

The Effect of Water, Sanitation and Hygiene (WaSH) on Nutrition, for Sri Lankan Children Under Five Years of Age

Marina Roshini Sooriyarachchi*

Department of Statistics, Faculty of Science, University of Colombo, Colombo, Sri Lanka

Abstract

This study aims to determine whether drinking, cooking, handwashing water, Sanitation and Hygiene (WaSH) are associated with each of the three nutrition measures stunting, wasting and underweight jointly after adjusting for important covariates and taking in to consideration the correlation within clusters, for the districts of Sri Lanka for children under 5 years. The data from the Demographic and Health survey 2016 gives detailed information on WaSH variables, Nutrition variables and a number of other probable prognostic factors. This data has been collected by the Department of Census and Statistics. The design of the sample is a two stage cluster design with census blocks at the first stage and households at the second stage. Joint Generalized Estimation Equation (GEE) estimation has been used within Generalized Linear models (GLM) for modeling the data. Important conclusions are that when it comes to stunting and wasting tap water is better for cooking and handwashing. Good sanitation improves stunting. Urban sector has less stunting than rural sector and this has less stunting than the estate sector. Western province has lower odds of stunting. Wasting mainly depends on the proxy of wealth. Well water for drinking improves underweight. Simple methods of living improve underweight.

Keywords

Stunting, Wasting, Underweight, Water, Sanitation, Hygiene, Joint Generalized Estimating Equations

Received: May 6, 2019 / Accepted: June 16, 2019 / Published online: June 24, 2019

© 2019 The Authors. Published by American Institute of Science. This Open Access article is under the CC BY license.

<http://creativecommons.org/licenses/by/4.0/>

1. Introduction

1.1. Background

The literature suggests that poor WaSH conditions have a detrimental effect on child growth and development, however, the relationship is a complex one confounded by many explanatory variables [1]. Freeman et al. [2] have found that sanitation is protective against height for age (stunting) but not for the other anthropometric measures. Rah et al. [3] have found that sanitation and hygiene improvements results in a significantly reduced Odds ratio of stunting but Water improvements had no effects on stunting. Raihan [4] mention that significance of WASH in the context

of wasting remains ambiguous. Halcrow et al [5] discuss about WaSH and nutrition to reduce stunting. This study has been done in Cambodia. They show through their integration program that health and nutrition and agriculture are also important for WaSH to be successful in preventing stunting.

Several large-scale Randomized Controlled Trials (RCTs) on WASH and nutrition, have recently been concluded, and while observational studies found a link between WASH and stunting in the past, and more recent studies found a slight positive linkage [6], the most recent SHINE and other trials were disappointing on the WASH-nutrition linkage. Key messages were that WASH interventions influence stunting through multiple direct biological mechanisms and by various social and economic mechanisms.

* Corresponding author
E-mail address: roshinis@hotmail.com

Several authors have identified the importance of WaSH on Nutrition. However, statistically their association shows poor significance with most of their p-values above the 5% level [7-9]. The German WaSH Network [10] indicates that much progress has been made on the WaSH Nutrition link. They admit that more research is needed. Studies in Bangladesh and Kenya do not show this link. The scope analysis document of the Water, Health and Nutrition (WHN) research group at International Water Management Institute (IWMI) mainly use some graphical analysis to give an initial picture. Thus more advanced analysis is needed.

1.2. Objectives of the Study

To determine whether drinking, cooking and handwashing water, Sanitation and Hygiene are associated with each of the three nutrition measures jointly after adjusting for important covariates and taking in to consideration the cluster correlation, for the districts in Sri Lanka for children under 5 years.

To establish how maternal and child health/ education/ knowledge and practices are related to each of these responses?

To determine which districts/provinces, sectors are worst affected and which areas should be concentrated on?

1.3. Data for the Study

The data for the study is from the Demographic and Health survey 2016 conducted by the Department of Census and Statistics, Sri Lanka. The sampling design is a two stage cluster design with the census blocks at the first stage and the households at the second stage. This design results in cluster correlation which has to be adjusted for in the analysis. Children under 5 years of age are selected from the main sample. The explanatory variables extracted from the survey data are:

1. Access to clean water - Main source of drinking water (select one of several categories), where water source is located (select one of several categories), Has anything been done to make the water safer to drink (Yes/No), What is done to make the water safer (select from several categories), what is the main source of water for cooking handwashing (select one from several categories).
2. Evidence of good sanitation - What kind of toilet facility does your family use (select one of several categories), do you share this with other households (Yes/No) How many HH's share this toilet (a Number), How the stools are disposed (select one of several categories).
3. Evidence of good hygiene - Disposal of garbage (select one of several categories), Mother's/child's washing of hands using soap after use of toilet (yes/no), Mother/child

washing hands with soap before having meals (Yes/No), Mother washing hands with soap before preparing meals (Yes/No).

4. Demography – Mother - Age (in years), Marital status (select one of several categories), does mother live in household (Yes/No), number of children (a Number), children born alive but died later (a number) Child - Sex (male/female), age, district (select one of several categories), sector select one of several categories.
5. Education/Literacy – Mother - Ever been to school (yes/no), highest level of education (select one of several categories).
6. Wealth Quintile - Main source of lighting (select one from several), main material of floor (select one from several),, main material of roof (select one from several),, main material of walls (select one from several),, electrical items owned by house (select one from several), vehicle's owned by household (select one from several), ownership of land, livestock, poultry etc. (select one from several), house owned/rented? (owned or rented) Own a mobile phone (Yes/No).
7. Feeding Practices - Ever breast feed? (yes/no), how long after birth (number of months), How long breast fed (in months)
8. Micronutrient intake – Mother - iron pills during pregnancy (yes/no), calcium pills (yes/no), folic acid pills (yes/no), worm treatment (yes/no), other vitamins (yes/no), Triposha (yes/no). child - Was child given syrup containing iron, vitamins (yes/no), Vitamin A mega dose (yes/no).
9. Health – child - treated for intestinal worms (yes/no), has child had diarrhea in the past two weeks (yes/no).

The response data extracted from the survey data was:

1. Whether child stunted or not.
2. Whether child wasted or not.
3. Whether child underweight or not.

1.4 Definitions and Methodology

Definitions

Stunting or height-for-age is a measure of linear growth retardation and cumulative growth deficits. Children whose height-for-age Z-score is below minus two standard deviations (-2SD) from the median of the reference population are considered short for their age (stunted).

The weight-for-height index measures body mass in relation to body height or length and describes current nutritional status. Children whose Z-score is below minus two standard

deviations (-2sd) from the median of the reference population are considered thin (wasted).

Underweight or weight-for-age is a composite index of height-for-age and weight-for-height that accounts for both acute and chronic undernutrition. Children whose Weight-for-age Z-score is below minus two standard deviations (-2SD) from the median of the reference population are classified as underweight.

Brief description of methodology

As the data are correlated within clusters there is little point in doing preliminary analysis such as descriptive and univariate analysis as these methods do not give valid results as these methods do not adjust for the correlations within cluster. Therefore, methods of advanced analysis which includes modeling are used.

2. Methodology

2.1. Description of Methodology

In this paper the authors address the issue of fitting generalized linear models (GLM's) in the presence of correlated observations, particularly when the data is clustered. In the usual GLM the responses obtained on each unit are considered independent. In this case the commonly used approach for the estimation of parameters is the method of maximum likelihood. However, if correlation is present and is not taken into account then the standard errors of the parameter estimates will not be valid. One method of solution to this issue is estimation using Generalized Estimating Equations (GEE). If the correlation is not taken into account then the standard errors of the parameter estimates will not be valid and hypothesis testing results will be non-replicable.

Generalized linear models were formulated by Nelder and Wedderburn [11] as a way of unifying statistical models with responses belonging to the exponential family. The

generalized linear model (GLM) as explained by Dobson [12] is a flexible generalization of ordinary least squares regression. It relates the random distribution of the response variable of a study to the systematic linear predictor of the study through a function called the link function.

Generalized Estimating Equations (GEE) are methods of parameter estimation for correlated data. GEE was introduced by Liang and Zeger [13] as a method of estimation of regression model parameters when dealing with correlated data. GEE methodology is a common choice when the outcome measure of interest is discrete (e.g. binary or count data, possibly from a binomial, Poisson or negative binomial distribution) rather than continuous. Our response data are binary as each variable takes one of two values yes/no. When these response variables are highly correlated it is appropriate to model these as a Joint GEE model. The theory behind the joint GEE model has been explained in a more technical paper published as a conference paper in the ICCSM in Singapore, 2019. [14] The more technical reader is referred to that paper.

2.2. The Joint GEE Modeling Setup

By modifying the theory in Lipsitz, Fitzmaurice et al. [15] the following methodology for our dataset are obtained.

Consider k binary response (outcome) variables. Let Y_{ik} be the k^{th} binary response ($k = 1, \dots, K$) collected on n subjects ($i = 1, \dots, n$). In the univariate case we consider each response variable to have its own set of covariates. For simplicity the important covariates selected from all K responses are put into the multivariate model. Let the J covariates for observation i and response k be denoted by X_{ijk} where $j = 1, \dots, J$.

The marginal model for each binary outcome Y_{ik} can be assumed to follow a logistic regression, where the marginal distribution of Y_{ik} is Bernoulli with success probability:

$$P_{ik} = \Pr(Y_{ik} = 1 | x_{ijk}, \beta_{jk}) = \exp(\sum_{j=1}^J \beta_{jk} x_{ijk}) / [1 + \exp(\sum_{j=1}^J \beta_{jk} x_{ijk})] \quad (1)$$

Where $i = 1, \dots, n$ and $k = 1, \dots, K$. [16].

The covariates are the same for all response variables however, we take the β 's to vary with the outcome. We propose a simple correlation structure between a pair of β 's for each outcome variable and this is taken to be the exchangeable structure. For the j^{th} covariate of the k^{th} response variable this is of the form:

$$R_{jk'j'k'} = \text{Corr}(\beta_{jk}, \beta_{j'k'}) = 1 \text{ for } j = j' \text{ and } k = k' \\ = \alpha \text{ otherwise} \quad (2)$$

We can now find $R_{kk'} = \text{Cov}(Y_{ik}, Y_{ik'}) = \text{Cov}(P_{ik}, P_{ik'})$ using equations (1) and (2) and the Delta theorem [17]. The joint distribution of Y_{ik} and $Y_{ik'}$ is bivariate binary (Bahadur, 1961) and in general given by:

$$f(Y_{ik}, Y_{ik'} | x_{ijk}, \beta_{jk}) = P_{ik}^{Y_{ik}} \{1 - P_{ik}\}^{1 - Y_{ik}} P_{ik'}^{Y_{ik'}} \{1 - P_{ik'}\}^{1 - Y_{ik'}} \{1 + R_{kk'} [(Y_{ik} - P_{ik}) (Y_{ik'} - P_{ik'})] / \sqrt{P_{ik} \{1 - P_{ik}\} P_{ik'} \{1 - P_{ik'}\}}\}$$

This result is used in the Generalized Estimating Equations scenario where the Brief Description of GEE is given below. When there is no missing data the GEE for estimating the parameter vector β_k are given by

$$U(\beta_{\sim k}) = \sum_{i=1}^n U_{ik}(\beta_{\sim k}) \sum_{i=1}^n D_{\sim 1k} V_{ik}^{-1} [Y_{ik} - P_{ik}(\beta_{\sim k})] = 0$$

Where $D_{ik} = \delta P_{ik}(\beta_k) / \delta \beta_k$ and δ indicates the partial derivative. Here V_{ik} is the “working” correlation matrix of the parameters. More details regarding the solving of the GEE is given in Lipsitz and Fitzmaurice et al. [15].

2.3. Model Selection

Initially the variables are selected separately for each univariate model. The process of selecting the model terms and the appropriate correlation structure for GEE models is complicated by the correlation within subject. Because the observations are not independent of each other, the residuals are not independent, and therefore common likelihood based methods and other measures of model fit from ordinary linear regression need to be adjusted. According to Ballinger [18] decisions about testing whether coefficients are equal to 0 are most commonly made using a Wald statistic. The Wald test statistic can be calculated by dividing the estimate of the parameter by its standard error. This has a standard normal distribution for large samples. It can be used to test the significance of individual parameters. A backward elimination procedure is used to select the important variables [19].

After the covariates are selected for each univariate model all these selected covariates are put into the multivariate model

$$\beta_i(jk) = \log(\text{odds of a positive response for level } j \text{ of the explanatory variable } i) - \log(\text{odds of a positive response for level } k \text{ of the explanatory variable } i)$$

This implies that:

$$\exp(\beta_i(jk)) = \text{odds ratio of a positive response for level } j \text{ compared to level } k \text{ of the explanatory variable } i.$$

3. Analysis and Results

Initially univariate GEE models were fitted to the three nutritional variables stunting, wasting and underweight. Several explanatory variables pertaining to WaSH and other important prognostic factors such as proxies for wealth, sector, Province, mother’s health, child’s health, Breast feeding, feeding practices, vaccination, mother’s education, parents occupation, pre-birth visits to doctor, vitamins for mother, midwife’s presence before, while and after birth were used. Backward elimination was used and the Wald’s statistic was used to select the significant variables at a 5% level.

3.1. Univariate GEE Modeling

Stunting

Univariate model

and backward elimination is used once again to select the most suitable multivariate GEE model.

Specification of the model

Initially to model the responses Y_{ik} as a function of the explanatory variables, univariate generalized linear model (GLM) was fitted using GEE methodology, with a binomial distribution for each of the responses. The GEE methodology was used as data are collected on the same units (households within census blocks). The binomial distribution was used as the response corresponds to yes/no answers.. The characteristic link function for binomial distribution i.e. the logistic link was used. Significant variables for the models were selected based on the Wald statistic by using the backward elimination procedure and the most appropriate model was chosen.

2.4. Interpretation of Parameter Estimates [16]

The parameter estimates of the model can be interpreted as log odds ratios. The odds ratio is a very useful measure in comparing values of the explanatory variables on the odds of the response variable being positive. This can be expressed as:

The model selected can be represented as:

$\text{Log} [P / (1-P)] = \beta_0 + \beta_1$ (water used for cooking and handwashing) + β_2 (flush/pit toilet) + β_3 (what is the fuel used for cooking) + β_4 (floor material) + β_5 (roof material) + β_6 (wall material) + β_7 (have clocks/watches) + β_8 (having radio) + β_9 (having refrigerator) + β_{10} (having computer) + β_{11} (having rice cooker) + β_{12} (having motor cycle) + β_{13} (owns house) + β_{14} (sector) + β_{15} (Western Province)

The left hand side (LHS) of the model gives the log odds of stunting. By taking the exponential of the coefficients β the odds ratio related to each variable can be determined. The model has been fitted using Proc Genmod in SAS 9.4. SAS also gives the associated p-value indicating the strength of the relationship.

Wasting

Univariate model

The model selected can be represented as

$\text{Log} [P/(1-P)] = \beta_0 + \beta_1$ (water used for cooking and handwashing) + β_2 (what is the fuel used for cooking) + β_3 (cooking smoke come into house) + β_4 (floor material) + β_5 (roof material) + β_6 (wall material) + β_7 (have clocks/watches) + β_8 (having radio) + β_9 (having television) + β_{10} (having mobile TP) + β_{11} (having land line TP) + β_{12} (having refrigerator) + β_{13} (having computer) + β_{14} (having rice cooker) + β_{15} (Having motor cycle)

*Underweight**Univariate model*

The model selected can be represented as

$\text{Log} [P/(1-P)] = \beta_0 + \beta_1$ (water used for drinking) + β_2 (what is the fuel used for cooking) + β_3 (owning agricultural land) + β_4 (Western province) + β_5 (wash hands with soap and water after going to toilet) + β_6 (faeces directly put into a commode or latrine)

3.2. Multivariate GEE Model

All the selected variables from the univariate models were put into the Multivariate GEE model and backward elimination was used to select the significant variables. As mentioned in section II the 3 sub-models consisting of this model were made to have common explanatory variables but different parameter estimates.

The multivariate GEE model is of the form as given below where $h=1$ corresponds to underweight, $h = 2$ corresponds to stunting and $h = 3$ corresponds to the wasting model.

$\text{Log} [P_h/(1-P_h)] = \beta_{0h} + \beta_{1h}$ (water used for drinking) + β_{2h} (what is the fuel used for cooking) + β_{3h} (Owning Agricultural Land) + β_{4h} (faeces put directly into commode or latrine) + β_{5h} (wash hands with soap and water) + β_{6h} (province) + β_{7h} (water used for cooking and hand washing) + β_{8h} (flush/pit toilet) + β_{9h} (floor material) + β_{10h} (roof material) + β_{11h} (wall material) + β_{12h} (having clocks/watches) + β_{13h} (having radio) + β_{14h} (having refrigerator) + β_{15h} (Having computer) + β_{16h} (Having rice cooker) + β_{17h} (Having Motor Cycle) + β_{18h} (Having own house) + β_{19h} (sector)

*The interpretation of the MGEE**The important results related to Underweight*

1. All respondents use either well or pipe born water for drinking. Those that use tap water for drinking have $\exp(\beta_{11}) = 9.5$ times significantly higher odds of underweight than those who use well water (p-value < 0.0001).
2. Those that use either electricity or gas have a $\exp(\beta_{21}) = 2.24$ times higher odds of underweight than those using

kerosene, wood, saw dust, rice husk, charcoal or other. (p-value = 0.0104).

3. Those who own agricultural land have a $\exp(\beta_{31}) = 0.219$ less odds of underweight compared to those who do not have agricultural land. (p-value < 0.0001).
4. Those who wash their hands with soap and water after going to the toilet have a $\exp(\beta_{51}) = 0.99$ less odds of underweight than those who do not. (p-value < 0.0001).
5. Those children whose faeces are directly put into a commode or latrine have lower underweight than those children whose faeces are washed into a commode or latrine and these have a lower underweight than children whose faeces are disposed in other ways. The odds of going from the former to the latter are $\exp(\beta_{41}) = 0.43$ with a p-value = 0.0001.
6. Those who's roof is of tiles, asbestos, Zinc / Aluminium sheets have a $\exp(\beta_{10, 1}) = 1.72$ higher odds of underweight than those who's roofs are made of metal sheet, cadjan/palmyrah/straw or other. (p-value < 0.0591).
7. Those that have their own house have a $\exp(\beta_{18, 1}) = 0.39$ lesser odds of underweight than those who do not.

Coefficients that have not been interpreted are not significant at the 5% level.

The important results related to stunting

1. All respondents use either well or pipe born water for drinking. Those that use tap water for drinking have $\exp(\beta_{12}) = 0.118$ times significantly lower odds of stunting than those who use well water (p-value = 0.0017).
2. Those that use either electricity or gas have a $\exp(\beta_{22}) = 0.078$ times lower odds of stunting than those using kerosene, wood, saw dust, rice husk, charcoal or other. (p-value < 0.0001).
3. Those who wash their hands with soap and water after going to the toilet have a $\exp(\beta_{52}) = 0.99$ less odds of stunting than those who do not. (p-value = 0.0332).
4. Those in the other provinces have a $\exp(\beta_{62}) = 11.8$ times higher odds of stunting compared to those in the Western province. (p-value = 0.0003).
5. Those who's roof is of tiles, asbestos, Zinc / Aluminium sheets have a $\exp(\beta_{10, 2}) = 0.1114$ lower odds of stunting than those who's roofs are made of metal sheet, cadjan/palmyrah/straw or other. (p-value = 0.0004).
6. The respondents whose walls are made of brick, cabook, cement blocks or stones have a $\exp(\beta_{11, 2}) = 0.003$ less odds of stunting compared to walls made of mud, cadjan, palmyrah, plank and wooden sheets. (p-value < 0.0001).

7. Respondents with clocks/watches have a $\exp(\beta_{12,2}) = 0.203$ lesser odds of stunting compared to those who do not. (p-value = 0.0100).
8. Respondents having a refrigerator has a $\exp(\beta_{14,2}) = 0.09$ less odds of stunting compared to otherwise. (p-value < 0.0001)
9. Respondents having a rice cooker have $\exp(\beta_{16,2}) = 0.084$ less odds of stunting than otherwise. (p-value < 0.0001).
10. If the respondent owns the house then the odds of stunting are $\exp(\beta_{18,2}) = 0.162$ less. (p-value < 0.0001).
11. Those in the urban sector have a $\exp(\beta_{19,2,(2,1)}) = 0.0088$ less odds of stunting compared to the estate sector. (p-value = 0.0005). Those in the rural sector have a $\exp(\beta_{19,2,(3,1)}) = 0.0212$ less odds of stunting compared to the estate sector (p-value = 0.0004).
9. Respondents having clock/watch have a $\exp(\beta_{12,3}) = 0.13$ less odds of wasting. (p-value = 0.0015).
10. Respondents having refrigerator have a $\exp(\beta_{14,3}) = 0.177$ less odds of wasting. (p-value < 0.0001).
11. Respondents having a computer have a $\exp(\beta_{15,3}) = 0.072$ less odds of wasting. (p-value = 0.0132).
12. Respondents having rice cooker have a $\exp(\beta_{16,3}) = 0.07$ less odds of wasting. (p-value < 0.0001).
13. Respondents owning a house have a $\exp(\beta_{18,3}) = 0.264$ lesser odds of wasting than those who do not. (p-value = 0.0138).

3.3. Other Important Results

1. The α in the working correlation matrix for the MGEE is 0.3398, indicating that adjusting for correlation is important.
2. The statistic QIC [20] is analogous to AIC for GEE models and this will help to compare the three univariate models with the multivariate model. The lower the statistic the better the model. QIC for underweight = 2886.5649, QIC for stunting = 1924.4848, QIC for wasting = 2298.5928, Total QIC for univariate models = 7109.6425, QIC for multivariate model = 4465.3866.

The QIC is 2644.26 lower for the multivariate model indicating that the MGEE is better than the univariate models.

4. Conclusions

To improve underweight well water is better for drinking, Simple methods of living are better, Agricultural lands and having own house give better nutrition and WaSH facilities are very useful here. To reduce stunting tap water is better for drinking. Good sanitation is better. Proxy to wealth is very important. Urban sector has less stunting than rural sector and this has less stunting than the estate sector. Western province has lower odds of stunting. Wasting mainly depends on the proxy of wealth. There is an indication that tap water for drinking improves wasting. Good sanitation is important to improve wasting. Possession of agricultural lands improves wasting.

Maternal and child health/ education/ knowledge and practices are not related to any of these responses.

The sector is only significant for stunting. The urban sector has less stunting followed by the rural sector and lastly the estate sector. For stunting the Western province does better

The important results related to wasting.

1. All respondents use either well or pipe born water for drinking Those that use tap water for drinking have $\exp(\beta_{13}) = 0.306$ times lower odds of wasting than those who use well water (p-value = 0.0257).
2. Those that use either electricity or gas for cooking have a $\exp(\beta_{23}) = 0.171$ times lower odds of wasting than those using kerosene, wood, saw dust, rice husk, charcoal or other for cooking (p-value < 0.0010).
3. Those who own agricultural land have a $\exp(\beta_{33}) = 0.231$ less odds of wasting compared to those who do not have agricultural land. (p-value < 0.0198).
4. Those who wash their hands with soap and water after going to the toilet have a $\exp(\beta_{53}) = 0.99$ less odds of wasting than those who do not. (p-value = 0.0025).
5. Those children whose faeces are directly put into a commode or latrine have lower wasting than those children whose faeces are washed into a commode or latrine and these have a lower underweight than children whose faeces are disposed in other ways. The odds of going from the former to the latter are $\exp(\beta_{43}) = 0.395$ with a p-value = 0.0237.
6. Those in the other provinces have a $\exp(\beta_{63}) = 9.03$ times higher odds of wasting compared to those in the Western province. (p-value = 0.0002).
7. Those who's roof is of tiles, asbestos, Zinc/Aluminium sheets have a $\exp(\beta_{10,3}) = 0.204$ lower odds of wasting than those who's roofs are made of metal sheet, cadjan/palmyrah/straw or other. (p-value = 0.0012).
8. The respondents whose walls are made of brick, cabook, cement blocks or stones have a $\exp(\beta_{11,3}) = 0.0068$ less odds of wasting compared to walls made of mud, cadjan,

than the other provinces.

The proxy for wealth is very important to improve stunting and wasting. However, it is not much relevant for underweight.

5. Discussion

5.1. Important Points

The Multivariate GEE model is very much better than the Univariate GEE models. The former gives much more sensible results than the later. As the Working correlation is quite high this shows the success of the GEE approach.

After adjusting for important prognostic factors WaSH is significantly important for nutrition variables. Of the other prognostic factors the most important are the wealth index of the household. This strongly effects stunting and wasting but not underweight. These important conclusions were derived by taking proper account of the design and analysis of the study.

5.2. Limitations of the Study

Only a single year's survey data was used as past years survey data have different formats. As there are many variables to be considered the models sometimes fail to converge. When this happens the variables leading to this non-convergence need to be removed from the model. Simple descriptive and univariate measures cannot be used to interpret the data as these do not adjust for cluster correlation.

5.3. How Our Results Are Tied up with What Is Known

Some researchers have found that WaSH is important for stunting. We found that all WaSH variables clean water, sanitation and Hygiene are important. Lot of researchers are confused about the role of wasting. We found that all WaSH variables are important. Few studies have been done on underweight while we showed that WaSH is most important here.

References

- [1] Cumming, O and Cairncross, S (2016). Can water, sanitation and hygiene help eliminate stunting? Current evidence and policy implication. *Maternal and Child Nutrition*. Wiley. 12 (51): 91-105.
- [2] Freeman, M. C. et al 2017. The impact of sanitation on infectious disease and nutritional status: A systematic review and meta-analysis. *International Journal of Hygiene and Environmental Health*. Volume 220, Issue. August 2017, Pages 928-949 6.
- [3] Rah, J. H., et al. (2015). Household sanitation and personal hygiene practices are associated with child stunting in rural India: a cross-sectional analysis of surveys. *BMJ Open* 2015; 5: e005180. doi: 10.1136/ bmjopen-2014-005180.
- [4] Raihan, M. J. et al. (2017). Examining the relationship between socio-economic status, WASH practices and wasting PLOS ONE. <https://doi.org/10.1371/journal.pone.0172134>.
- [5] G. Halcrow, S. Lala, L. Sherburne, T. Tho & M. Griffiths (Australia). Integrating WASH and nutrition to reduce stunting in Cambodia: from discourse to practice. 40th WEDC International Conference, Loughborough, UK, 2017.
- [6] Humphreys, L. (2013). Mobile social media: Future challenges and opportunities. *Sage journals*. <https://doi.org/10.1177/2050157912459499>.
- [7] Kavosi, E, et al. (2014). Prevalence and determinants of under-nutrition among children under six: a cross-sectional survey in Fars province, Iran. *Int J Health Policy MNanag*. 2014 Jul; 3 (2): 71–76.
- [8] Kimani, E. W. M. et al/ (2014), Vulnerability to Food Insecurity in Urban Slums: Experiences from Nairobi, Kenya. *Journal of Urban Health* Volume 91, Issue 6, pp 1098–1113.
- [9] IMPROVING NUTRITION OUTCOMES WITH BETTER WATER, SANITATION AND HYGIENE. <https://www.unicef.org/media>.
- [10] <http://www.washnet.de/en/epaper/> Retrieved in April, 2018.
- [11] Nelder, P. Wedderburn. J. A. *Generalized Linear Models*. Chapman and Hall. London.
- [12] Dobson A. et al. *An Introduction to Generalized Linear Models*, 4th edition. CRC press.
- [13] Kung-Yee Liang; Scott L. Zeger. *Longitudinal Data Analysis Using Generalized Linear Models*. *Biometrika*, Vol. 73, No. 1. (Apr., 1986), pp. 13-22.
- [14] Sooriyachchi, M. R. JOINT GENERALIZED ESTIMATING EQUATIONS (GEE) FOR MULTIVARIATE BINARY OUTCOMES: AN APPLICATION TO NUTRITIONAL DATA FOR SRI LANKAN CHILDREN UNDER FIVE YEARS OF AGE. Published in the proceedings of the International Conference in Computational Statistics and Mathematics (ICCSM), 2019, Singapore.
- [15] Lipsitz, S. R., Fitzmaurice, G. M., et al. (2009) Joint generalized estimating equations for multivariate longitudinal binary outcomes with missing data: An application to AIDS data. January 2009. *Journal of the Royal Statistical Society Series A (Statistics in Society)* 172 (1): 3-20.
- [16] Collett, D. (2003). *Modeling Survival Data in Medical Research*. New York: Chapman & Hall/CRC.
- [17] Casella, G. Berger, R. (2002) *Statistical Inference*, 2nd Edition. Duxbury Press.
- [18] Ballinger, G. A. (2004). *Using Generalized Estimating Equations for Longitudinal Data Analysis*. Sage Journals. <https://doi.org/10.1177/1094428104263672>.
- [19] Agresti, A. (2012) *Categorical Data Analysis* 3rd Edition, Wiley, USA.
- [20] Pan, W. (2001) Akaike's Information Criterion in Generalized Estimating Equations. *Biometrics*. Volume 57, Issue 1, Pages 120-125.