Modelling Child Growth Indicators:
A multidimensional and Bayesian based Approach

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BACKGROUND AND SITE

Child malnutrition is an important indicator of public health status and associated with morbidity and mortality. Malnutrition accounts for about 45% of the under-fives mortality in middle and low income countries. (Black et al 2013). South Africa is one of the nations with a high child metabolic syndrome due to among other causes malnutrition. There's is therefore a need to understand child growth indicators in order to reduce the double burden of children stunting, wasting and underweight. (UNICEF 2012). Our main aim was to investigate child growth indicators while controlling for demographic and potential malnutrition related confounders, for children aged 1-5 years in Agincourt sub-district, rural north–east South Africa in 2007.

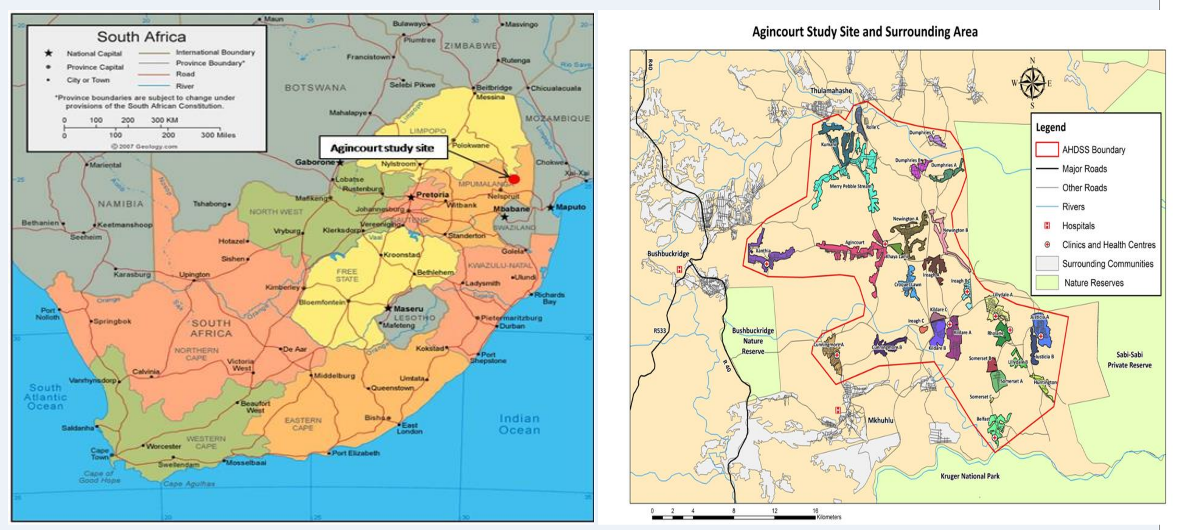

Figure 1a and b: Map of South Africa and Agincourt Study Site

Child growth is often modelled in single dimensions but in reality it is multidimensional in nature that is linear (height related) and ponderal (weight-height related). To model child growth as multidimensional, we utilized classical inference and Bayesian inferences to assess how well the different approaches concur. This will control for confounders that are inevitable when using a single dimension approach.

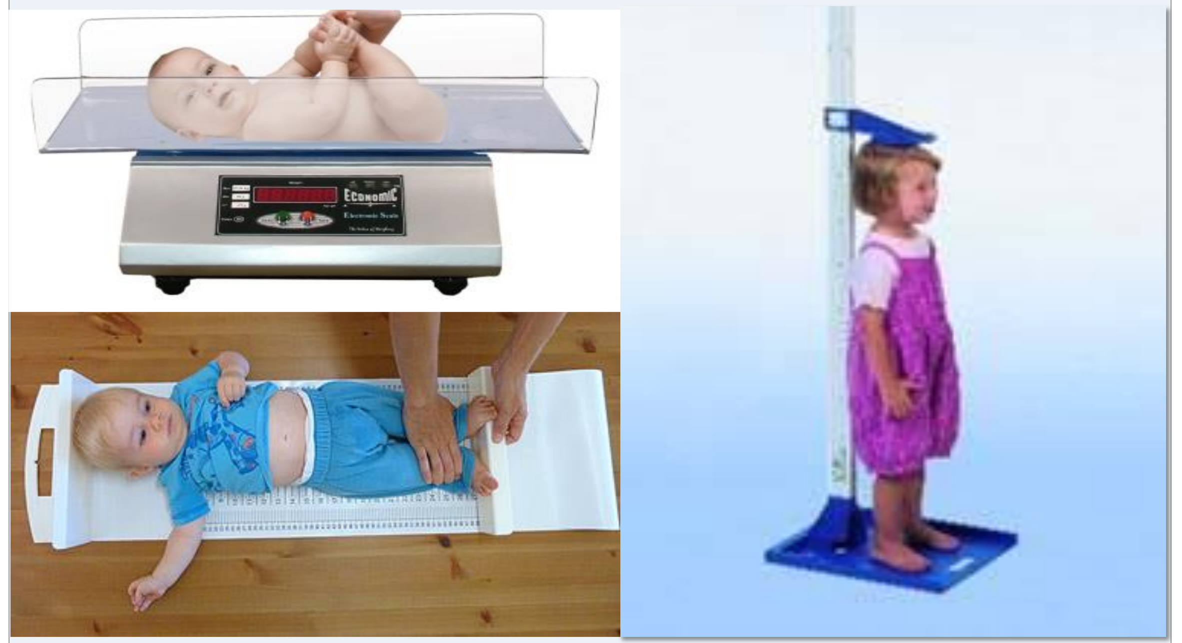

Figure 2: Measuring height (length) and weight of children.

Source: *Ekta Belwa-HHM 2013-011, http://www.topendsports.com/testing/products/baby-height-scale.htm*

METHODS AND RESULTS

STATISTICAL METHODS

The statistical methods employed were multivariate; Hotelling's t-test on the raw data and residuals. Maximum likelihood based estimation and also structural equation models of the seemingly unrelated regression type were employed. The performance of the pooled t test in unequal variance scenario is superior to the performance of the Welch's test in equal variance scenario (Bhattacharyya 2013).The violation of equal variance assumption is serious if the sample sizes are different (Scheffe' 1959, 1970).It is the combination of unequal sample size and unequal variance that have inaccurate probability estimates.

We also fit the models using the Bayesian multivariate Normal and informative and non-informative priors with the posterior parameters shown here.

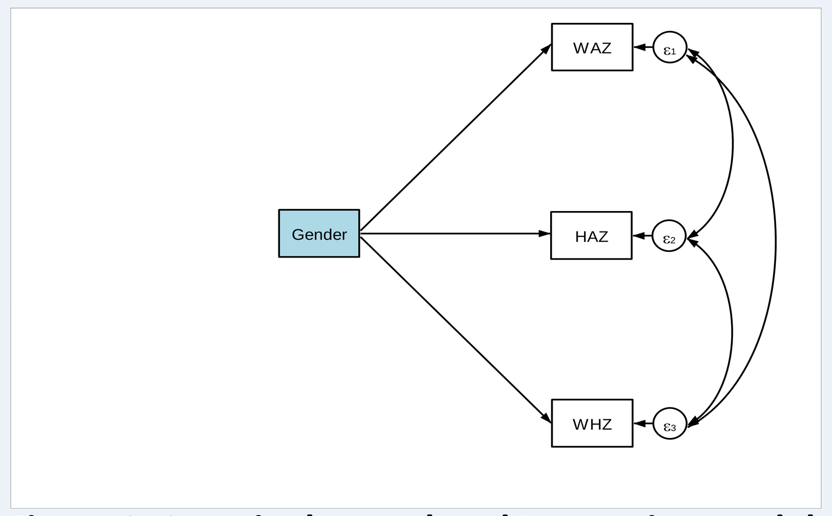

Figure 3: Seemingly Unrelated Regression model

RESULTS

Analysis of the child growth indicators individually (WAZ, HAZ and WHZ), as well as each of the Bivariate Normal pairs, did not show any significant difference on gender (boys versus girls). However, the Hotelling's T-Test in Stata for the Trivariate Normal of the stratum specific (boys alone and girls alone) multivariable regression adjusting for the same variables affecting nutrition showed a significant difference. These results were also consistent with the manual Hotelling's T-Test as well as the Bayesian approach in R and WinBUGS14.

FREQUENTIST AND BAYESIAN ESTIMATION

Frequentist Approach Unbiased Hotelling's t-squared test

$$t^2 = \left(\bar{X} - \bar{Y}\right)^T \left[\Sigma\left(\frac{1}{n_x} + \frac{1}{n_y}\right)\right]^{-1} \left(\bar{X} - \bar{Y}\right) \sim T^2(p, n_x + n_y - 2)$$

$$\text{where, } \Sigma_{pooled} = \frac{(n_x - 1)\Sigma_x + (n_y - 1)\Sigma_y}{(n_x - 1) + (n_y - 1)}$$

Bayesian Multivariate Normal Approach

Posterior distribution =Likelihood * Prior

$$L(Y|\mu,\Sigma) = (2\pi)^{-\frac{np}{2}} |\Sigma|^{-\frac{n}{2}} \exp\left(-\frac{1}{2}\sum_{1}^{n}(y_i - \mu)^{\mathrm{T}} \Sigma^{-1} (y_i - \mu)\right)$$

$$f(\mu|\mu_o, V) = (2\pi)^{-\frac{p}{2}} |V|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\mu - \mu_o)^{\mathrm{T}} V^{-1} (\mu - \mu_o)\right)$$

$$f(\mu|y,\Sigma) = L(y|\mu,\Sigma) * f(\mu|\mu_o, V)$$

The Posterior Multivariate Normal Distribution is such that:

$$\mu | \bar{Y} \sim MVN\left(\mu_n = A^{-1}B = \frac{n\Sigma^{-1}\bar{Y} + V^{-1}\mu_o}{(n\Sigma^{-1} + V^{-1})}, \Sigma_n = A^{-1} = \frac{1}{(n\Sigma^{-1} + V^{-1})}\right)$$

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Table 1: Descriptive statistics on measures of central tendency and variability of malnutrition indices

	MEANS				Covariance-Males		
	Male	Female	Diff		WAZ	HAZ	WHZ
WAZ	-0.51809	-0.60265625	0.084571	WAZ	1.435215	0.909602	1.365155
HAZ	-0.99095	-0.912925	-0.07803	HAZ	0.909602	1.508602	0.125967
WHZ	0.005345	-0.1566625	0.162007	WHZ	1.365155	0.125967	1.921288
	VARIANCES				Covariance-Females		
	Male	Female			WAZ	HAZ	WHZ
WAZ	1.435215	1.236338019		WAZ	1.236338	0.707794	1.162811
HAZ	1.508602	1.278335298		HAZ	0.707794	1.278335	-0.03991
WHZ	1.921288	1.697935604		WHZ	1.162811	-0.03991	1.697936
Differences Transpose					Covariance-Pooled		
	0.084571	-0.07803	0.162007012		WAZ	HAZ	WHZ
				WAZ	1.33652	0.809452	1.264739
				HAZ	0.809452	1.394329	0.043649
		T-squared	T	WHZ	1.264739	0.043649	1.810446
		6.077503269	2.46 (p=0.04 5)				

DISCUSSION AND CONCLUSIONS

Results from the single dimensional models testing for differences in boys and girls, were not statistically significant. However the multidimensional model showed statistically significant differences.

Pooled variance in T test is an exact procedure in the sense that the underlying algorithm works perfectly if the assumptions hold unlike the unpooled variance in t test that is only an approximation. Generally, the pooled variance t-test performs better in case of equal variance; compared to unpooled variance t test performance in unequal variance cases (Bhattacharyya 2013).

It is useful in Public Health research to have rigour in the methodologies upon which policies impacting on child related epidemiological transitions, to be innovative in sync with the advances in the field of study.

ACKNOWLEDGEMENTS

We would like to thank the Welcome Trust S2ACABT for awarding the funding which is supporting the first Masters in Biostatistics fellows who are the second author to the fifth author.

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