Modeling the dynamics of human body growth and maintenance

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Abstract

Detailed individual level simulation models are needed for better policy analysis to combat the costly obesity trends. Current models largely focus on adulthood and do not capture variations across individuals. In this paper I develop a simple simulation model spanning the full life cycle of an individual that captures both weight changes and growth in height. The model is tested for consistency with growth charts, robustness under different energy intake scenarios, and consistency with other empirical sources including a previous model from the literature and the experience of a lost ocean traveler. The results suggest the model structure is capable of capturing the key trends in growth and weight dynamics, however better data sources are needed to estimate a few of the model parameters empirically.

Introduction

The obesity trends across the world are alarming. The percentage of Americans who are obese has doubled to near 30% during the past four decades, and close to two third of the population is overweight (Bray and Bouchard 2004; Ogden et al. 2006). This trend is leading to significant costs and loss of quality life (Wang et al. 2008). Multiple levels of factors, from biological to environmental, are involved in creating the obesity problem and thus a systems approach to analyze the problem and assess interventions is called for (Huang et al. 2009). Models that can assess the potential impact of alternative interventions are needed in assessing effectiveness of alternative policies. Such models can facilitate policy analysis by expanding the boundaries of our mental models and enhancing learning from evidence (Sterman 2006). However due to ethical and practical considerations in data collection available dynamic models for obesity rely on short-term time series data and small sample sizes (Butte et al. 2007; Christiansen et al. 2005; Flatt 2004; Hall 2010a; Kozusko 2001) which reduces their direct applicability for policy analysis at the population level. While this literature provides a great starting point for modeling individual level body weight dynamics, none of the current models include both childhood and adulthood dynamics. Moreover, the current models focus on modeling a single "average" adult and do not capture the impact of demographic and individual variations. Simulating population level weight gain and loss dynamics, and assessing alternative interventions in a new population group, requires dynamic models that 1) Capture the full life-cycle individual-level body weight dynamics realistically, building on biological processes that regulate energy balance in body, and thus have robust formulations. 2) Connect individual level and population level dynamics in a generalizeable fashion and capture variations across individuals that lead to obesity. 3) Express the impact of interventions on energy intake and physical activity for different individuals. In this paper we focus on developing a model that satisfies the first requirement and can be used to build models addressing the other two requirements as well.

Modeling Body Weight Dynamics

Several models of body weight dynamics have been discussed in the literature (Abdel-Hamid 2002; Butte et al. 2007; Christiansen and Garby 2002; Christiansen et al. 2005; Flatt 2004; Hall 2010a; Kozusko 2001; Kozusko 2002;

Song and Thomas 2007; Thomas et al. 2009). These models vary in their level of complexity and the feedback mechanisms they capture. Common across most these models are the stock variables fat mass (FM) and fat free mass (FFM) which constitute the majority of body weight in a normal person. More detailed models may consider the stocks of glycogen, protein, and extracellular fluid mass and adaptive thermogenesis among others (Flatt 2004; Hall 2006, 2010b). While additional complexity could be important in evaluating dynamics that unfold in hours or days, results of comparative studies by Hall and colleagues (Chow and Hall 2008; Hall 2010a) suggest that for longer term dynamics FM and FFM provide much explanatory power with very little complexity. I therefore rely on these two variables as the main stocks of body mass in our model. Because we also model individual's growth, a third stock variable capturing height is also included. There is currently no unified model for childhood and adulthood body weight and height dynamics in the literature. The current model create one such model by combining insights from the previous literature, most notably the models in literature by Hall (2010a) and Butte, Christiansen et al.(2007), and developing a new framework that considers energy supply and demand, their allocation, and the contribution of those allocation decisions to growth and weight loss.

Energy supply comes from energy intake (EI) and consuming body mass. Total energy intake is the most important factor about food and beverage consumed by an individual and nutrient composition is of secondary effect in modeling weight dynamics. Nutrient composition could become relevant in dynamics of growth, but we assume nutrient composition is relatively constant and therefore shortages in total energy would be a good proxy for nutrients needed for growth. Energy could also come from burning FM or FFM (either due to starvation, or if either mass is beyond what the body needs). These three sources create the total energy supply in our equations.

Factors influencing energy demand include demand for maintenance of the body and energy demand for growth or processing of current body mass. Equation 1 summarizes these factors following Hall (Hall 2010a). The maintenance energy demand depends on basal metabolic rate (BMR) which contributes to 50-75% of energy expenditure, the physical activity energy needs, and the energy for digestion of food and nutrients consumed ($\lambda.EI$). BMR ($= K + \gamma_L.FFM + \gamma_F.FM$) depends on an individual variation factor (*k*) and the body composition (energy needs for maintaining FM and FFM). Energy expenditure attributed to physical activity (PA) is largely proportional to the total weight (BW=FM+FFM) and the intensity of PA, thus the term $PA.BW$. In the current model we assume PA values are given as exogenous inputs. The energy required for developing new mass (or digesting existing mass) is captured in the term $\eta_L.\frac{dFFM}{dt} + \eta_F.\frac{dFM}{dt}$. Also following Butte Christiansen et al. (2007) we note that $\gamma_F$and γ_L are a function of age (Tanner stage) in children, before they stabilize in adulthood.

$$TME = k + \gamma_L.FFM + \gamma_F.FM + PA.BW + \eta_L.\frac{dFFM}{dt} + \eta_F.\frac{dFM}{dt} + \beta.EI \quad (1)$$

We model energy demand for growth based on comparing current weight with the desired weight of individual in near future (i.e. *dl* years ahead) and the required body composition changes along with achieving that weight change. The weight change rate indicated to reach that desired level within *dl* periods is used to calculate current energy needs for growth. Desired weight is determined based on the desired height and desired body mass index (BMI[1]) for the individual at time *t+dl*, both modified around values from 50th percentile of CDC growth charts (Kuczmarski et al. 2000). Desired height (Equation 2) is a weighted average of CDC growth charts, projected to dl periods ahead, and the current height plus the expected growth between t and t+dl. This average is then adjusted based on a factor that captures variations across individuals and different ethnicities in potential height. This factor (*h(Age)*) represents differences in genetic factors that influence potential height an individual can achieve and varies with age during growth years because there is much more (fractional) variability in potential height in the early years of life. Desired BMI is a weighted average of CDC median for an individual with the same age and gender, and current individual BMI (Equation 3).

$$H_{Desired}(t) = \left(\left(H(t)/h(Age) + H_{CDC}(Age+dl) - H_{CDC}(Age)\right) * (1-sw) + sw * H_{CDC}(Age+dl)\right).h(Age)$$
(2)

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[1] Body Mass Index, BMI, is defined as weight (in Kg) divided by height (in meters) to the power of two (BW/H^2) and is widely used as a measure of obesity, where adults with BMI>30 are considered obese and those over 25 are considered overweight.

$$BMI_{Desired}(t) = BMI_{CDC}(Age + dl).sb + BMI(t)(1 - sb) \quad (3)$$

The desired weight change is then partitioned into desired changes in FFM and FM. To do so, the desired Fat Mass Index ($FMI_{Desired}$) is calculated using the results of a regression model that was estimated separately for men and women as well as children and adults and reported in Appendix 1. These regressions predict FMI as a function of age, gender, ethnicity, BMI, and height. The desired FM and FFM are then calculated (Equations 4 and 5), and the energy needs for growth in *FFM* (Fat Free Energy Demand: *FFED*) and FM (Fat Mass Energy Demand: *FMED*) will be determined so that the required mass is created within *dl* periods. If current FM (or FFM) are beyond the desired values, the extra energy that could be supplied from such reserve mass is calculated as negative FMED and FFED, and will be considered as a potential energy supply. These calculations take into account both the energy stored/released in/from tissue and the energy needs for generating new tissue or disintegrating existing tissue. These required parameters are all taken from the literature (Hall 2010a). Note that in these, and other equations, where Age is used, we allow the model to differentiate between calendar age and the growth equivalent age. Some individuals may grow faster, reach puberty earlier, and reach their maximum height at an earlier age, where as others may grow more slowly than their calendar age suggests. All the biological processes modeled use the growth equivalent age, which varies around calendar age by a constant factor.

$$FM_{Desired}(t) = FMI_{Desired}(Age + dl).H_{Desired}{}^{2} \quad (4)$$

$$FFM_{Desired}(t) = (BMI_{Desired} - FMI_{Desired}(Age + dl)).H_{Desired}{}^{2} \quad (5)$$

$$FMED = \begin{cases} \frac{FM_{Desired} - FM}{dl} * (\rho_L + \eta_L) & FM_{Desired} > FM \\ \frac{FM_{Desired} - FM}{tmin} * (\rho_L - \eta_L) & FM_{Desired} \le FM \end{cases} \quad (6)$$

$$FFED = \begin{cases} \frac{FFM_{Desired} - FFM}{dl} * (\rho_L + \eta_L) & FFM_{Desired} > FFM \\ \frac{FFM_{Desired} - FFM}{tmin} * (\rho_L - \eta_L) & FFM_{Desired} \le FFM \end{cases} \quad (7)$$

This model can take energy intake (EI) as an exogenous input. However, in practice reliable EI data is not available for large samples and over long time horizons, so we use an alternative set of expressions to endogenously generate EI values for a simulated individual. This equation is only used for testing different scenarios with endogenous energy intake and does not represent a real individual trajectory. It is set up so that energy needs for body maintenance (TMI) and growth (positive values of FFED and FMED) are captured. However it does not reduce the energy intake if sum of FFED and FMED are negative (i.e. the person is overweight and thus can lose weight and supply energy). If that effect is also included, the model practically would assume the individual will always adjust her energy intake based on a diet that brings her quickly to the desired weight and body composition.

$$EI = TMI + Max(0, FFED + FMED) \quad (8)$$

A key formulation for this model is the allocation of energy from different sources to different demands of the body. This formulation takes into consideration five potential sources of energy supply and demand, and allocates energy according to a market-based allocation mechanism. Specifically the energy is demanded for maintenance (TME), required fat mass growth (Max(0,FMED)), required lean mass growth (Max(0,FFED), reserve lean mass deposit, and reserve fat mass deposit. The latter two components store whatever energy left over from EI after allocating the sources of energy to other three demanded needs. This extra energy is partitioned between the FM and FFM according to the empirically driven partitioning function in equation (Chow and Hall 2008; Forbes 2000).

$$Fraction\ of\ Extra\ Energy\ to\ FM = 1/(1 + p.FM) \quad (9)$$

The energy is supplied from five potential sources. EI is the primary source. Reserve FM and FFM deposits can provide additional energy if there is demand for it (Max(0,-FMED) and Max(0,-FFED)). Finally, when other supply sources fall too short, required FM and FFM could be disintegrated to supply the maintenance energy and keep the individual alive. The parameter tmin specifies the minimum time to disintegrate and digest tissue and sets the maximum amount these latter sources can supply.

Once the sources of supply and demand for energy and the maximum levels of supply/demand for each source are determined, we use the Vensim ™ function that offers a market clearing price mechanism to allocate resources from multiple sources to multiple demanders. The details of this allocation algorithm go beyond the scope of this paper, but the basic idea is that different demand/supply sources have different priorities. These priorities are conceptually similar to prices at which demand/supply materializes in a market: if a demand source has very high priority, it will consume the resources at very high market prices. A supplier with low priority will supply the resource at low prices. The market clearing price is calculated by balancing out different supply and demand sources, so that at some level of priority (e.g. market price) the total supply and demand are equal. That (aggregate) priority level then sets the amount supplied/demanded by each source, based on source priorities. To operationalize this function we need to set individual priority functions (similar to supply or demand curves) for different sources. These priority functions and the resulting demand/supply source matching is reported in Table 1. In each cell of the table we identify if the given supply source (row) may supply energy to the given demand source (column). For example body will use supply of EI to satisfy TME with no reservation, thus the Y marker in the relevant cell. N means the priority of supply source is higher than demand, and therefore no supply will be provided from this supply source to the corresponding demand (e.g. essential FFM will not be used to generate reserve FM). We also identify the priority and width parameters used for defining the supply and demand curves[2] in the simulations.

Table 1- Priorities of different energy supply and demand sources in energy allocation process.

Demand / **Supply**	TME (10,1)	Required FFM (6,1)	Required FM (6,1)	Reserve FFM (2,1)	Reserve FM (2,1)
EI (0,1)	Y	Y	Y	Y	Y
Required FFM (9,1.2)	Y	N	N	NA	N
Required FM (8.9,1)	Y	N	N	N	NA
Reserve FM(4,1)	Y	NA	Y	NA	N
Reserve FM (4,1)	Y	Y	NA	N	NA

Finally individual height is adjusted towards the desired height (from Equation 1). This adjustment is a function of energy availability for required FFM growth (EA_{FFM}), if energy is limited for this demand, the height growth will be hampered. Catch up growth is possible if enough nutrition is provided later, but only during childhood (up to the age of 20 in this model). Equation 10 specifies this formulation.

$$\frac{dH}{dt} = \frac{H_{Desired} - H}{dl} * EA_{FFM}{}^{\alpha} \qquad (10)$$

Figure 1, provides an overview of the causal pathways in the individual level model. The model is initialized based on input initial values that a user provides to specify Birth Date, Gender, Ethnicity, BMI, growth equivalent age factor, and relative height of a simulated individual. Initial FM and FFM are determined using total weight (from initial BMI and Height) and population level estimates of fat fraction from regression results (reported in appendix 1). Key parameter values are listed in Table 2 and full equations are available in the model provided online with the submitted paper.

Table 2- Model parameters and their explanation

Param	**Value**	**Unit**	**Comment**

[2] Supply/demand curves follow the integral under a triangular function centered around priority with the given width. The height of the curve is the maximum supply/demand for the specific source. See Vensim help files on Many-to-many allocation functions and related supply/demand curves.

dl	1	Year	Growth projection horizon
PA	2555	Kcal/kg/Year	Physical activity level for an average individual based on 7 Kcal/Kg/Day
η_L	230	Kcal/Kg	Energy need for turnover of lean mass
η_F	180	Kcal/Kg	Energy need for turnover of fat mass
β	0.1	Dimensionless	Thermic effect of feeding
α	0.3	Dimensionless	Sensitivity of height growth to energy availability
p	0.502	1/Kg	Scaling factor for partitioning equation
sb	0.3	Dimensionless	Weight of CDC based projection on desired weight
tmin	0.1	Year	Minimum time to transform mass to energy
k	100000	Kcal/Year	Basic energy expenditure for the individual
ρ_L	1800	Kcal/Kg	Energy density of lean mass
ρ_F	9400	Kcal/Kg	Energy density of fat mass
γ_L	$(7482 + 1314.\mathrm{Male})e^{-\frac{Max(0,Age-8)}{5}} + 8030$	Kcal/Kg/Year	Energy requirement for sustaining lean mass changes with age and also depends on gender.
γ_F	1168	Kcal/Kg/Year	Energy requirement for sustaining fat mass.
sw	0.5	Dimensionless	Weight of CDC based projections on desired height

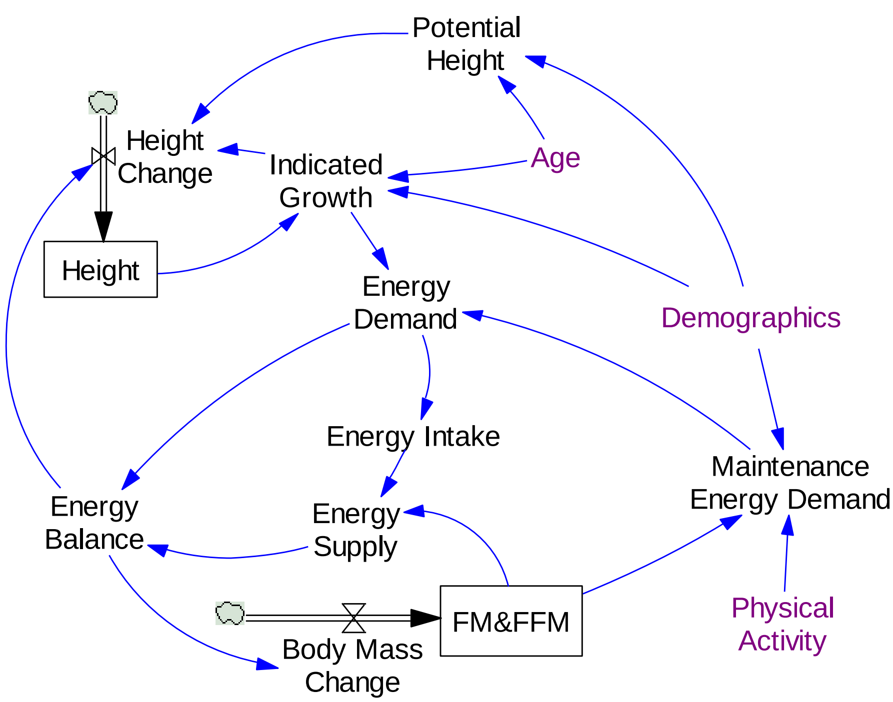

Figure 1- Overview of individual level model and its major feedback loops. Not all causal connections are shown and the fat mass (FM) and fat free mass (FFM) are combined to keep the visualization simple.

Results

In this paper we report some preliminary results from the model developed above. We first explore the base case behavior of the model in a scenario where Energy Intake (EI) is set at the equilibrium value required for basic growth, and compare the results with CDC growth charges and predictions from the fitted regression models. We would then test the behavior of the model under several scenarios to assess its robustness and suitability for policy applications.

In Figure 2 we compare the behavior of the model and different empirical sources regarding height and BMI for a simulated white male (identifier 1) and a white female (identifier 2) followed from birth to age 80. The empirical height and BMI values are coming from the CDC charts. The model matches the CDC Height projections very closely, which is expected due to the fact that desired height comes from these charts (Equation 2) and there is no significant energy shortage in these scenarios to hamper growth. The behavior of BMI is slightly different from the CDC charts, specifically, BMI lags CDC chart values during childhood. To understand this consider that desired BMI follows a weighted average of current BMI and the CDC projections (Equation 3). The impact of current BMI on desired BMI make it lag the CDC chart values and thus creates a gap between the real BMI and the CDC graphs. This effect is most important when CDC values for BMI change rapidly, i.e. in early ages. In fact if the weight parameter, *sb*, is changed to 1 (giving full weight to CDC charts), then the gap between the graphs shrinks considerably.

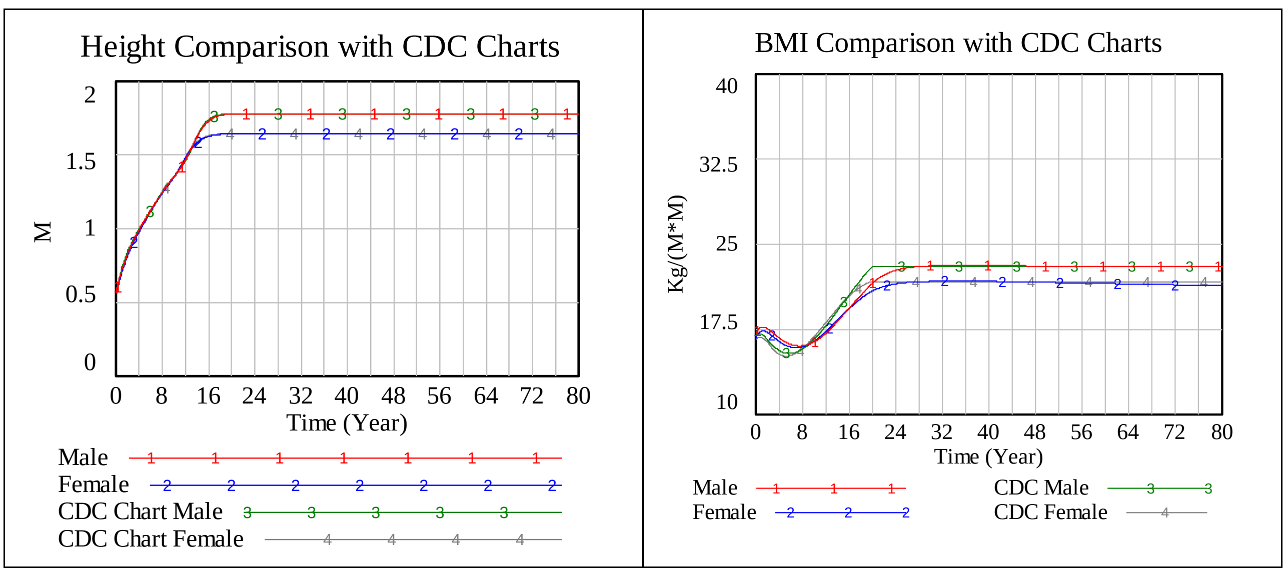

Figure 2-Comparison of height and BMI model projections against CDC growth charts.

Next we compare the behavior of key model variables across 6 different individuals (Hispanic Male/Female, White Male/Female, and Black Male/Female with indicators 1-6 respectively). These results are reported in Figure 3. Consistent with empirical observations, simulated male subjects are taller, heavier, and have a larger BMI. Fat fraction starts high for the male but goes down while it slowly growths for the female. The impact of ethnicity is limited in general and is most pronounced on height differences (blacks are slightly taller than whites who are slightly taller than Hispanics) and childhood fat fraction which is slightly higher for Hispanic children. Overall the variations by gender and ethnicity are modeled to follow the empirical observations and simulations are consistent with those basic trends.

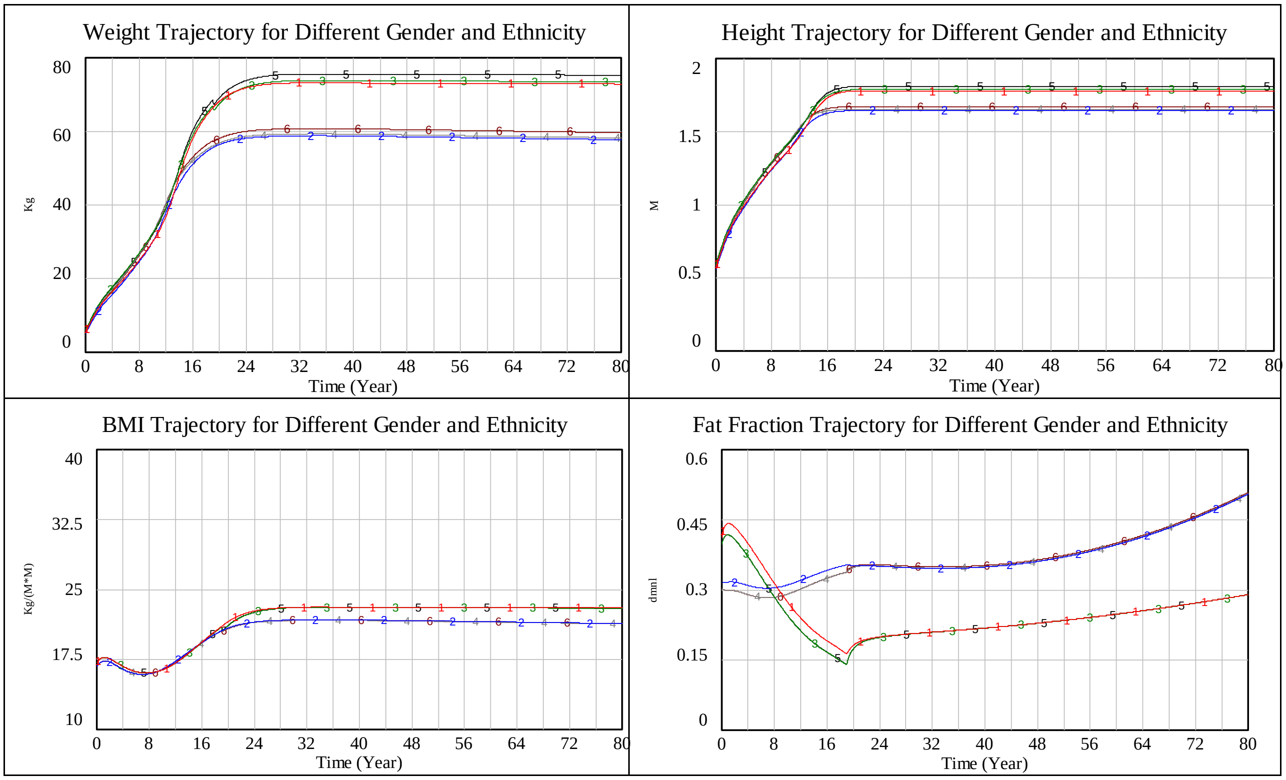

Figure 3- Base case simulations for 6 representative individuals with different gender and ethnicities (Line markers are: 1: Hispanic male; 2: Hispanic female; 3: white male; 4: white female; 5: black male; 6: black female). Weight, Height, BMI, and Fat Fraction are reported over 80 years of life from birth.

The third set of results assesses the behavior of the model under a wide range of input EI trajectories to assess the robustness of the formulations and their plausibility (See Figure 4). In each scenario we report the four variables height (1), weight (2), fat fraction (3), and BMI (4) for a single white, female simulated individual. Panel a reports the base case results which will be used as a comparison point. Individual's weight and BMI in this setting are almost constant in adulthood due to the assumption that EI equals the desired value for maintenance and growth. These small variations are due to asymmetric nature of EI equation (see Equation 8; note that negative values for FFED+FMED do not reduce EI). The first experiment, Panel b, increases the EI by 1% beyond the equilibrium level throughout life. As a result the individual consistently gains weight throughout her life. Panels c and d, in contrast, report on experiments where individual is consuming less energy than is required by her body. In panel b the individual consistently suffers from a 10% shortage in energy intake, below what is required for maintenance and catch up growth. As a result she has significant problems with weight gain and also she does not grow to her full potential for height by adulthood. In panel d the individual is getting 1% less EI than is needed for both maintenance and growth during childhood and only maintenance of her current body mass during adulthood. This is achieved by removing the second argument in Equation 8 (*Max(0,FMED+FFED)*) when the individual reaches age 20. As a result she grows to adulthood without any major problem (only slight chronic under-weighing). However due to removal of the extra energy needed for catch up growth, she loses significant weight and starves by the end of simulation. This experiment shows the important role of the assumptions going into the EI equation. Specifically if catch up growth energy needs are included in EI calculations, the individual is more likely to survive shortages of energy because her base level needs are significantly more.

Finally, panels e and f report on an individual exposed to sinusoidal oscillations in EI with amplitudes 10% of equilibrium EI. Similar to the previous two experiments, panel e includes the growth catch up term in EI calculations but panel f does not. As a result in the first case the individual's weight and BMI oscillate around a steady state value, where is in the second experiment the individual faces a long term decline in weight. This decline is generated by the asymmetry in weight gain vs. loss due to the energy needs for processing body mass into/from energy. As a result upward (growth) cycles are slightly more energy consuming per kilogram of body weight generated, than are downward (diet) cycles, which leads to a downward shift in weight over time.

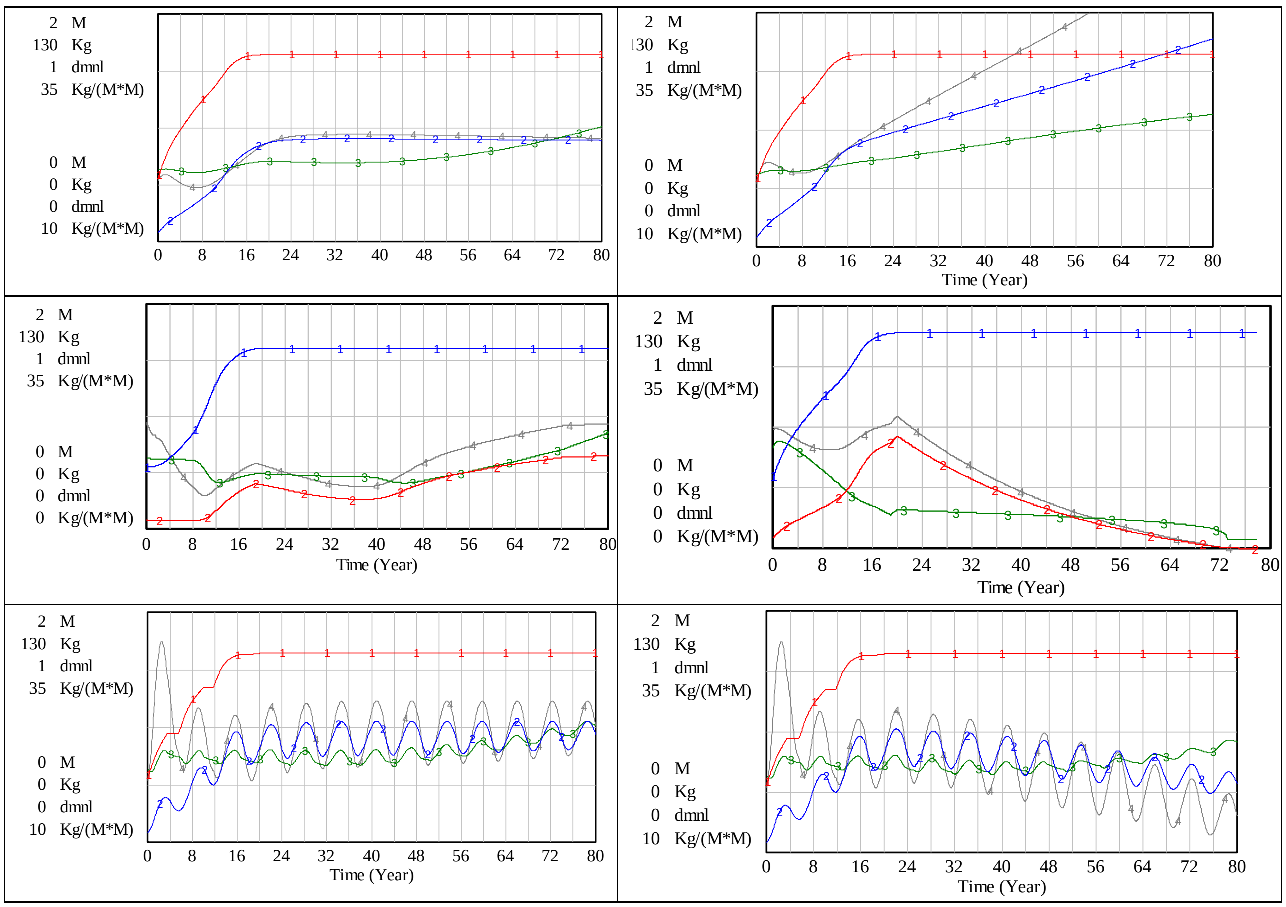

Figure 4-Model behavior under different energy intake (EI) scenarios. Height (1), Weight (2), Fat Fraction (3), and BMI (4) are reported for 6 different scenarios: a) Base case (equilibrium) b) 1% more EI than required for growth and maintenance. c) 10% less energy than required for growth and maintenance. d) 1% less energy than required for growth and maintenance, during childhood, and only maintenance during adulthood. e) EI oscillating with 10% amplitude around required levels for growth and maintenance. f) Same as e, except no growth catch up energy is included during adulthood.

Finally, we compare the models predictions with two other empirical sources. First, we compare the models projections with those provided by an empirically validated model by Hall (Hall 2010a). In this experiment we track the weight changes of an 80 kg and a 120 kg middle aged female over a 10 year period, where the individual starts with equilibrium energy intake and then starts and maintains a diet cutting down on her energy intake by 500Kcal/day for the next decade. Hall reports on this experiment in his paper, and we replicate the experiment for a white female starting at age 30[3]. The results are reported in Figure 5 and are compared with Hall's results. In short the two simulations are fairly consistent, with Hall's model taking slightly longer to reach steady state.

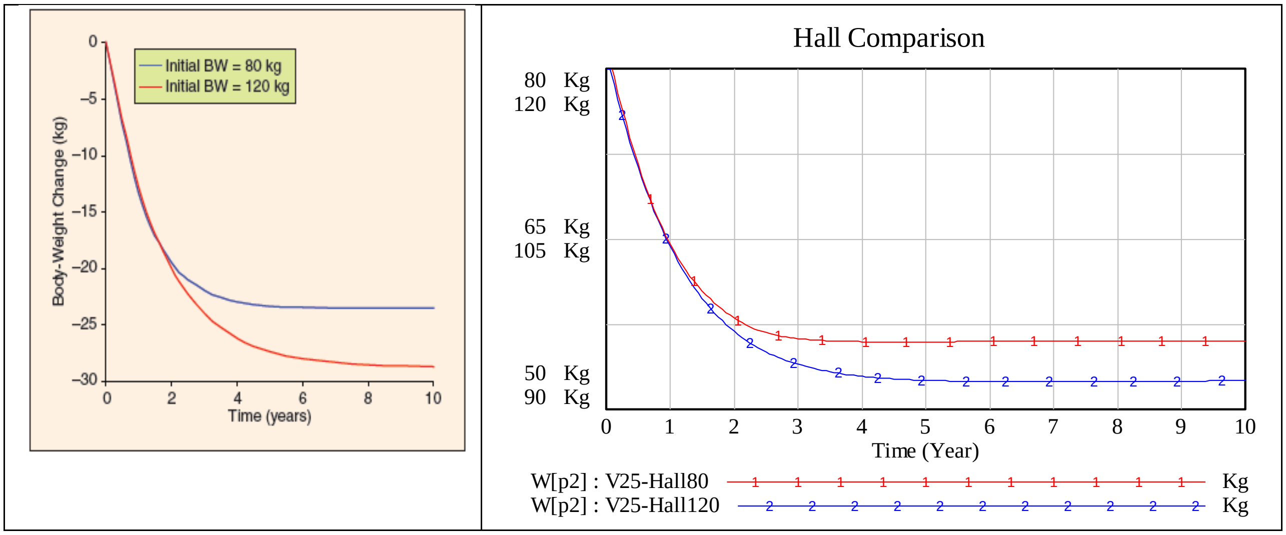

Figure 5- Comparison of model results (right) with Hall (Hall 2010a) (left) projections in simulating weight change of an adult female starting from 80/120 kg initial weight and equilibrium EI, taking a diet that reduces her EI by 500 Kcal/day, and continuing that for 10 years.

In a second empirically motivated experiment we simulate the fate of Louis Zamporini, the American athlete and serviceman in second world war. After his airplane crashed over Pacific ocean in September 1941, Zamporini and a colleague stayed on a raft for a period of 47 days with almost no food beyond a few small fish they could catch. A third serviceman succumbed to starvation during this ordeal. The two survivors were then arrested by Japanese forces as they had drifted across the Pacific ocean to Japanese territories and remained a prisoner of war for the rest of the WWII. Zamporini's story is documented in the book "Unbroken" (Hillenbrand 2010). Accordingly, within this time period he had gone from being very athletic and weighting 76 kg to weighing as little as 36 kg. The simulation starts from a similar initial state (his fitness is reflected by lower initial fat fraction than typical) and tracks his fate in the absence of any energy intake for 47 days. The result is a loss of weight to 39 kg (Figure 6), which is roughly consistent with Zamporini's experience. In the simulation he takes several months to catch up to his previous weight, when eating at the level required for both maintenance and body mass catch up.

[3] Hall's model does not distinguish individuals based on age, gender, or ethnicity, and only applies to adults. However only very slight variations would be observed if we simulated an adult from a different demographic.

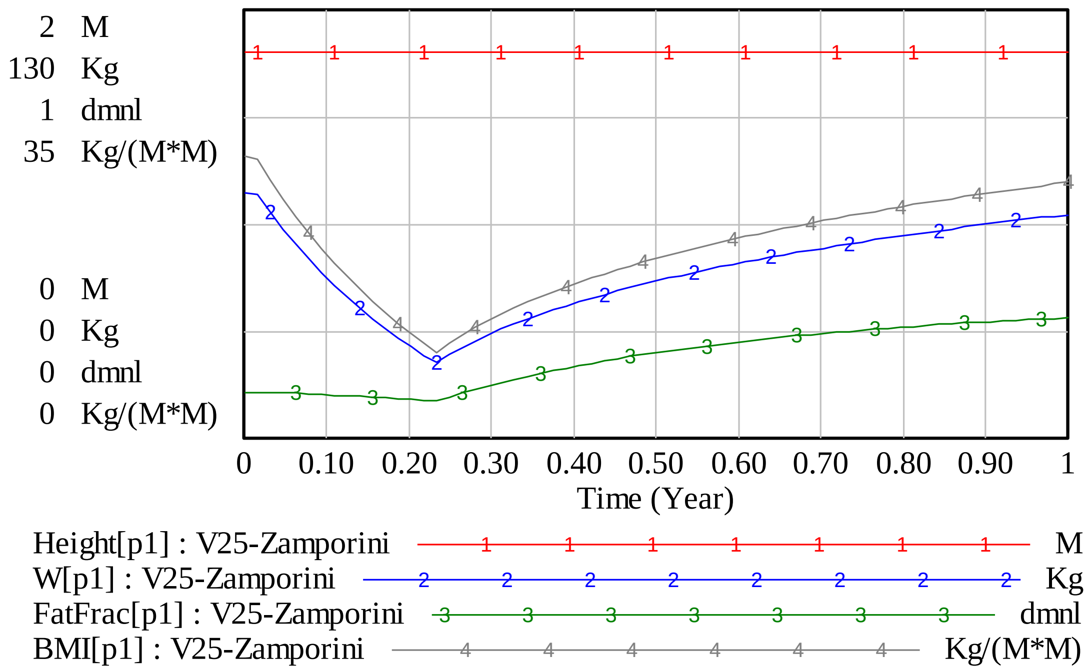

Figure 6- Simulation replicating the experience of Louis Zamporini in 47 days of having almost no energy intake when lost on Pacific ocean.

Discussion and Future Work

In this paper I have developed one of the first integrated models of body growth and maintenance that spans both childhood and adulthood, includes height dynamics, and differentiates individuals based on gender and ethnicity. The model provides projections for weight and height dynamics that are roughly consistent with CDC growth charts. It also shows qualitatively reasonable behavior under different extreme scenarios as well as in comparison with empirically motivated test cases. As a result the model can be a good test bed for analyzing the differential impact of different interventions that target obesity with different emphasis on various population groups.

A few shortcomings of this research offer opportunities for further research. First, the model parameters are largely taken from the previous literature, however a few important parameters including the weighting factors for determining desired height and weight (sb and sw; see Equations 2 and 3), the sensitivity of height growth to energy availability (α), and the growth projection horizon (dl) are currently set at base case values based on exploratory analysis but have not been calibrated to empirical data. Population level data for body weight, height, and composition is available through national surveys such as the National Health and Nutrition Examination Survey (NHANES) which could inform such calibration. However no time series data is available over long time horizons (beyond a few weeks) that includes accurate energy intake measurements. Given the central role of energy intake in body weight dynamics, one will need to estimate an equation that determines EI endogenously, while also predicting the population level distributions for body weight, height, BMI, and body composition. Further validation could be pursued through comparing the model predictions against empirical tests of diet and physical activity programs. Moreover, the model should be further compared with existing simulation models in the field to provide a clear understanding of similarities and differences across different models and whether they have any policy implications.

Appendix 1- Regression results used for assessing fat mass index and initial fat fraction.

Desired fat mass index (Fat Mass/Height^2) for an individual is estimated using step-wise linear regressions that are fitted to NHANES 2000-2008 data on body fat mass, BMI, height, age, and ethnicity. Only the best fitting model is reported where all independent variables are significant at 0.001 level. BMI (kg/M^2), Age (years), and Height (M) are continuous variables while Hispanic and Child (i.e. under 20) are binary variables. FMI is in Kg/M^2 and Fat Fraction is a dimensionless value between 0 and 1.

Male Child: FMI=BMI*0.177335+BMI^2*0.00701678+Hispanic*0.468919-Age*0.34449+2.70458,

Male Adult: FMI=BMI*0.0277482+BMI^2*0.00756044+Age^2*0.000343892-0.186475

Female Child: FMI=BMI*0.40371+BMI^2*0.0032376+Hispanic*0.32056-2.72373

Female Adult: FMI=BMI*0.490372+BMI^2*0.00176694-Age*0.108299+Age^2*0.0015991+ Height*2.83091-6.79844

Initial Fat Fraction (FM/BW) for an individual is estimated using step-wise linear regressions that are fitted to NHANES 2000-2008 data on body fat mass, BMI, height, age, and ethnicity. Only the best fitting model is reported where all independent variables are significant at 0.001 level.

Male: FF=sqrt(BMI)*9.15649+Hispanic* 1.57162+Age* 0.0813697+Child*28.3113-Child*Age*1.55691-26.5456

Female: FF=-11.77+ sqrt(BMI)*13.9054-Height*3.35054+BMI*Height^2*0.126261+ Hispanic*1.23887+Age*0.0158701+Child*2.46072-Child*Age*0.117857-BMI*0.956517

References

Abdel-Hamid, T.K. 2002. Modeling the dynamics of human energy regulation and its implications for obesity treatment. *System Dynamics Review* **18**(4) 431-471.

Bray, G.A., C. Bouchard. 2004. *Handbook of obesity : etiology and pathophysiology*. Marcel Dekker, New York.

Butte, N.F., E. Christiansen, T.I.A. Sorensen. 2007. Energy Imbalance Underlying the Development of Childhood Obesity. *Obesity* **15**(12) 3056-3066.

Chow, C.C., K.D. Hall. 2008. The Dynamics of Human Body Weight Change. *PLoS Computational Biology* **4**(3) e1000045.
Christiansen, E., L. Garby. 2002. Prediction of body weight changes caused by changes in energy balance. *European Journal of Clinical Investigation* **32**(11) 826-830.
Christiansen, E., L. Garby, T.I.A. Sørensen. 2005. Quantitative analysis of the energy requirements for development of obesity. *Journal of Theoretical Biology* **234**(1) 99-106.
Flatt, J.-P. 2004. Carbohydrate-Fat Interactions and Obesity Examined by a Two-Compartment Computer Model. *Obesity* **12**(12) 2013-2022.
Forbes, G.B. 2000. Body fat content influences the body composition response to nutrition and exercise. *Ann N Y Acad Sci* **904** 359-365.
Hall, K.D. 2006. Computational model of in vivo human energy metabolism during semistarvation and refeeding. *American Journal Of Physiology. Endocrinology And Metabolism* **291**(1) E23-E37.
Hall, K.D. 2010a. Mechanisms of metabolic fuel selection: modeling human metabolism and body-weight change. *IEEE Engineering In Medicine And Biology Magazine* **29**(1) 36-41.
Hall, K.D. 2010b. Predicting metabolic adaptation, body weight change, and energy intake in humans. *American Journal Of Physiology. Endocrinology And Metabolism* **298**(3) E449-E466.
Hillenbrand, L. 2010. *Unbroken : a World War II story of survival, resilience, and redemption*, 1st ed. Random House, New York.
Huang, T.T., A. Drewnosksi, S. Kumanyika, T.A. Glass. 2009. A systems-oriented multilevel framework for addressing obesity in the 21st century. *Preventing Chronic Disease* **6**(3) 1-10.
Kozusko, F. 2001. Body weight setpoint, metabolic adaption and human starvation. *Bull. Math. Biol.* **63**(2) 393-403.
Kozusko, F.P. 2002. The effects of body composition on setpoint based weight loss. *Mathematical and Computer Modelling* **35**(9-10) 973-982.
Kuczmarski, R.J., C.L. Ogden, L.M. Grummer-Strawn, K.M. Flegal, S.S. Guo, R. Wei, Z. Mei, L.R. Curtin, A.F. Roche, C.L. Johnson. 2000. CDC growth charts: United States. *Adv Data*(314) 1-27.
Ogden, C.L., M.D. Carroll, L.R. Curtin, M.A. McDowell, C.J. Tabak, K.M. Flegal. 2006. Prevalence of overweight and obesity in the United States, 1999-2004. *JAMA: The Journal Of The American Medical Association* **295**(13) 1549-1555.
Song, B., D.M. Thomas. 2007. Dynamics of starvation in humans. *Journal Of Mathematical Biology* **54**(1) 27-43.
Sterman, J.D. 2006. Learning from evidence in a complex world. *Am J Public Health* **96**(3) 505-514.
Thomas, D.M., A. Ciesla, J.A. Levine, J.G. Stevens, C.K. Martin. 2009. A mathematical model of weight change with adaptation. *Mathematical biosciences and engineering : MBE* **6**(4) 873-887.
Wang, Y., M.A. Beydoun, L. Liang, B. Caballero, S.K. Kumanyika. 2008. Will all Americans become overweight or obese? estimating the progression and cost of the US obesity epidemic. *Obesity (Silver Spring, Md.)* **16**(10) 2323-2330.