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Regression-Based Prediction of Net Energy Expenditure in Children Performing Activities at High Altitude

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ABSTRACT We developed a simple, non-invasive, and affordable method for estimating net energy expenditure (EE) in children performing activities at high altitude. A regression-based method predicts net oxygen consumption (VO_2) from net heart rate (HR) along with several covariates. The method is atypical in that, the "net" measures are taken as the difference between exercise and resting VO_2 (ΔVO_2) and the difference between exercise and resting HR (ΔHR); ΔVO_2 partially corrects for resting metabolic rate and for posture, and ΔHR controls for inter-individual variation in physiology and for posture. Twenty children between 8 and 13 years of age, born and raised in La Paz, Bolivia (altitude 3,600 m), made up the reference sample. Anthropometric measures were taken, and VO_2 was assessed while the children performed graded exercise tests on a cycle ergometer. A repeated-measures prediction equation was developed, and maximum likelihood estimates of parameters were found from 75 observations on 20 children. The final model included the variables ΔHR, ΔHR^2, weight, and sex. The effectiveness of the method was established using leave-one-out cross-validation, yielding a prediction error rate of 0.126 for a mean ΔVO_2 of 0.693 (SD 0.315). The correlation between the predicted and measured ΔVO_2 was $r = 0.917$, suggesting that a useful prediction equation can be produced using paired VO_2 and HR measurements on a relatively small reference sample. The resulting prediction equation can be used for estimating EE from HR in free-living children performing habitual activities in the Bolivian Andes. Am. J. Hum. Biol. 15:554–565, 2003.

INTRODUCTION

Assessment of energy expenditure (EE) has become increasingly important with a mounting awareness of its association with physical activity, obesity, growth and development, health, and work levels (Bailey et al., 1995). While much effort over the last decade has gone into quantifying EE in adults performing subsistence labor tasks (e.g., Katzmarzyk et al., 1994; Leonard et al., 1995, 1996, 1997), less work has been done on children (discussed in Johnson et al., 1998; Benefice and Cames, 1999; Trost et al., 2000). This reflects, in part, problems of measuring EE in children. These difficulties stem from the invasiveness of procedures to measure EE and from measurement equipment that is not sized for children.

Assessing EE in children performing subsistence labor tasks (e.g., herding, fetching water, or working in fields) is challenging because measurements must be taken outside of the laboratory setting. While several methods have been developed to assess EE in field settings, including the factorial method, double-labeled water, the flex heart rate (HR) method, and the use of portable equipment, each method has several limitations, discussed in more detail later. A few particularly important limitations are the lack of tabulated activity-specific energy costs for children in the factorial method, the inability to measure EE over a few hours or for specific activities by the double-labeled water method, and the need for individual calibration using VO_2 measuring equipment with the flex HR method. Additional difficulties in assessing EE arise in harsh environments and high-altitude settings. Extreme cold and high winds compel the use of sturdier equipment, and the low pressure of oxygen in the atmosphere necessitates custom, portable equipment. Oxygen analyzers, such as the Aerosport Team 100, cannot be used

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at atmospheric pressures below 670 hPa (~500 mmHg, altitudes above 3,400 m on a standard day) (C. Beall, 1999, personal communication to IS-M). The Cosmed K4 portable oxygen analyzer can be used at lower atmospheric pressures, but its high price makes the machine inaccessible for many researchers.

Thus, there is a need to explore alternative methods for estimating the EE children spend on performing subsistence labor in harsh environments. The ideal method would be simple, non-invasive, and affordable and would not require individual calibration. Our particular interest is in assessing net EE of children living in high-altitude regions where labor tasks performed by children make up an important part of the economy and may play a role in survival (Collins, 1983, 1985; Thomas, 1976). Here we develop a method that estimates oxygen consumption (VO_2) as a proxy for predicting EE. A regression model is developed for estimating net VO_2 from net HR along with several covariates. An atypical aspect of our approach is use of the difference between exercise and resting VO_2 (ΔVO_2) and the difference between exercise and resting HR (ΔHR) as the primary measures. The reasoning is that ΔVO_2 partially corrects for resting metabolic rate (RMR) and posture, and ΔHR controls for inter-individual variation in physiology (e.g., the difference in resting heart rate or in stroke volumes due to training or other factors) and posture. We applied the method by developing a prediction equation from a sample of Bolivian children living in the Andean highlands at about 3,600 m. The effectiveness of the method was established using leave-one-out cross-validation.

Limitations of current approaches

Energy expenditure, defined as the rate at which heat is produced by the body, is ideally measured by direct calorimetry. Direct calorimetry measures EE as the rate at which heat is lost from the body to the environment. A subject must be enclosed in a chamber, and heat production is measured (Consolazio et al., 1963). Direct calorimetry has been most widely used in animal studies (Mount et al., 1967), but it has also been used in studies of humans (Bonjour et al., 1976). Indirect calorimetry estimates heat production using a proxy measure, usually a quantitative measurement of the chemical by-products of metabolism. Typically the by-products reflect respiratory gas exchange, like the volume of O_2 consumption (VO_2) and CO_2 production (VCO_2), or CO_2 production measured as excretion of isotopes. Other indirect methods include measurements of time and task-specific energy costs such as the factorial method or heart rate monitoring (Flex-HR method). Methods that involve the estimation of EE from the rate of respiratory gas exchange have been used on adults in the laboratory ("on-line" oxygen analyzers, Brutsaert et al., 1999; Mc Murray et al., 1998; or metabolic carts, Cicutti and Jetté, 1991; Cooper et al., 1984; Rowland et al., 1997) and in the field (Douglas bag method, Booyens and Hervey, 1960; Borghols et al., 1978; Goldsmith and Hale, 1971; Katzmarzyk et al., 1996; and portable respirometers, Billat et al., 2001; Doyon et al., 2001). However, the methods are either invasive, expensive, require complex equipment, or are not designed for children. Indirect estimation by excretion of isotopes in CO_2 (double-labeled water method, Davies, 1996; Livingstone et al., 1992; Wells and Davies, 1996) has the disadvantage that only total daily energy expenditure (TDEE) over several days can be estimated, not EE for any specific activity (Ceesay et al., 1989; Kashiwazaki, 1999). Furthermore, isotopes are very expensive, allowing only small-scale studies.

The factorial method estimates energy costs using tabulated data for task-specific metabolic costs, the subject's basal metabolic rate (BMR), and the amount of time spent on a task. This method has been widely used (e.g., Leonard, 1991; Leonard et al., 1995; 1997; Smith, 1981; Spurr et al., 1996; Westerterp, 1991) but has a number of problems when used for children. Most importantly, the task-specific tables are primarily applicable to adults. Additionally, metabolic constants are provided for a limited number of activities that are not well described, and the prediction equations for BMR derived from Western populations may not be suitable for individuals in non-industrial settings (Geissler et al., 1986).

Changes in HR are known to be strongly correlated with changes in heat production (Benedict, 1907), VO_2, and physical activity (Lindhard, cited in Booyens and Hervey, 1960). These relationships have been shown in sheep (Brockway and McEwan, 1969;

Webster, 1967) and birds (Culick et al., 1990; Wooley and Owen, 1977). The ease of measuring HR motivated the development of the flex-HR method for assessing EE and TDEE in humans under field conditions (Spurr et al., 1988). The method uses HR to predict EE for various activities based on a calibration curve. The curve is composed of two different slopes, which describe low and high EE activities; the HR at the intercept is designated the "flex-HR". Because of inter-individual variability, a calibration curve for each subject must be developed in a laboratory setting or with the help of a portable gas analyzer. The flex-HR method has been used to measure EE in adults (Katzmarzyk et al., 1994; Lambert et al., 1994; Leonard et al., 1995, 1996; 1997; Moon and Butte, 1996; Spurr et al., 1996, 1997) and children (Filozof et al., 1999; Livingstone et al., 2000; Panter-Brick et al., 1996a,b; Spurr et al., 1996, 1997). The method has several advantages: it can be used on free-living individuals performing habitual activities, it is relatively non-invasive (Murgatroyd et al., 1993), and it is acceptable to children (Sarton-Miller, 2000). The method provides useful results, even without conversion to EE, through intergroup comparisons of the percentage of time spent above the flex point (Panter-Brick et al., 1996b). Murayama and Ohtsuka (1999) propose the same approach, with a few modifications, that Panter-Brick took to simplify EE estimation in field settings.

The flex-HR method, however, has several disadvantages. First, calibration curves must be developed for each subject; this requires the availability of equipment for gas analysis (Murgatroyd et al., 1993). Second, determination of the flex point can be problematic because of different interpretations of its definition. For example, the following is one definition of the flex-HR point: the average of the highest HR at rest and the lowest HR during exercise. By this definition, different exercises used for calibration will result in different lowest exercise HRs. This leads to different flex-HR points, resulting in different slopes (Panter-Brick et al., 1996a; Spurr et al., 1988). Third, the method does not work well for light activities, and several ad hoc methods have been developed using the product of a constant and BMR to estimate EE for activities falling below the flex point (Ceesay et al., 1989; Schofield, 1985; Norgan, 1996). However, EE for activities performed at, or immediately below, the flex point is underestimated (Spurr et al., 1997). Despite the increasing popularity of HR monitoring, the flex-HR method is still experimental (Panter-Brick et al., 1996b), and the need for individual calibration is at odds with the goal of a simple, non-invasive, affordable method.

In contrast to direct and indirect calorimetric methods that rely on thermodynamic laws, accelerometery, which relies on the laws of Newtonian mechanics, has become a new focus of interest in the estimation of EE. The acceleration of a point on the body, measured with an accelerometer, is directly proportional to muscular force and therefore related to EE (Benefice and Cames, 1999). For activities that have dynamic properties, the direct relationship between body acceleration and EE can be used. An important limitation of accelerometry is that it does not measure static EE, i.e., the EE of standing still with a load on the back or the head. Many accelerometers measure movement only on one axis (Caltrac is used for vertical movement) and therefore appear to have limited value for assessing EE in a field study with activities in many directions (Allor and Pivarnik, 2001; Johnson et al., 1998). More accurate estimation of EE requires that multiple accelerometers be attached to specific points of the body in order to represent all the mobile elements. This results in discomfort and may interfere with the physical activity to be measured (Nichols et al., 1999; Westerterp, 1999). Finally the calculation of EE, based on the theory of dynamic equilibrium, requires complex computation, especially when multiple accelerometers are used (Jakicic et al., 1999).

Multiple regression modeling

Although prediction of energy cost from a single variable such as running speed has been used in the past (Walker et al., 1999), the use of HR as one of the covariates in a regression–prediction model is a recent approach for estimating VO_2 over a range of activities. The approach addresses many of the problems of the flex-HR method. Once a regression-based prediction equation is developed from a sample of reference individuals, it can be used to predict VO_2 for a target sample of individuals without the need for individual calibration.

The success of the regression approach depends strongly on how well the method controls for inter-individual variability and posture. Inter-individual variability refers to the variation in the physiology of the heart, such as different resting heart rates or stroke volumes reflecting differences in training or other factors. Posture may also influence the relationship between VO_2 and HR. For example, for a given VO_2, there will be a decrease in HR in the standing position, compared to the sitting position. This effect results from an increase in stroke volume that is a consequence of an increase in return blood volume caused by gravitational forces (Ceesay et al., 1989; Dauncey and James, 1979). Previous work has addressed inter-individual variability or posture in limited ways, such as controlling for surface area (Goldsmith et al., 1966; Inaoka and Suzuki, 1982), lean body mass, body cell mass, height and VO_2/weight (Inaoka and Suzuki, 1982), slope/weight (Cooper et al., 1984); body mass (Culik et al., 1990; Hiilloskorpi et al., 1999), age and gender (Hiilloskorpi et al., 1999; Inaoka and Suzuki, 1982), and ΔHR (Inaoka and Suzuki, 1982). We propose herein a more complete approach using combined methods and ideas of Inaoka and Suzuki (1982), Culik et al. (1990), and Hiilloskorpi et al. (1999). The approach we adopt is to predict net VO_2 from net HR, that is ΔVO_2 from ΔHR, rather than predicting VO_2 from HR, in conjunction with other individual covariates. The reasoning is that ΔVO_2 partially corrects for posture and resting metabolic rate (RMR), and ΔHR controls for posture and inter-individual variation in physiology; individual covariates (sex, age, weight, etc.) control for additional inter-individual variation not captured by controlling for RMR (Goldsmith et al., 1966). Our approach is particularly targeted to assessment of EE in children performing subsistence labor tasks, based on extensions to methods previously proposed for use in children. Of these studies, one considered different sets of activities and postures and built several equations, including one for sleeping (Treuth et al., 1998), but did not simultaneously adjust for BMR, independent covariates and postures; also, the regressions were developed on an individual basis. Another study of children addressed RMR and HR adjusted for different resting stages (Bailey et al., 1995), but no regression was built.

In this study, we use data from a sample of Bolivian children born and living at an altitude of 3,600 m in the city of La Paz. The original study objective was to identify and troubleshoot problems in measuring maximum VO_2 (VO_2 max) in non-Western children, i.e., children unfamiliar with the equipment (ergocycle) and with the concept of pushing oneself to maximum effort. Other criteria for evaluating VO_2 max were studied, because the usual criteria for VO_2 max (maximal HR, presence of a "plateau" or respiratory quotient >1.2) could not be used in this population (Sarton-Miller, 1998). For all children we had measured oxygen consumption and HRs for a series of workloads performed on an ergocycle in a laboratory setting. Anthropometric measurements were taken for each participant. With these data, we explored regression-based prediction equations in which ΔVO_2 could be estimated (as a proxy for task-specific EE) from HR in children engaged in non-laboratory activities.

After we controlled for repeated measures, which would otherwise underestimate standard errors of the parameter estimates, the most parsimonious prediction equation included ΔHR, ΔHR^2, body mass, and sex while excluding age, height, arm circumference, and skinfold. Leave-one-out cross-validation showed that, even with a relatively small reference sample (75 observations on 20 children), the model had a usefully small prediction error rate (0.127 L/min) and a high correlation ($r = 0.917$) between predicted and measured ΔVO_2.

SUBJECTS AND METHODS

Subjects

The study was conducted in La Paz, Bolivia (3,600 m). Twenty 8- to 13-year-old children (13 boys and 7 girls) born and raised in La Paz were recruited by contacting parents working as employees in hotels or the Instituto Boliviano de Biologia de Altura (IBBA). Only subjects who had not yet reached sexual maturation (boys) or menarche (girls) were enrolled into the study. Sexual maturation is delayed in this population, as has been observed for other high-altitude populations in the region (Gonzales et al., 1996; Greksa, 1990).

The purposes of the measurements were explained to the parents and to the children by local personnel from IBBA and consent was obtained from the parents. Subject testing was performed in a laboratory setting with a physician present (HS) to ensure that subjects were healthy and could participate in the study with minimal health risks.

Anthropometry

Anthropometric measures (body mass, height, mid-upper arm circumference, and skinfold thickness) were assessed by prescribed methods (Frisancho, 1993). Body mass was measured to the nearest 0.5 kg with a calibrated scale, and height was measured to the nearest cm with a stadiometer. Arm circumference was taken with a tape measure to the nearest mm, and skinfold measurements (triceps, biceps, subscapular, supraillliac, and calf) were taken with a Lange skinfold caliper to the nearest mm. Each skinfold was taken as the average of three separate measurements.

Oxygen consumption testing and HR monitoring

Oxygen consumption was measured by the protocol described in Brutsaert et al. (1999) using a graded exercise test on a mechanically braked cycle ergometer. Children were given an opportunity to become familiar with the ergometer and its use, since many of the children had no experience using a bicycle. (The steep streets of La Paz discourage the widespread use of bicycles.) Resting position HR and VO_2 were measured for the first 3 min while the subject was sitting still on the bicycle. After that, the subject pedaled against the lowest workload (0.25 or 0.5 kg, depending on a child's size and ability). Every 3 min thereafter, the workload was increased in increments of 0.25 kg for a total of from three to five different levels. Subjects were encouraged to pedal at a speed of about 60 rpm. Each subject's maximum VO_2 was reached at the last workload.

Heart rate was measured continuously with a Polar Vantage XL heart rate monitor (Polar Electro Oy, Finland). The device has a lightweight transmitter, which is held on the chest by a belt, with dry electrodes on the inner surface and a watch-like device attached to the wrist. Heart rate was recorded every 5 sec and then averaged over 30 sec.

Throughout the test, the subject inspired room air through a low-resistance breathing valve. Expired fractions of VO_2 and VCO_2 were measured continuously from a mixing chamber by gas analyzers (provided by T. Brutsaert) calibrated to gas standards before the test. Oxygen was measured with an Applied Electrochemistry S-3A oxygen analyzer, (Ametek, Pittsburgh, PA, USA) and CO_2 was measured using a Beckman LB-2 CO_2 analyzer (Beckman Instruments, Inc., Fullerton, CA, USA) as described in Brutseart et al. (1999, 2000). Data were processed by an automated oxygen uptake system (REP-200B, Rayfield Electronics, Waitsfield, VT, USA) and recorded every 30 sec. For each subject, resting VO_2 and HR were taken as an average of the last two measurements made before adding the first workload. For each exercise, VO_2 was taken as an average of the final two values at that level. These values were matched to the corresponding average HR.

Statistical methods

The prediction equation was developed as a regression of a series of variables on ΔVO_2. Because measures on the reference subjects are repeated for individuals at different exercise levels, we used a repeated measures regression and maximum likelihood parameter estimation.

Individual-level covariates considered in the regression were sex, age, weight, height, arm circumference, sum of three skin folds (hereafter, skinfold), and delta heart rate (ΔHR and ΔHR^2) measured for $N = 20$ individuals. There were m_i exercises, where m_i ranged from 3 to 5, each at a different load, for the ith individual. Most covariates are fixed across all exercises within an individual; only ΔHR changed for each exercise level. Call $\mathbf{x}_{ik} = (x_{i1k}, x_{i2k}, \ldots, x_{ink})$ an array of n covariates for the ith individual (i from 1 to N) and for the kth exercise (k from 1 to m_i). Outcomes are a series of m_i ΔVO_2 measures $\mathbf{v}_i = (v_{i1}, v_{i2}, \ldots, v_{im})$ for the ith individual. Raw ΔVO_2 values were multiplied by 100 for all analyses.

A series of n parameters were estimated, $\beta = (\beta_1, \beta_2, \ldots, \beta_n)$, that quantify the effects of ΔHR and other covariates on ΔVO_2. Workload was not included as a covariate in the regression equations, since our purpose was to develop a general prediction equation to estimate VO_2 across a wide variety of workloads. The effect of covariates for the ith individual was modeled on the mean value of ΔVO_2 as $\mu_i = \mu + \mathbf{x}_i'\boldsymbol{\beta}$. If there had been but a single exercise measured for all individuals (that is, if m was 1), then linear regression using ordinary least-squares methods could have been used to estimate the parameters of the prediction equation. To accommodate the repeated measures, however, and to provide a more flexible modeling and estimation framework, maximum likelihood estimation was used. The equivalent regression model using a likelihood approach is to maximize the likelihood

$$L = \prod_{i=1}^{N} f_v(v_i|\mu + \mathbf{x}_i'\boldsymbol{\beta}, \sigma) \quad (1)$$

where f_v is the distribution of ΔVO_2 around the regression line $\mu + \mathbf{x}_i'\boldsymbol{\beta}$, with a variance of σ^2; f_v is assumed to be a normal distribution. With repeated measures (different exercise levels) on each individual, the likelihood must be modified to incorporate individual-specific effects, which controls for correlations among repeated measures. Suppose there is some value z_i for the ith individual that quantifies the individual-level effect on mean ΔVO_2. Rather than measuring or estimating separate values of this covariate for each individual, we assume that z is distributed among individuals as a normal distribution, $g_z(z|0, \sigma_z)$, with a mean of zero and a variance (σ_z^2) that can be estimated from the observations. The resulting likelihood is taken as an expectation over the distribution of g_z:

$$L = \prod_{i=1}^{N} \int_{-\infty}^{\infty} g_z(z|0, \sigma_z) \prod_{k=1}^{m_i} f_v(v_{ik}|\mu + \mathbf{x}_{ik}'\boldsymbol{\beta} + z, \sigma)dz \quad (2)$$

Values of $\boldsymbol{\beta}$, μ, σ, and σ_z that maximize Eq. (2) are the maximum likelihood estimates of these parameters.

Model selection

Initially parameters for all covariates except exercise level were included in the regression. Covariates were eliminated sequentially until the most parsimonious set of parameters were found. The selection criterion we used was minimum Akaike's Information Criterion (AIC) (Akaike, 1973, 1992; Burnham and Anderson, 1998). This criterion penalizes models for having an excess number of parameters or for fitting poorly to the data. The final model included the set of parameters that minimized AIC.

Numerical methods

Parameter estimates were found by maximizing numerically evaluated likelihoods using the *mle* programming language (Holman, 2000). Numerical integration was done by a closed trapezoidal approximation over 100 points. Standard errors of the parameter estimates were found from the inverse of the observed Fisher's information matrix.

Model evaluation

Given parameter estimates $\hat{\boldsymbol{\beta}}$, $\hat{\mu}$, $\hat{\sigma}$, $\hat{\sigma}_z$ and for the prediction equation, the next step is model evaluation, with the goal of assessing how well the resulting prediction equation predicts ΔVO_2 given a sample with a known ΔVO_2. We used leave-one-out cross-validation (Efron, 1982), which has been shown to provide reasonable estimates of prediction error for smooth functions (Efron, 1983).

The procedure for leave-one-out cross-validation is that multiple prediction equations are developed, each time withholding one observation, and then predicting a value for the withheld observation. Here, we found parameter estimates for 75 different regression equations, each time withholding, in sequence, one observation. Each resulting prediction equation was then used to predict ΔVO_2 for the withheld observation. The error of prediction for that observation was taken as the difference between the measured ΔVO_2 and the ΔVO_2 predicted from the equation. Since the measured ΔVO_2 for each observation is not included in the regression equation used to predict ΔVO_2, the procedure effectively eliminates biases of using a reference sample for validation (Efron, 1982). The cross-validated prediction error rate was computed as the mean of the squared difference between the measured and predicted ΔVO_2. The cross-validated prediction error rate can be used as an estimate of the prediction standard error and can be used to compute prediction intervals.

RESULTS

Our sample was made up of repeated observations on 20 children, for a total of 75 observations. Descriptive statistics for the variables in the Bolivian data set are given in Table 1. The most parsimonious model, assessed by AIC, included the four covariates ΔHR, ΔHR^2, weight, and sex, and excluded age, height, arm circumference, and skinfold. A normal distribution for ΔVO_2 was found by AIC to fit the data substantially better than did a lognormal distribution. The parameter estimates for the most parsimonious model are given in Table 2.

The cross-validated prediction error rate was 0.127 L/min for a mean ΔVO_2 of 0.693 (SD 0.315). An F-test for the difference between the variance in prediction error and ΔVO_2 yields 30.3, which suggests the prediction error variance is significantly lower than the variance in ΔVO_2. Figure 1 shows the difference between measured ΔVO_2 and the cross-validated predicted ΔVO_2. The mean difference is 0.0013 (SD 0.127, SE 0.0015), and is not significantly different from the expected difference of zero. Figure 2 shows the excellent correspondence between the predicted values of ΔVO_2 and measured values ΔVO_2, as well as the 95% prediction interval. The correlation between the predicted and measured ΔVO_2 is $r = 0.917$, indicating that the predicted ΔVO_2 "explains" about 84% of the measured ΔVO_2. Figure 3 shows cross-validated predicted ΔVO_2 within each child at different exercise levels. The ΔVO_2 values are predicted from a regression developed without the observation used for prediction, and the variable for exercise level is not included in any way in the regression. The predicted ΔVO_2 values generally show a pattern of linear increase for a constant increment in exercise load within a child, suggesting that the prediction equation can be used to predict ΔVO_2 over a wide range of activities for which the exercise load itself is not quantified.

Examples of estimating EE from ΔHR are given in Table 3 for one child engaged in three subsistence activities. The child's heart rate was assessed as the average over about 8 min of activity. Because the activities took place using upright postures, standing RHR was taken and averaged over 4 min. Parameter estimates from Table 2 were used to compute ΔVO_2 and EE for each activity. For example, the activity *feeding animals*, ΔHR was computed as 109.44 − 91.5 = 17.94. ΔVO_2 was then found as $(\mu + \beta_{\Delta HR} \times 17.94 + \beta_{\Delta HR^2} \times 17.94^2 + \beta_{weight} \times 36.5 + \beta_{sex} \times 1)/100 = 0.357$. A 100α% prediction interval can be computed as $0.357 \pm 0.1267 \times t_{1-\alpha/2}$, so that the 95% prediction interval is 0.109–0.605 for this example. The increase in EE for this activity was found by converting 1 L of O_2 = 20.1 kJ or 4.803 kcal.

DISCUSSION

The purpose of this research was to develop a non-invasive and affordable technique to estimate energy expenditure in children performing tasks under non-laboratory field conditions (e.g., where children perform subsistence labor tasks). Indirect calorimetry, where EE is calculated from VO_2 (EE = VO_2 × energy equivalent of 1 L of O_2) (Norgan, 1996), is widely recognized as a useful way to estimate EE (Murgatroyd et al., 1993). Even so, direct measurement of VO_2 is difficult under natural workload conditions and is particularly challenging under extreme conditions like high altitude, where extreme cold, wind, and low atmospheric pressure prevail. The flex-HR method has been successfully used under these conditions; however, the need for individual calibration makes the method more difficult and expensive. Our results suggest that VO_2 can be predicted from variables that are easier to measure, specifically heart rate

TABLE 1. Summary statistics for variables for the Bolivian data set

Variable	Age (yr)	Weight (kg)	Height (cm)	Arm circumference (cm)	Skinfold (mm)	ΔHR (beats/min)	100 × ΔVO_2 (L/min)
Mean	11.0	33.8	138.4	21.4	58.2	51.1	69.3
Std dev	1.54	4.91	7.90	1.93	19.6	24.1	31.5
Minimum	8.3	25.0	114.3	19.0	33.8	6.0	16.0
Maximum	13.4	42.5	152.0	25.8	112.3	110.5	132.0

*TABLE 2. Parameter estimates for the most parsimonious prediction model (excluded variables: age, height, arm circumference, and skinfold)**

Parameter	Estimate	SE	t
σ_z	8.524	1.732	4.92
μ	−69.80	16.17	−4.32
$\beta_{\Delta HR}$	1.725	0.1830	9.43
$\beta_{\Delta HR^2}$	−0.004971	0.00166	−3.00
β_{weight}	1.664	0.4892	3.40
β_{sex}	15.31	5.071	3.02
σ	8.219	0.7773	10.6

* Log likelihood, −280.06; AIC, 574.12; 75 observations on 20 high-altitude Bolivian children.

(HR) and individual covariates like weight and sex, once a prediction equation has been developed from a small reference sample. Measuring heart rate is relatively simple and requires minimal subject cooperation and competence, whereas direct measurement of VO_2 requires a high degree of subject cooperation and training.

Heart rate can be monitored and recorded using simple electronic devices that operate well even in high-altitude environments (Sarton-Miller, 2000), so our approach should work under natural workload conditions in extreme environments. The lightweight transmitter, which is held on the chest by a belt, and the watch-like sensor do not materially interfere with a subject's activity. In fact, many children enjoy wearing the watch (Murgatroyd et al., 1993; Sarton-Miller, 2000).

The relationship between VO_2 and HR may be influenced by posture. For example, for a given VO_2, there will be a decrease in HR in the standing position, compared to the sitting position. This effect results from an increase in stroke volume that is a consequence of an increase in return blood volume caused by gravitational forces (Ceesay et al., 1989; Dauncey and James, 1979). In this study, the calculation of net EE with the delta approach should, in part, correct for posture since for a higher HR in sitting position (bicycling), a higher sitting HR is seen. Nevertheless, we investigated only one posture, so that additional adjustments for posture warrants further investigation. Additional research is also needed to determine whether a reference sample using one posture and one type of exercise can be usefully applied to target samples using another posture or exercises.

Basal metabolic rate (BMR) also needs to be considered in a regression model, because it varies among individuals by body mass, age, but also by environmental or behavioral factors (Ulijaszek, 1995). Because BMR is difficult to measure, we used resting metabolic rate (RMR) as a proxy for BMR. We believe that RMR is best taken when measured in the same posture used for the exercise. In this study, sitting RMR was measured as the subject sat still on the bicycle. For a standing RMR, we would ask the subject to stand still. However, additional research using true RMR instead of sitting RMR is warranted. Finally, we used only a single measure of resting heart rate in this study; additional research is needed to examine the effect of variability within subjects in resting

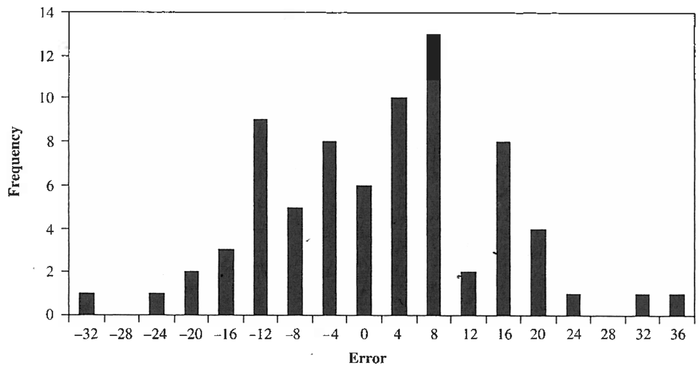

Fig. 1. Difference between measured 100 × ΔVO_2 and 100 × ΔVO_2 predicted from a regression equation that did not include the corresponding observation (cross-validated); the mean difference is −0.129 and is not significantly different from the expected difference of zero.

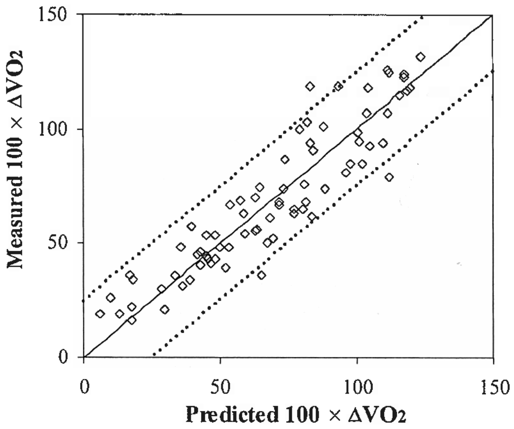

Fig. 2. Cross-validated predicted ΔVO_2 versus measured ΔVO_2 for high-altitude Bolivian children, based on the prediction equation given by parameter estimates in Table 2. Dotted lines enclose the 95% prediction interval based on the cross-validated prediction error rate.

heart rate on estimated EE. We suspect that some of this variability is cancelled by the use of ΔHR.

The proposed method predicts ΔVO_2 (rather than VO_2) from ΔHR (rather than HR) in conjunction with other individual covariates, so that net VO_2 or net EE of specific activities is being estimated. The use of delta values and individual covariates addresses, in part, inter-individual variability and removes the need for individual calibration as required for the flex-HR method. This "differential" approach is one way to adjust for metabolic rate that seems to work well in this application. Adjusted values have previously been calculated as ratios, i.e., activity VO_2:(VO_2 max—sitting RMR) and activity HR:(HR max—sitting resting HR) (Bailey et al., 1995). Caution should be employed, however, as the use of ratios can lead to serious problems of data interpretation. These problems stem from the underlying assumptions that the variables involve in the ratio will demonstrate proportionality and that the regression line expressing the relationship between them will pass through the origin. For many biological variables, these assumptions are not met (Sarton-Miller et al., 1997).

The prediction equation was developed using repeated measures on 20 children for a total of 75 observations. With this sample size, the prediction equation performed quite well, with a correlation between the predicted and measured ΔVO_2 of $r = 0.917$. The present research cannot address whether the prediction equation developed for Bolivian children living in the Andean highlands is applicable to other conditions like low altitude, hot environments, or for lower workload conditions. Additional research will need to assess whether a single prediction equation is required for each combination of population and environment, or

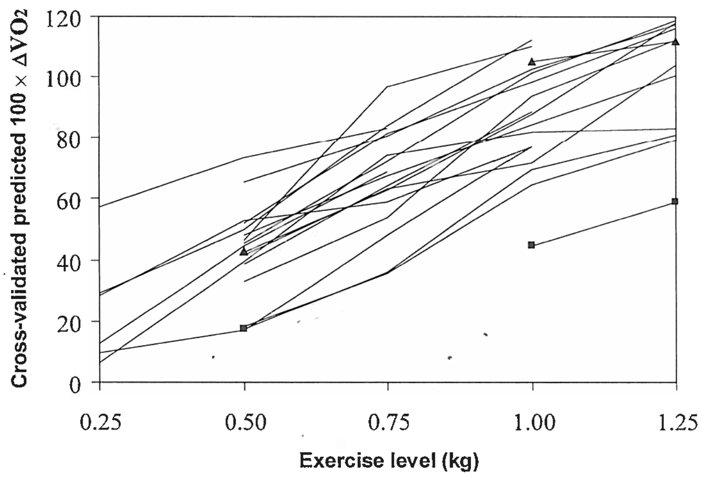

Fig. 3. Cross-validated predicted ΔVO_2 at different exercise levels for children in the reference sample. Each line shows results for a single child. Symbols show values for children who skipped one exercise level (0.75 kg).

TABLE 3. Examples of estimated energy expenditure (EE) for three subsistence labor tasks estimated from ΔHR (ΔHR = exercise HR − resting HR) measured on one 12-year-old male child weighing 36.5 kg, living in La Paz, Bolivia

Activity	Exercise HR (beats/min)	Standing RHR (beats/min)	ΔVO_2 (L/min)	EE (kJ/min)	EE (kcal/min)
Feeding animals	109.44	91.5	0.357	7.173	1.714
Shoveling manure	123.25	91.5	0.564	11.33	2.707
Washing dishes	103.75	91.5	0.262	5.272	1.260

whether one equation is universally applicable. Future research must also address whether the method can be applied outside the restricted age range (8–13 years), range of body weights (26–39 kg in girls and 30–42.5 kg in boys), and maturation status (girls prior to menarche and boys prior to sexual maturation) that characterize our sample. Even if separate prediction equations are required for different populations, ages, or environments, our results suggest that a useful prediction equation can be produced using paired net VO_2 and net HR measurements on a relatively small reference sample; the resulting regression can then be applied more broadly in the same population and environment.

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