the large variations in the timing and tempo of growth between individuals (15).

It is well known that physical dimensions influence motor performance (12) and play an important role in the success of individuals in sport (3, 34). This is particularly prevalent during adolescence where biological maturation has been shown to affect physical performance in a range of sports. In such sports, early maturing individuals mostly outperform their later maturing counterparts; except in sports where the body dimensions associated with early maturation could be a disadvantage such as figure skating, gymnastics, and dancing (13, 15). This confounding influence of biological maturation on performance in youth sports is of particular interest in talent identification (21). Consequently, Vaeyens and colleagues (34) reported that failing to control for maturation significantly confounds the identification of talented athletes, especially in sports where anthropometrical and physical fitness variables are strongly correlated with successful performance outcomes.

There are numerous ways to assess an individual's biological maturation. The traditional clinical methods consist of assessing skeletal age through X-ray of the wrist or the assessment of secondary sex characteristics (15). When assessing skeletal age using X-ray techniques, an X-ray image from the left wrist is used to compare an individual's bone and grades of skeletal maturity indicators are combined to estimate skeletal age that are then compared with reference data (4, 10, 30). The assessment of sexual maturation uses the onset and development of secondary sex characteristics (breasts, genitals and pubic hair) compared to reference images. Both of these methods have been used extensively in youth populations to classify individuals according to their maturity status. However, these techniques involve considerable exposure to radiation or may be considered invasive in some cultures. Therefore, more recently, Dual-energy X-ray Absorptiometry (DXA) has been used as an alternative to the X-ray method (25) as it only exposes participants to one-tenth of the radiation dose (9) or about 0.001 millisievert (mSv), which is less than natural background radiation or equivalent to the amount of radiation experienced during a three-hour session of television viewing according to the US Department of Energy (32). Furthermore, a self-observation technique has been used as an alternative to the assessment of sexual maturation by a physician (7, 28). Hence, it is clear that researchers have attempted to overcome some of the ethical, medical and logistical limitations of traditional methods of assessing biological maturation.

One increasingly commonly used method for assessing biological maturity is a non-invasive calculation of BA using anthropometric measures that incorporates the known proportionality in differences in leg and trunk length growth (19). The rationale behind this method is the known difference in timing between height, sitting height and leg length. Therefore, these authors (19) argued that the changing relationship between these variables over time provides a good base for the prediction of APHV. This equation predicts the years from APHV and terms this BA as a ‘maturity offset’ (years from APHV) using measures of stature, body mass, leg length, sitting height and CA to predict a maturity offset. Using this predicted BA and the CA at time of measurement the APHV can be estimated. In the aforementioned study (19), sex-specific prediction equations were developed using a Canadian sample of 228 children (113 boys, 115 girls) between four years prior and three years post APHV and cross-validated using Canadian and Belgian reference samples. The researchers emphasize that the accuracy of the prediction equation involves an error of one year 95% of the time. However, they suggest that the prediction of this maturity offset is only applicable in a sample of youths between 10-18 years. Malina and Koziel (16) attempted to validate this non-invasive method of predicting APHV in an external sample of Polish boys between 8 and 18 years but showed that there was a systematic discrepancy between predicted and observed APHV; where this value was underestimated at younger ages and overestimated in the older age groups within the study. These findings were consistent with the limitations of the equation discussed in the original publication (19) and show a potential problematic application of the prediction equation in boys younger than 11 and older than 16 years. Furthermore, even when used within these age brackets, the prediction of APHV lacks validity as demonstrated by Mills and colleagues (18) who concluded that equation-based methods appear to overestimate the timing of PHV when they are applied in the year or stage immediately preceding PHV. Therefore, the original prediction equation by Mirwald and colleagues has considerable limitations, especially for individuals further removed from their APHV (16, 19, 20) and therefore warrant the cautious use of these prediction equations.

Despite these clear limitations, the use of the APHV prediction equation has been widespread in talent identification and talent development research within youth sports (5, 17, 34). This is not surprising as a practical, non-invasive and relatively accurate estimation of an athlete's maturity is of particular interest to talent identification and development as these processes require large numbers of youth athletes to be assessed in limited periods of time. However, the potential erroneous prediction of APHV embedded in the original prediction equation limits its usability and warrants an enhancement of the original equation. Indeed, Moore et al.

(20) developed new equations based on the original dataset (19) that would account for the overfitting (i.e. the inclusion of artificially large coefficients or when co-variance in the data is based on spurious associations (20)) generated by the original equations and validated them in external sample of British and Canadian children. The authors succeeded in simplifying the original equations by removing predictors and argued that these new equations should theoretically produce better fits across a range of external samples. However, they stated that the prediction error from these equations likely still increases to a greater degree the further a child is away from their actual APHV. Although commendable, these new equations do not produce more valid estimations for children who are further removed from their APHV. This increase in error in the tails of the distribution is potentially due to the linear estimation of an inherently non-linear biological process, such as somatic growth during the adolescent growth spurt (24). Therefore, this study developed a new equation for the prediction of APHV from anthropometric variables in boys by fitting a non-linear relationship between anthropometric predictors and a maturity ratio (CA/APHV) to the original data from the Mirwald et al. (2002) publication. Using a maturity ratio as a response variable might prove to be useful as adolescents move into adulthood, and the rate of growth decreases. It was therefore hypothesized that this new model would yield similar prediction accuracy overall, but a more valid prediction in the tails of the original data (boys relatively far removed from APHV). Moreover, it was expected that this new equation could be validated in an external sample of youth soccer players, thereby consolidating the use of the new prediction equation in a population of youth male athletes.

METHODS

Participants

Data set one (Mirwald Baxter-Jones: MBJ): developing a new equation using the original dataset (2)

The University of Saskatchewan's Pediatric Bone Mineral Accrual Study (PBMAS) (1991 to present) used a mixed longitudinal study design. Between 1991 and 1993, 251 Canadian boys (n=115) and girls (n=136) were recruited from two elementary schools in Saskatoon, Saskatchewan, Canada (2). The study by Baxter-Jones and colleagues was designed to assess factors associated with bone acquisition in growing children. Participants were between 8.0 and 15.0 years of age at baseline; ages ranged between 8.0 and 21.0 years across the initial 7-years of the study. 98% of participants were Caucasian. All children were healthy with no conditions known to affect growth. Growth parameters were measured semi-annually. Written informed consent was obtained from parents of participating children between 1991 and 1993. The University of Saskatchewan's Research Ethics Board approved all procedures.

Data set two (Belgian Soccer Players: BSP): validating the new equation using a new dataset of Belgian soccer players

This study involved 1330 high level male youth soccer players who were recruited from Belgian soccer academies. Athletes were aged between 8.0-17.0 years and from various ethnic backgrounds, with the majority of players of Caucasian descent. Due to the large number of participants however, their ethnicity was not established. The data were collected longitudinally - testing was conducted during the same month each year across a period of six years, resulting in a total of 4829 observations, with each player having between 1-19 observations. The research was approved by the appropriate local University Hospital ethical review panel and written informed consent was received from all participants and their parent(s) or guardian(s) prior to inclusion in the study.

Procedures

Dataset one: MBJ

Anthropometric measures included stature and body mass, following the anthropometric standards outlined by Ross and Marfell-Jones (26). Stature was recorded without shoes to the nearest 0.1 cm against a wall mounted stadiometer (Holtain; United Kingdom). Body mass was measured on a calibrated digital scale to the nearest 0.5 kg (Model 1631, Tanita, Japan). A decimal chronologic age (CA, years) was determined by identifying the numbers of days between an individual's date of birth and the date at the assessment occasion. A measure of somatic maturation was defined by identifying the CA of attainment of peak linear growth during adolescence (peak height velocity [PHV]). To determine the CA at PHV, whole year height velocities were calculated for each participant. A cubic spline fitting procedure was applied to each individual's whole year velocity values and the CA at the highest point was estimated (GraphPad Prism 5, GraphPad Software, San Diego, CA, USA). A biological age (BA) was then calculated by subtracting the CA at PHV from the CA at time of measurement for each individual. For the present paper only male data was used.

Dataset two: BSP

Stature (Harpenden portable stadiometer; Holtain, United Kingdom) and sitting height (Harpenden sitting table; Holtain, United Kingdom) were measured for all participants to the nearest 0.1cm, with leg length calculated by subtracting sitting height from stature. Body mass was assessed to the nearest 0.1 kg (model BC-420SMA, Tanita, Japan) and from body mass, the body mass to stature ratio was derived. All assessments were conducted according to the anthropometric standards outlined by Ross and Marfell-Jones (26). A decimal CA was obtained by calculating the number of days between an individual's date of birth and the date at the assessment occasion.

Statistical Analysis

The first phase of the analyses was to fit a variety of different models to the data used to develop the original equation (MBJ). The goal of these models was to predict the maturity offset, defined as the difference between the player's CA and their APHV. The second phase of this analysis was to refit each of these models to predict APHV in a data set consisting of Belgian high level soccer players (BSP, 6). In the second phase of these analyses, the same fitting procedures were used to predict a maturity ratio (maturity ratio = CA/APHV) rather than a maturity offset (maturity offset = CA - APHV)

Phase one: predicting a maturity offset

In reanalysing the data from Mirwald et al. (19), several theoretically appropriate models were compared to identify the model with the most appropriate fit, assessed by how well the predicted values of the model match the observed data values. First, the linear model developed by these authors was evaluated, which includes interactions between leg length and sitting height, between CA and leg length, and between CA and sitting height, as well as the body mass to stature ratio. Afterwards, a second model was implemented including these variables, as well as the main effects for leg length, sitting height and age. However, as some non-linearity was apparent in the data, polynomial terms were added to account for this. Given the presence of some non-linearity in the residual analysis, Generalised Additive Models (GAMs) were also considered (11). These involve fitting smooth relationships between the predictive and response variable. Due to the complexity of these relationships, only the main effects of each factor were considered. Cubic splines were used as the smoothing function.

Phase two: predicting a maturity ratio

In the final model, the maturity ratio rather than the maturity offset was used as the outcome variable. Using a maturity ratio as the response variable is particularly useful as adolescents move into adulthood, and the rate of growth decreases. Similar to the procedure used in phase one, both linear, polynomial and general additive models were fitted to the maturity ratio response.

All models were compared using the coefficient of determination (R-squared) as a measure of how much of the variation in the offset could be explained by the anthropometric variables. Analysis of the residuals was also conducted to determine how well each of the models fit, especially for the youngest and oldest players in the data set. All models were fitted in version 3.2.3 of the R statistical software system (R Core Team, (23)), with plots constructed using the ggplot2 package (36), and linear mixed models fitted using the MASS package (35).

RESULTS

Dataset one: MBJ

Phase one: predicting a maturity offset

Figure 1 shows the relationship between CA, stature, body mass and leg length with BA (years from PHV) for the data in Mirwald et al. (19). The range for the maturity offset measurements range from four years before APHV (BA = -4) and three years after APHV

(BA = +3). The relationships between these variables and the BA were identified to be generally positive, but in some cases non-linear. This supports the further examination of the data using non-linear models. Table 1 provides the model parameters for: a) the original model; b) the model with main effects and interactions; c) the main effects only model; d) the polynomial model; e) the generalised additive model when the maturity ration is estimated. The Akaike Information Criterion (AIC, Sakamoto et al. (27)) and the adjusted R^2 values for each of the models are also included in table 1. Both of these measures indicate that the polynomial model with interaction terms yields the best fit when predicting the offset. This is indicated by the smaller AIC and the larger adjusted R^2.

** INSERT FIGURE 1 HERE **

** INSERT TABLE 1 HERE **

Phase two: predicting a maturity ratio

One of the issues with all of these models is that there is a small but systematic relationship between the model residuals and the fitted offsets. This relationship indicates that as the offset becomes larger in absolute value, the fit of the model to the data becomes poorer. The residual plots for each of these models are provided (see Figure, SDC 1, Residuals versus fitted values scatterplots for the different models used to predict a maturity offset in the MBJ data set). However, when using the maturity ratio as the outcome variable, an improved model fit was evident (see Figure, SDC 2, Residuals versus fitted values scatterplots for the different models used to predict a maturity ratio in the MBJ data set). The model parameters, AIC and R^2 for the same set of models as Table 1 but with a ratio response, are given in Table 2. The main-effects-only model was omitted as there are significant interactions. Like the maturity offset model, the best fitting model appeared to be the polynomial model. Table 2 provides a thorough description of all models fitted and the various comparative measures related to goodness of fit. When performing a residual analysis on the models using the maturity ratio, the systematic pattern in the residuals observed in the prediction of the maturity offset is diminished. This is particularly true for the polynomial and GAM models and, to a lesser degree, with the main effects and interaction model. This suggests that a ratio response fit provides a better fit when the difference between the APHV and the observed CA is large. The polynomial prediction equation that yielded the best model fit for the estimation of a maturity ratio can be found below:

$$\begin{aligned} Maturity\ ratio &= 6.986547255416 + (0.115802846632 * Chronological\ Age) \\ &+ (0.001450825199 * Chronological\ Age^2) + (0.004518400406 \\ &* Body\ Mass) - (0.000034086447 * Body\ Mass^2) - (0.151951447289 \\ &* Stature) + (0.000932836659 * Stature^2) - (0.000001656585 \\ &* Stature^3) + (0.032198263733 * Leg\ Length) - (0.000269025264 \\ &* Leg\ Length^2) - (0.000760897942 * (Stature * Chronological\ Age)) \end{aligned}$$

** INSERT TABLE 2 HERE **

Dataset two: BSP

In contrast to the MBJ dataset, an assessment of APHV based on whole-year height velocities derived from longitudinal follow up was not provided in the BSP dataset, so the estimates from each model provided a best guess of maturity. When using the model from Mirwald et al. (18), the relationships between each of the variables and the maturity offset estimates did not seem to be smooth (Figure 2). An improved fit is obtained when the maturity offset is defined as a ratio rather than a difference (Figure 3). In particular, the variation of the fitted values across different values of each of the factors was more uniform than when using maturity offset as the outcome variable (Figure 4), even for leg length which showed high variation for larger leg lengths.

** INSERT FIGURE 2 HERE **

** INSERT FIGURE 3 HERE **

** INSERT FIGURE 4 HERE **

DISCUSSION

The aim of this study was to improve the accuracy of the maturity offset and APHV prediction previously proposed by Mirwald et al. (19). These sex-specific prediction equations have been critically reviewed, widely accepted and frequently applied by researchers (569 citations of the original study, Scopus on 01/06/20167). However, both the original publication and a subsequent validation study (16) identified that there is a systematic error when predicting APHV from anthropometric variables whereby the prediction of maturity offset was increasingly inaccurate at the upper and lower classification limits. In fact, both studies concluded that the equation for boys in particular could really only be used in individuals of an average maturity range between the ages of 12-16 years. Also, the most accurate predictions were found to occur around the APHV of the individual (13.8 ± 0.8 years in averagely maturing boys). These findings indicate that perhaps there is a viable alternative to the original equations that allows for a more accurate estimation of APHV throughout the 12-16 year age span. Although Moore et al. (20) proposed simplified versions of the original equations that do not require the assessment of sitting height, the same consistent errors seemed to be apparent when using these enhanced equations. The results of the present study however, have resulted in an updated equation that better accounts for the systematic prediction error as individuals are further removed from their APHV.

Somatic growth is not a linear process. Research has frequently demonstrated growth peaks in early infancy and during the adolescent growth spurt (15). Therefore, this research modelled a non-linear relationship between anthropometric measures and a novel response variable. While the original prediction included only linear predictors, the use of a polynomial equation allows a more accurate representation of the non-linear relationship between the anthropometric variables and maturity offset (Figure 1). Furthermore, the use of a maturity ratio (CA / APHV) rather than a maturity offset (CA - APHV) seems to yield a better model fit in both the general sample and the athletic sample, even when the difference between the APHV and the observed CA is large. Hence, the inclusion of polynomial terms and the prediction of a ratio rather than an offset resulted in a superior prediction of APHV over using linear models in both the MBJ and the BSP datasets. However, this is not novel information as the original manuscript (19) already concluded that as the maturity offset increased, the prediction error increased as well. This was later confirmed to be the original equation's most significant limitation by Malina and Koziel (16). The new prediction equation has the same explained variance than the old equation, but there seems to be no systematic change in the prediction error as the predicted maturity ratio changes. This finding indicates that the current equation provides more reliable estimations of APHV than the original model (19), even when age is further removed from APHV. This increased accuracy of the new calculation will allow researchers and practitioners to determine APHV and maturity offset from anthropometric measures with greater confidence across a wide range of ages and maturity statuses. This presents researchers with the opportunity to reliably collect maturity data non-invasively and with minimal cost and time required when compared with more traditional longitudinal measurements or estimations (DXA, X-ray, etc.) of APHV. However, validating these new predictive models using longitudinal datasets should be the scope of future research.

One of the major strengths of this study is the successful application of the prediction equation to an external sample of high level youth athletes. The validation of the new maturity ratio prediction in youth soccer players in this study is demonstrated by the fitted vs residual plots (SDC 1 and SDC 2). Ideally, a good model fit is indicated by residuals that 'bounce randomly' around the 0 line, the residuals forming of a horizontal band around the 0 line and no clear outlying residuals. These criteria all seem to be met when a polynomial model is used to predict a maturity ratio. Furthermore, smaller AICs indicate a better model fit. As the AIC in the polynomial model yields ideal residual vs fitted plots and a low AIC, this model can be presumed to adequately fit the data. The validation of the newly developed prediction equation using 'out-of-sample testing' is particularly important as the original equation was frequently used in samples that were distinctly different that the original sample (5, 34). First of all, accurately determining maturation in youth athletes - both pre and post APHV - is of great importance as it allows researchers and coaches to account for the confounding effect an advanced or delayed maturation might have on performance. Furthermore, accurately monitoring maturation via relatively quick and non-invasive anthropometric measures, should aid in classifying youth athletes according to their biological maturity. This could ultimately result in a reduction in risk of physical injury (8), fairer match play, and decreased drop-out from team sports (14, 29). Finally, retrospective estimation of the APHV in athletes older than their predicted APHV might help map career progressions of successful athletes, a commonly used methodology in talent identification and development research. A second advantage of an accurate prediction of APHV in youth athletes is that training practice can be planned around the APHV of athletes. Philippaerts et al. (22) showed that peak growth in physical performance in young soccer players coincides with peak growth in height and weight and therefore differences in maturity status between players should be taken into account when planning individualized training interventions.

Although this study has clearly identifiable strengths, there are also limitations to utilizing the prediction equations from this study in samples of general and athletic populations. First of all, it is important to note that despite the improvement in accuracy of the new maturity ratio estimation, longitudinal measurement of PHV provides much more accurate estimations of

APHV. However, they are rarely viable alternatives for non-elite sporting academies or smaller sporting organisations, largely due to budget and time constraints. In circumstances such as these, the estimation of maturity ratio from anthropometric variables developed in this study might offer the best alternative. However, future studies should investigate construct validity of these novel equations using DXA imaging, X-ray or sexual maturation assessments. A second limitation is this study's inability to produce sex-specific prediction equations. Hence, the prediction equations derived from this study only refer to a male population. In the future, research should attempt to use similar models to describe the relationship between anthropometric variables and a maturity ratio in a sample of females.

CONCLUSION

In conclusion, this study overcomes some of the limitations of the prediction of APHV - as suggested by Mirwald et al. (19) - by modelling a non-linear relationship between anthropometric variables and a maturity ratio rather than a maturity offset. Furthermore, this study has established the practical validity of the novel equation in an external sample of high level soccer players. This has significantly improved the applicability of this prediction equation within a population of 11-16 year old boys. Hence, this newly developed method of estimating APHV should henceforth become standard practice for the non-invasive assessment of maturity from anthropometric variables.

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Table 1: Fitted models for models with maturity offset defined as a difference (Actual Age – Age at Peak Velocity). For each variable, the regression coefficient (Estimate), standard error, test statistic and p-value are provided.

Model	Variable	Estimate	SE	t value	P-value	AIC	R2
(a) Original model	Intercept	-9.206	0.095	-97.066	0.000	3048.7	88.88%
	Body Mass/Stature Ratio	0.023	0.004	5.046	0.000		
	Leg Length * Sitting Height	0.000	0.000	6.790	0.000		
	Leg Length * Chronological Age	-0.002	0.000	-4.935	0.000		
	Sitting Height * Chronological Age	0.007	0.000	22.248	0.000		
(b) Main Effects and Interactions	Intercept	-21.290	1.962	-10.851	0.000	3000.1	89.22%
	Leg Length	-0.052	0.070	-0.745	0.456		
	Stature	0.127	0.039	3.286	0.001		
	Chronological Age	0.597	0.168	3.555	0.000		
	Body Mass/Stature Ratio	0.020	0.004	4.416	0.000		
	Leg Length * Height	0.000	0.000	-0.776	0.438		
	Leg Length * Chronological Age	-0.004	0.005	-0.799	0.424		
	Stature * Chronological Age	0.001	0.003	0.387	0.699		
(c) Main Effects Only	Intercept	-16.796	0.298	-56.399	0.000	3006.6	89.16%
	Leg Length	-0.130	0.009	-14.961	0.000		
	Stature	0.122	0.006	21.726	0.000		
	Chronological Age	0.474	0.013	35.384	0.000		
	Body Mass	0.011	0.003	4.132	0.000		
(d) Polynomial Model	Intercept	82.63104	18.684	4.423	0.000	2923.6	89.72%
	Chronological Age	1.03482	0.181	5.711	0.000		
	Chronological Age^2	0.04002	0.008	4.709	0.000		
	Body Mass	-0.04496	0.039	-1.143	0.253		
	Body $Mass^2$	-0.00101	0.000	-5.255	0.000		
	Stature	-2.05143	0.364	-5.633	0.000		
	$Stature^2$	0.01329	0.002	5.898	0.000		
	$Stature^3$	-0.00003	0.000	-5.44	0.000		
	Leg Length	0.39035	0.110	3.56	0.000		
	Leg $Length^2$	-0.00404	0.001	-5.092	0.000		
	Leg Length * Chronological Age	-0.01043	0.002	-4.836	0.000		
	Body Mass * Leg Length	0.00215	0.001	3.106	0.002		
(e) Generalised Additive Model	Intercept	-3.700	0.189	-19.531	0.000	2930.7	89.71%
	Chronological Age (1)	1.542	0.176	8.750	0.000		
	Chronological Age (2)	1.962	0.204	9.608	0.000		
	Chronological Age (3)	2.646	0.142	18.698	0.000		
	Chronological Age (4)	3.668	0.404	9.090	0.000		
	Chronological Age (5)	3.950	0.201	19.700	0.000		
	Leg Length (1)	-2.124	0.226	-9.382	0.000		
	Leg Length (2)	-4.743	0.528	-8.989	0.000		
	Leg Length (3)	-4.091	0.262	-15.590	0.000		
	Body Mass (1)	13.286	0.701	18.948	0.000		
	Body Mass (2)	26.359	1.508	17.482	0.000		
	Body Mass (3)	21.294	0.912	23.349	0.000		
	Body Mass/Stature Ratio (1)	-6.161	0.591	-10.424	0.000		
	Body Mass/Stature Ratio (2)	-10.385	0.617	-16.833	0.000		
	Body Mass/Stature Ratio (3)	-18.780	1.169	-16.064	0.000		
	Body Mass/Stature Ratio (4)	-17.526	0.862	-20.339	0.000		

Note: For each model the Akaike information criterion (AIC) value (smaller is better) and adjusted R^2 (larger is better) are provided. (a) Model reported in Mirwald et. al. (2002) (b) Model including effects of height, age, leg length, height/weight ratio and interactions (c) Main effects model containing height, weight, age and leg length *(d) Linear model including interactions and polynomial terms – (1) indicates a linear term, (2) a quadratic term and (3) a cubic term (d) Generalised additive model with cubic splines. Knots were equally spaced across the range of the predictive variable and AIC was used to determine the number of knots.*

Table 2: Fitted models for models with maturity offset defined as a ratio (Actual Age / Age at Peak Velocity). For each variable, the regression coefficient (Estimate), standard error, test statistic and p-value are provided.

Model	Variable	Estimate	SE	t value	P-value	AIC	R^2
(a) Original model	Intercept	0.332	0.007	50.103	0.000	-5888.4	89.72%
	Body Mass/Stature Ratio	0.001	0.000	4.778	0.000		
	Leg Length * Sitting Height	0.000	0.000	6.450	0.000		
	Leg Length * Chronological Age	0.000	0.000	-4.807	0.000		
	Sitting Height * Chronological Age	0.001	0.000	23.385	0.000		
(b) Main Effects and Interactions	Intercept	-0.333	0.051	-6.539	0.000	-5964.9	90.19%
	Chronological Age * Stature	0.035	0.001	36.735	0.000		
	Body Mass	0.003	0.001	2.933	0.003		
	Stature	0.006	0.001	4.650	0.000		
	Leg Length	-0.002	0.003	-0.901	0.368		
	Body Mass * Stature	0.000	0.000	2.082	0.038		
	Body Mass * Leg Length	0.000	0.000	-2.922	0.004		
(c) Polynomial Model	Intercept	6.98655	1.287	5.431	0.000	-6062.1	90.82%
	Chronological Age	0.11580	0.012	9.273	0.000		
	Chronological Age^2	0.00145	0.001	2.477	0.013		
	Body Mass	0.00452	0.001	5.027	0.000		
	Body $Mass^2$	-0.00003	0.000	-4.272	0.000		
	Stature	-0.15195	0.025	-6.05	0.000		
	$Stature^2$	0.00093	0.000	6.004	0.000		
	$Stature^3$	0.00000	0.000	-5.191	0.000		
	Leg Length	0.03220	0.007	4.449	0.000		
	Leg $Length^2$	-0.00027	0.000	-5.852	0.000		
	Stature * Chronological Age	-0.00076	0.000	-5.114	0.000		
(d) Generalised Additive Model	Intercept	1.493	0.037	40.000	0.000	-6038.6	90.64%
	Chronological Age (1)	0.467	0.017	28.270	0.000		
	Chronological Age (2)	0.252	0.008	30.870	0.000		
	Leg Length (1)	-0.156	0.015	-10.280	0.000		
	Leg Length (2)	-0.201	0.015	-13.270	0.000		
	Leg Length (3)	-0.406	0.032	-12.780	0.000		
	Leg Length (4)	-0.314	0.019	-16.390	0.000		
	Body Mass (1)	0.986	0.038	26.260	0.000		
	Body Mass (2)	1.997	0.081	24.780	0.000		
	Body Mass (3)	1.580	0.062	25.410	0.000		
	Body Mass/Stature Ratio	-0.045	0.002	-23.190	0.000		

Note: For each model the Akaike information criterion (AIC) value (smaller is better) and adjusted R^2 (larger is better) are provided. (a) Model reported in Mirwald et. al. (2002) (b) Model including effects of height, age, leg length, height/weight ratio and interactions (c) Main effects model containing height, weight, age and leg length (d) Linear model including interactions and polynomial terms – (1) indicates a linear term, (2) a quadratic term and (3) a cubic term (d) Generalised additive model with cubic splines. Knots were equally spaced across the range of the predictive variable and AIC was used to determine the number of knots.

List of Figures

Supplemental Digital Content

SDC 1 – Figure in TIF format

SDC 2 – Figure in TIF format