Estimating the effects of energy imbalance on changes in body weight in children

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ABSTRACT
Background: Estimating changes in weight from changes in energy balance is important for predicting the effect of obesity prevention interventions.

Objective: The objective was to develop and validate an equation for predicting the mean weight of a population of children in response to a change in total energy intake (TEI) or total energy expenditure (TEE).

Design: In 963 children with a mean (±SD) age of 8.1 ± 2.8 y (range: 4–18 y) and weight of 31.5 ± 17.6 kg, TEE was measured by using doubly labeled water. Log weight (dependent variable) and log TEE (independent variable) were analyzed in a linear regression model with height, age, and sex as covariates. It was assumed that points of dynamic balance, called “settling points,” occur for populations wherein energy is in balance (TEE = TEI), weight is stable (ignoring growth), and energy flux (EnFlux) equals TEE.

Results: TEE (or EnFlux) explained 74% of the variance in weight. The unstandardized regression coefficient was 0.45 (95% CI: 0.38, 0.51; R^2 = 0.86) after including covariates. Conversion into proportional changes (time, to time), gave the equation (weight/weight) = (EnFlux/EnFlux)^0.45. In 3 longitudinal studies (n = 212; mean follow-up of 3.4 y), the equation predicted the mean follow-up measured weight to within 0.5%.

Conclusions: The relation of EnFlux with weight was positive, which implied that a high TEI (rather than low physical activity and low TEE) was the main determinant of high body weight. Two populations of children with a 10% difference in mean EnFlux would have a 4.5% difference in mean weight. Am J Clin Nutr 2006; 83:859–63.

KEY WORDS Energy intake, energy expenditure, energy balance, weight change, children

INTRODUCTION

The prevalence of childhood obesity is high and is on the increase in many countries (1), which has lead to questions about identifying the most effective interventions at a population level. Unfortunately, there are few population intervention studies with anthropometric outcomes (2), and, therefore, evidence-based decisions about the most effective and cost-effective interventions in which to invest will have to rely on modeled estimates (3).

Such modeling needs a logic pathway of the relations between input and outcome variables and a series of coefficients for each relation, so that quantitative changes can be estimated. An example of a logic pathway linking interventions that change patterns of eating and physical activity or inactivity to outcomes of changes in overweight and obesity prevalence is shown in Figure 1. This study focused on the component of the pathway that links changes in energy balance to changes in body weight.

Modeling the effects of energy imbalance on individual weight changes is complex (4–7), and simpler methods are needed. Hill et al (8) took the approach of back-extrapolating from changes in mean population weight with an assumed 50% efficiency of converting excess energy into storage. They derived a very small value (median: ≈125 kJ/d) for the progressive, daily positive energy imbalance needed to explain the population weight gain in adults over time—a concept they called the “energy gap.” However, Butte and Ellis (9) presented data in children suggesting that this energy gap was substantially higher than the predictions of Hill et al (8). Another option for estimating these energy gaps is the use of the concept of comparing one point of dynamic balance, or “settling point” (10)—ie, the steady state in which energy intake (EI) and expenditure (EE), and body weight are all in equilibrium—with another settling point that has a higher or lower balance of intake, expenditure, and weight.

The purposes of this study were to use EE data from studies that have used the doubly labeled water technique in children and adolescents to quantify the relation between EE and body weight, to convert this quantified relation into an equation that predicts the body weight settling points for populations as a function of the EI and EE at which energy balance is achieved, and to validate this equation against longitudinal studies in which EE was measured on 2 occasions.

SUBJECTS AND METHODS

Subjects

Data from studies that measured EE by using the doubly labeled water technique (11) in normal children and adolescents...
aged 4–18 y were obtained from 7 centers—4 in the United States (data mostly available in 12) and 1 each in Brazil (nons- 
tunted children only; 13), Australia (14), and New Zealand (15). 
The inclusion of several centers in the database meant that dif-
f erences in methods, ages, and ethnicities would be spread across 
the dataset and would help to reduce study bias. Body weight, 
height, daily total EE (TEE), sex, age, ethnicity, and study center 
were the variables included in the analysis. Body weight was 
the dependent variable of interest, TEE was the major predictor 
variable of interest, and the other variables were included as 
covariates. Three centers were able to provide individual data for 
children who underwent follow-up measurements of TEE sev-

eral years after baseline, and we used these data to compare the 
measured weight at follow-up against the weight predicted from 
our equation. 

Written informed consent was obtained from the parents or 
guardians of all of the children. Ethical approval was obtained 
from each of the participating institutions. 

Assumptions 
We made 2 assumptions in converting this cross-sectional 
relation into a generalizable coefficient that could be used for 
predicting differences in body weight, given differences in EI 
and EE. First, we assumed that, on average across the study 
population, the TEE was equivalent to total EI (TEI). Over the 
period in which the TEE measurements were made (usually 
≈ 1–2 wk), there will have been a small mismatch between 
the average TEE and TEI because of the children’s growth in that 
period, but this mismatch is on the order of 2% (16), and we 
egnored it for the purposes of this study. Second, we assumed 
that, if the population is in energy balance, then the average 
energy flux (EnFlux) under those equilibrium conditions is the 
amount of daily energy in and out while the subject is in energy 

balance (EnFlux = TEE = TEI), and that EnFlux is related to 
the average body weight of the population. This point of dynamic 
balance is termed the “settling point” (4) or steady state value for 
the mean body weight (ignoring the small effects of growth), 
which corresponds to the mean EnFlux. The terms TEE and TEI 
are used for showing the raw data, and their equivalent term, 
EnFlux, is used for the equations and implications. 

Statistical analysis 
We computed the characteristics of the sample and performed 
2 simple regression analyses. First, we regressed TEE or TEI 
onto body weight. Because the relation between body mass and 
TEE is known to be exponential across mammalian species (17), 
we used natural logarithms for weight and TEE or TEI for the 
second regression. The use of logs reduced the skewness of the 
weight and TEE or TEI variables and also increased the linearity 
and reduced the heteroscedasticity of their relation. 

We used the term lnEnFlux (= lnTEE = lnTEI) in a hierar-
chical multiple regression with lnWeight (lnkg) as the dependent 
variable and lnEnFlux (lnkjd), height (cm), age (y), and sex 
(males = 0, females = 1) as the first set of variables. We then 
assessed the value of including study center, ethnicity, and in-
teraction terms (ie, age × lnEnFlux and sex × lnEnFlux) as 
variables by examining changes to the adjusted R2 value. Study 
center and ethnicity were coded in 2 sets of 7 dummy variables 
each. For the longitudinal analyses, we included the changes in 
age, height, and EnFlux (= TEE) in the equation to predict 
changes in weight. We used SPSS software (version 12.0.1; 
SPSS Inc, Chicago, IL) for all analyses. 

RESULTS 
The characteristics of the total study sample (n = 963) and 
center-specific samples are shown in Table 1. The sample cov-
ered a broad range of ages (3.9–18.8 y), weights (13.6–141.2 
kg), TEE (2848–24 757 kJ/d), and ethnicities. 

The positive relation between body weight and TEE or TEI on 
the arithmetic (R2 = 0.71) and logarithmic (R2 = 0.74) scales is 
shown in Figure 2. At the first step of the hierarchical regression, 
the model included height, age, and sex with the lnEnFlux variable 
henceforth called lnEnFlux). This model explained 86% of the 
variance in lnWeight, and the unstandardized regression coeffi-
cient for lnEnFlux was 0.45 (95% CI: 0.38, 0.51). lnEnFlux (P < 
0.001), height (P < 0.001), age (P = 0.009), and sex (P = 0.031) 
were all statistically significant. The inclusion of the dummy 
variables for study center and ethnicity and the interaction terms 

TABLE 1 
Characteristics of the study population

<table>
<thead>
<tr>
<th>Center</th>
<th>Age</th>
<th>Weight</th>
<th>Height</th>
<th>TEE</th>
<th>Ethnicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>y</td>
<td>kg</td>
<td>cm</td>
<td>kJ/d</td>
<td></td>
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</tr>
<tr>
<td>Arizona (n = 225 M, 212 F)</td>
<td>5.9 ± 1.0 (3.9–9.7)</td>
<td>22.6 ± 5.6 (13.6–44.2)</td>
<td>115.9 ± 7.3 (100–142)</td>
<td>6222 ± 1166 (2848–10 899)</td>
<td>229 P, 192 W, 12 H, 4 B</td>
</tr>
<tr>
<td>Louisiana (n = 66 M, 65 F)</td>
<td>10.8 ± 0.6 (9.6–13.0)</td>
<td>40.8 ± 10.8 (24.9–75.9)</td>
<td>145.1 ± 7.1 (130–166)</td>
<td>9580 ± 1531 (6478–15 112)</td>
<td>67 W, 64 B</td>
</tr>
<tr>
<td>Texas (n = 4 M, 97 F)</td>
<td>8.5 ± 0.4 (7.4–9.4)</td>
<td>27.9 ± 4.2 (19.3–41.1)</td>
<td>130.0 ± 5.3 (117–143)</td>
<td>7370 ± 1252 (5304–14 142)</td>
<td>51 W, 28 B, 18 H</td>
</tr>
<tr>
<td>Boston (n = 21 M, 27 F)</td>
<td>14.6 ± 2.7 (12.2–18.8)</td>
<td>78.6 ± 27.9 (41.5–135.8)</td>
<td>164.4 ± 8.4 (140–189)</td>
<td>13 272 ± 2933 (7921–19 421)</td>
<td>51 W, 3 B, 3 H, 1 A</td>
</tr>
<tr>
<td>Brazil (n = 29 M, 26 F)</td>
<td>10.1 ± 1.3 (7.8–12.9)</td>
<td>28.9 ± 5.9 (17.1–44.0)</td>
<td>130.4 ± 10.5 (106–153)</td>
<td>8466 ± 1596 (4729–12 667)</td>
<td>55 Br</td>
</tr>
<tr>
<td>Australia (n = 52 M, 54 F)</td>
<td>7.8 ± 0.9 (6.0–9.6)</td>
<td>27.8 ± 6.2 (19.1–50.2)</td>
<td>127.5 ± 7.8 (114–155)</td>
<td>7688 ± 1174 (5020–10 604)</td>
<td>106 W</td>
</tr>
<tr>
<td>New Zealand (n = 40 M, 39 F)</td>
<td>10.0 ± 2.8 (5.5–14.7)</td>
<td>41.8 ± 20.0 (18.3–141.2)</td>
<td>139.9 ± 17.3 (107–175)</td>
<td>10 487 ± 3464 (5951–24 757)</td>
<td>53 P, 26 W</td>
</tr>
<tr>
<td>Total (n = 443 M, 520 F)</td>
<td>8.1 ± 2.8 (3.9–18.8)</td>
<td>31.5 ± 17.6 (13.6–141.2)</td>
<td>128.3 ± 16.5 (100–189)</td>
<td>7858 ± 2620 (2848–24 757)</td>
<td>493 W, 229 P, 99 B, 55</td>
</tr>
</tbody>
</table>

1 TEE, total energy expenditure; P, Pima Indian; W, white or European; H, Hispanic; B, black; A, Asian; Br, Brazilian; Pl, Pacific Islander. 
2 x ± SD; range in parentheses (all such values).
age × lnEnFlux and sex × lnEnFlux at the second step increased the adjusted $R^2$ to 0.89. Whereas many of the interaction and dummy variables were statistically significant in the full model, they added considerable complexity to the equations given here (see below), and their total added contribution toward explaining the variance in lnWeight was small (3%). For these reasons, they have not been included in the equation transformations below.

The following equation is based on the unstandardized coefficients derived from the first regression model:

$$\ln\text{Weight} = 0.45(\ln\text{EnFlux}) + 0.018(\text{height}) - 0.012(\text{age}) + 0.022(\text{sex}) - 2.838 (1)$$

The antilog of both sides of equation 1 is taken in the following equation:

$$\text{Weight} = \text{EnFlux}^{0.45} \times e^{0.018\text{height}} \times e^{-0.012\text{age}} \times e^{0.022\text{sex}} \times e^{-2.838}$$

Equation 2 is transformed into a ratio from time1 to time2 for considering the same population at different time points (sex and constant variables cancel out), as shown in the following equation:

$$\left(\frac{\text{Weight}_2}{\text{weight}_1}\right) = \left(\frac{\text{EnFlux}_2}{\text{EnFlux}_1}\right)^{0.45} \times (e^{0.018\text{height}_2}/e^{0.018\text{height}_1}) \times (e^{0.012\text{age}_1}/e^{0.012\text{age}_2}) (3)$$

If height and age are considered the same, these variables also cancel out, as shown in the following equation:

$$\left(\frac{\text{Weight}_2}{\text{weight}_1}\right) = (\text{EnFlux}_2/\text{EnFlux}_1)^{0.45} (4)$$

which can represent a “what if” scenario for a population: eg, what would be the mean weight of a population with the same age, height, and sex mix if the population were consuming 10% more or 10% less energy? Equation 4 has been plotted for a range of values for percentage differences in EnFlux and body-weight settling points (Figure 3). Within the range shown, the slope is not quite linear: a 10% higher EnFlux resulted in a predicted settling point weight 4.36% higher, and a 10% lower EnFlux resulted in a 4.61% lower body weight.

To test the validity of the above equations, we used 3 studies (18–20) in which TEE, height, and weight had been measured twice in the same children or adolescents some years apart. The study by Spadano et al (20) measured 24 girls on 3 occasions; we used only the first and last measurements for the current study. The weighted mean follow-up duration for all longitudinal studies was 3.4 y. The characteristics of the 212 subjects with longitudinal data are shown in Table 2, which compares the mean observed follow-up body weight with the predicted follow-up weight for each study by using equation 3. For each of the follow-up populations, there were no significant differences between the observed and the predicted final mean weights. For the whole follow-up population, the predicted final mean weight (53.19 kg) was within ±250 g (<0.5%) of the observed mean weight (53.44 kg).

DISCUSSION

We have used the cross-sectional relation between TEE and body weight as the basis for predicting the mean weight of a
population of children with a given total equilibrium energy flux (where EnFlux = TEE = TEI when in energy balance). The validation of the equation with the use of longitudinal studies was very tight: it predicted the follow-up weight to within \( \pm 250 \) g.

The equation would predict that, if the whole study population of 963 children was, for example, eating 10\% less energy (785 kJ/d or \( \approx 450 \) mL of a soft drink), their mean weight would be \( \approx 4.5 \% \) (1.4 kg) lower. If this population was eating the same amounts but was instead far more active (eg, walking 2.5 h more to burn an extra 785 kJ/d; \( n = 21 \)), the same reduction in body weight would be expected.

The first fundamental point of the study is that the relation between body weight and EnFlux (TEE) was strongly positive and not negative. If most of the variation in body weight (once age, height, and sex were taken into account) was due to differences in the physical activity levels of the children, then the relation should have been negative (ie, higher TEE associated with a lower weight). That the overall relation is positive suggests that it is higher TEI that is the major determinant of a higher body weight. In other words, a high TEI drives an increase in body weight, which in turn increases fat-free mass and resting metabolic rate (22, 23) until TEE matches TEI and body weight reaches its new settling point of body weight for that EnFlux. Differences in physical activity levels and body composition, however, undoubtedly explain much of the variation around the positive regression line.

The longitudinal data have provided strong empirical validity for the prediction equation; nevertheless, it is important to examine the assumptions that have been made in the process of deriving this equation. The assumption that TEE data from doubly labeled water studies can be considered the equivalent of TEI and EnFlux data is probably reasonable, because the energy cost of growth over the measurement period of 1–2 wk is small enough (16) to be ignored. Over several years, however, the energy contribution to growth is substantial and, in the case of the longitudinal data, this contribution was accounted for by having height and age in the equation.

Another assumption was the use of “settling points,” or states of dynamic equilibrium between EnFlux and body weight. At the individual level, TEI and TEE fluctuate substantially on a daily basis, whereas body weight varies (generally in an upward direction in children) over weeks, months, and years. However, if the mean values for body weight and EnFlux are considered at a population level, many of these individual fluctuations cancel each other out, and, if the measurement “snapshot” is over a short period, then the cost of growth can probably be ignored.

Notwithstanding these cautions, equation 4 can be used to answer questions posed in the logic pathway outlined in Figure 1. For example, the difference in median body weights of 10–15-y-old children between 2 national nutrition surveys in Australia in 1985 and 1995 was \( \approx 8 \) % (range: 45.3–48.9 kg; \( n = 24 \)). On the basis of these mean weights, how much more energy were children eating to sustain their higher body weight in 1995 than in 1985? Equation 4 estimates that they were eating 19\% more, which compares to the reported increase in TEI of 13\% (range: 8266–9345 kJ/d) between the 2 surveys (24). TEI was measured by using a 24-h dietary recall, which is known to underestimate TEI because of underreporting (25). Secular reductions in physical activity (26) may also contribute to this discrepancy.

One way to describe the energy gap between these 2 Australian surveys is in terms of the 19\% increase in EI (\( \approx 1500 \) kJ/d), which is rather large. Another way is to convert the population weight gain (3.6 kg) into excess energy in storage (\( \approx 119 \) MJ at 33 MJ/kg), assuming an energy efficiency of storage (\( \approx 50 \)%), and then to divide it by the number of days of the study (\( n = 8 \)). This calculation gives a very small value of \( \approx 65 \) kJ excess energy/d (3.6 kg \( \times 33 \) MJ/kg \( \times 2 \div 3650 \) d = 65 kJ/d).

The reconciliation between the large and small estimates of the energy gap is that the large estimate (1500 kJ/d) is the final energy gap needed to sustain that higher weight (independent of the time needed to achieve that weight), whereas the smaller value (65 kJ/d) is the daily positive energy balance needed every day over 10 \( y \) to achieve that higher weight. Unfortunately, this latter approach is often misinterpreted to mean that only small behavioral changes are needed to reverse the obesity epidemic (27–29). The misinterpretation is to equate the initial EI needed to create the positive energy balance on day 1 with the daily positive energy balance needed over a period of 10 \( y \).

One issue not considered in this study is the potential for behavioral compensation or other interaction resulting from a
change in behavior such that the full effect of the initial energy change is not carried through to energy imbalance (30, 31). This is depicted in the left-hand side of Figure 1. For example, having more time for physical education at school may trigger other changes in physical activity or dietary intake so that the net energy imbalance is lower than expected (32).

In conclusion, we have presented a validated model for estimating the difference in the mean body weights of populations of children who have different equilibrium energy fluxes, which seem to be principally driven by differences in WEI. The equation could be used to model the effect of populationwide obesity prevention interventions on mean body weight and obesity prevalence, but caution is needed in applying such models to individual persons. Modeling the effectiveness of various population interventions should provide public health decision makers with an important interim guide to investment in obesity prevention while they await more empirical weight-change studies in children and adolescents.

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