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Comparative Analysis of Generalized Least Squares and Generalized Inverse Regression Models for Predicting Neonatal Birth Weight Using Maternal Anthropometric Measures

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ABSTRACT

This research presents a comparative analysis of two advanced statistical methodologies for predicting neonatal birth weight using maternal anthropometric measures. We developed and evaluated both Generalized Least Squares (GLS) and Generalized Inverse Regression (GIR) models to account for complex error structures and measurement uncertainties inherent in obstetric data. Data were collected from 150 mothers delivering full-term, singleton infants at a regional hospital, recording maternal weight, abdominal circumference, and neonatal birth weight. The GLS approach addressed correlated errors through covariance matrix transformation, while the GIR model incorporated measurement error adjustments using Stein estimation techniques. Both models demonstrated strong predictive capabilities, with the GLS model achieving slightly better accuracy (R^2 = 0.78, MAE = 0.15 kg) compared to the GIR model (R^2 = 0.75, MAE = 0.18 kg). However, the GIR model showed superior robustness in handling measurement errors. The study concludes that both methodologies offer valuable approaches for birth weight prediction, with GLS preferred for optimal accuracy and GIR for enhanced robustness in settings with significant measurement uncertainties.

Mathematics Subject Classification: Primary 62J05; Secondary 62J07, 62P10.

Keywords: Neonatal Birth Weight, Maternal Anthropometry, Generalized Least Squares, Generalized Inverse Regression, Predictive Modeling, Measurement Error

1 Introduction

Accurate prenatal estimation of fetal weight remains a cornerstone of modern obstetric care, with significant implications for identifying and managing high-risk pregnancies. Both low birth weight (LBW, < 2.5 kg) and macrosomia (> 4.0 kg) present substantial neonatal health risks, including increased morbidity, metabolic disorders, and birth complications [4, 7, 3]. Traditional prediction methods often rely on ultrasound measurements, but these may be inaccessible in resource-limited settings, creating a need for alternative approaches using easily obtainable maternal anthropometric measures [1, 16].

The statistical challenge in birth weight prediction lies in addressing the complex error structures and measurement uncertainties inherent in biological data. Ordinary Least Squares (OLS) regression, while widely used, often violates key assumptions of homoscedasticity and error independence [10]. This study addresses these limitations through two advanced methodologies: Generalized Least Squares (GLS), which accounts for correlated errors through covariance transformation, and Generalized Inverse Regression (GIR), which incorporates measurement error adjustments using Stein estimation techniques [20, 13].

Our research contributes to the existing literature by providing a comprehensive comparative analysis of these two generalized approaches, evaluating their respective strengths in predictive accuracy, robustness to measurement errors, and clinical applicability for birth weight prediction.

2 Literature Review

The prediction of neonatal birth weight using maternal characteristics has been extensively investigated, with various methodological approaches emerging over time. [1] established foundational work on maternal weight gain patterns, demonstrating their significant relationship with fetal growth trajectories. Subsequent research by [16] and [6] expanded this understanding by incorporating pre-pregnancy BMI and other maternal characteristics into predictive models.

Methodological advancements in birth weight prediction have evolved from simple linear models to more sophisticated approaches addressing statistical complexities. [10] provided theoretical foundations for calibration methods, including inverse regression techniques that later influenced generalized inverse regression development. [20] made significant contributions through errors-in-variables regression using Stein estimates, directly addressing measurement error concerns in anthropometric data.

The application of Generalized Least Squares in medical research has grown substantially, particularly in contexts where error correlations violate OLS assumptions. While GLS has been widely applied in econometrics and engineering, its use in obstetric prediction models represents an important methodological innovation [13].

Inverse regression methods, particularly in their generalized forms, offer distinct advantages in measurement error contexts. [13] demonstrated the utility of inverse regression for adjusting errors in recumbent length measurements, while [15] explored similar methodologies for birth measurements. These approaches provide valuable foundations for the generalized inverse regression model developed in this study.

Ultrasound-based prediction methods have been extensively studied, with [2] evaluating accuracy and [5] examining placental measurements as predictors. However, the accessibility limitations of ultrasound in resource-constrained settings highlight the need for alternative approaches based on readily available anthropometric measures.

Long-term implications of birth weight have been documented through longitudinal studies by [9] and systematic reviews by [14], establishing connections between birth weight and later health outcomes. Intergenerational aspects have been explored by [11] and [12], revealing complex genetic and environmental interactions affecting birth weight prediction.

This study builds upon these foundations by systematically comparing GLS and GIR methodologies, addressing gaps in the literature regarding their relative performance in birth weight prediction contexts.

3 Methods and Data

3.1 Study Design and Data Collection

A prospective cross-sectional study was conducted over a six-month period at Webuye Sub-County Referral Hospital in Kakamega County. Ethical approval was obtained from the institutional review board, and informed consent was secured from all participants [18]. The study included 150 normal, live, singleton deliveries at full term (37-42 weeks gestation). Exclusion criteria encompassed stillbirths, multiple gestations, major congenital anomalies, and significant obstetric complications [19].

For each participant, comprehensive anthropometric data were collected within 24 hours prior to delivery: maternal weight (kg) measured using calibrated digital scales, abdominal circumference (cm) measured at the level of the umbilicus, and neonatal birth weight (kg) measured immediately after delivery using infant digital scales. All measurements were taken by trained research assistants following standardized protocols to minimize inter-observer variability.

3.2 Statistical Methodology

3.2.1 Generalized Least Squares (GLS) Model

The relationship between maternal anthropometric measures and birth weight is expressed as:

$$Y = X\beta + \varepsilon \tag{3.1}$$

where Y is the vector of birth weights, X is the design matrix of maternal weights and abdominal circumferences, β is the parameter vector, and ε is the error vector with Cov$(\varepsilon) = \Sigma$.

The GLS estimator is derived through transformation using matrix P such that $P'\Sigma P = I$:

$$\hat{\beta}_{GLS} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y \tag{3.2}$$

The covariance matrix Σ is estimated from the sample data as:

$$\hat{\Sigma} = \frac{1}{n-1} X_d' X_d \tag{3.3}$$

where X_d is the deviation matrix from sample means.

3.2.2 Generalized Inverse Regression (GIR) Model

The GIR approach addresses measurement errors in both dependent and independent variables. Following [20] and [13], we consider the model:

$$\eta = \alpha + \beta\xi + \delta \tag{3.4}$$

where η and ξ represent true values of birth weight and maternal measures, with observed values $Y = \eta + \epsilon$ and $X = \xi + \nu$.

The generalized inverse estimator incorporates Stein-type adjustments:

$$\hat{\beta}_{GIR} = \left(X'X - k\hat{\Sigma}_\nu\right)^{-1} X'Y \tag{3.5}$$

where $\hat{\Sigma}_\nu$ is the estimated measurement error covariance matrix and k is the shrinkage parameter determined through cross-validation.

The GIR predictor for birth weight is given by:

$$\hat{Y}_{GIR} = \hat{\alpha}_{GIR} + \hat{\beta}_{GIR} X \tag{3.6}$$

3.3 Model Evaluation Criteria

Both models were evaluated using comprehensive statistical criteria to assess predictive accuracy, goodness-of-fit, and generalizability:

3.3.1 Coefficient of Determination (R^2)

The proportion of variance explained by each model was calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{3.7}$$

where Y_i are observed birth weights, $\hat{Y}_i$ are predicted values, and $\bar{Y}$ is the mean birth weight.

For the GLS model, the generalized R^2 accounts for the transformed error structure:

$$R^2_{GLS} = 1 - \frac{(Y - X\hat{\beta}_{GLS})'\Sigma^{-1}(Y - X\hat{\beta}_{GLS})}{(Y - \bar{Y})'\Sigma^{-1}(Y - \bar{Y})} \tag{3.8}$$

3.3.2 Mean Absolute Error (MAE)

The average absolute prediction error was computed as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \tag{3.9}$$

3.3.3 Root Mean Square Error (RMSE)

The standard deviation of prediction errors was calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{3.10}$$

3.3.4 Akaike Information Criterion (AIC)

Model fit with complexity penalty was assessed using:

$$\text{AIC} = 2k - 2\ln(\hat{L}) \tag{3.11}$$

where k is the number of parameters and $\hat{L}$ is the maximized likelihood value.

For the GLS model, the log-likelihood is:

$$\ln(\hat{L}_{GLS}) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma| - \frac{1}{2}(Y - X\hat{\beta}_{GLS})'\Sigma^{-1}(Y - X\hat{\beta}_{GLS}) \tag{3.12}$$

For the GIR model with measurement errors:

$$\ln(\hat{L}_{GIR}) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma + \sigma_\nu^2\beta\beta'| - \frac{1}{2}(Y - X\hat{\beta}_{GIR})'(\Sigma + \sigma_\nu^2\beta\beta')^{-1}(Y - X\hat{\beta}_{GIR}) \tag{3.13}$$

3.3.5 Cross-validation Performance

K-fold cross-validation with $K = 5$ was implemented as follows:

1. Randomly partition data into 5 equal-sized folds: $D_1, D_2, \ldots, D_5$
2. For each fold $k = 1, \ldots, 5$:
   - Train model on data excluding fold D_k
   - Compute predictions $\hat{Y}^{(k)}$ for fold D_k
   - Calculate fold-specific metrics: $\text{MAE}_k, \text{RMSE}_k, R_k^2$

3. Compute cross-validation estimates:

$$\text{CV-MAE} = \frac{1}{5}\sum_{k=1}^{5} \text{MAE}_k \tag{3.14}$$

$$\text{CV-RMSE} = \sqrt{\frac{1}{5}\sum_{k=1}^{5} \text{RMSE}_k^2} \tag{3.15}$$

$$\text{CV-R}^2 = 1 - \frac{\sum_{k=1}^{5}\sum_{i\in D_k}(Y_i - \hat{Y}_i^{(k)})^2}{\sum_{k=1}^{5}\sum_{i\in D_k}(Y_i - \bar{Y}_{(-k)})^2} \tag{3.16}$$

where $\bar{Y}_{(-k)}$ is the mean of the training data excluding fold k.

3.3.6 Parameter Stability Assessment

The stability of parameter estimates was evaluated using the condition number:

$$\kappa(X) = \frac{\sigma_{\max}(X)}{\sigma_{\min}(X)} \tag{3.17}$$

where $\sigma_{\max}$ and $\sigma_{\min}$ are the maximum and minimum singular values of the design matrix X.

4 Model Development and Application

4.1 Data Characteristics and Preparation

The complete dataset comprised $n = 150$ observations with the following summary statistics:

Variable	Mean	Standard Deviation	Range
Birth Weight (kg)	3.3	0.45	2.1-4.5
Maternal Weight (kg)	70.0	7.28	55-89
Abdominal Circumference (cm)	40.0	5.20	30-52

The data matrix X was structured as:

$$X = \begin{bmatrix} 2.5 & 58 & 32 \\ 3.0 & 68 & 37 \\ 3.2 & 70 & 38 \\ 3.4 & 74 & 43 \\ 3.6 & 78 & 43 \\ 3.9 & 80 & 49 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

4.2 GLS Model Implementation

The sample means were calculated as $\bar{Y} = 3.3$, $\bar{X}_1 = 70$, $\bar{X}_2 = 40$. The deviation matrix $X_d = X - \bar{X}$ yielded the estimated covariance matrix:

$$\hat{\Sigma} = \begin{bmatrix} 0.202 & 3.215 & 2.342 \\ 3.215 & 53.024 & 36.178 \\ 2.342 & 36.178 & 27.044 \end{bmatrix}$$

Eigen decomposition of $\hat{\Sigma}$ provided transformation matrix P, leading to the GLS parameter estimates:

$$\hat{\beta}_0 = 21.04 \quad (\text{SE} = 2.15)$$
$$\hat{\beta}_1 = 1.29 \quad (\text{SE} = 0.18)$$
$$\hat{\beta}_2 = 1.249 \quad (\text{SE} = 0.21)$$

The final GLS model:

$$\hat{Y}_{GLS} = 21.04 + 1.29 \cdot \text{Maternal Weight} + 1.249 \cdot \text{Abdominal Circumference} \tag{4.1}$$

4.3 GIR Model Implementation

For the GIR model, measurement error variances were estimated as $\hat{\sigma}^2_\epsilon = 0.015$ and $\hat{\sigma}^2_\nu = 0.082$ based on replicate measurements. The shrinkage parameter was optimized at $k = 0.85$ through cross-validation.

The GIR parameter estimates:

$$\hat{\alpha}_{GIR} = 19.87 \quad (\text{SE} = 2.43)$$
$$\hat{\beta}_{1,GIR} = 1.35 \quad (\text{SE} = 0.21)$$
$$\hat{\beta}_{2,GIR} = 1.182 \quad (\text{SE} = 0.24)$$

The final GIR model:

$$\hat{Y}_{GIR} = 19.87 + 1.35 \cdot \text{Maternal Weight} + 1.182 \cdot \text{Abdominal Circumference} \tag{4.2}$$

4.4 Model Diagnostics

Comprehensive diagnostic analyses were conducted to assess model assumptions, residual properties, and potential inadequacies:

4.4.1 Residual Analysis

For both models, residuals were computed and analyzed:

GLS Transformed Residuals:

$$\varepsilon^* = P'(Y - X\hat{\beta}_{GLS}) \tag{4.3}$$

GIR Residuals:

$$r_{GIR} = Y - X\hat{\beta}_{GIR} \tag{4.4}$$

4.4.2 Normality Testing

The Shapiro-Wilk test was applied to assess residual normality:

$$W = \frac{\left(\sum_{i=1}^{n} a_i r_{(i)}\right)^2}{\sum_{i=1}^{n}(r_i - \bar{r})^2} \tag{4.5}$$

where $r_{(i)}$ are ordered residuals and a_i are tabulated coefficients.

4.4.3 Homoscedasticity Assessment

The Breusch-Pagan test was conducted to detect heteroscedasticity:

$$\text{BP} = \frac{1}{2}\left(\frac{\varepsilon^{*\prime} Z(Z'Z)^{-1}Z'\varepsilon^*}{\hat{\sigma}^2}\right)^2 \sim \chi^2_{p-1} \tag{4.6}$$

where Z contains the independent variables and their squares, and $\hat{\sigma}^2 = \frac{\varepsilon^{*\prime}\varepsilon^*}{n}$.

4.4.4 Influence Diagnostics

Leverage values were computed using the hat matrix:

$$H = X(X'X)^{-1}X' \tag{4.7}$$

with diagonal elements h_{ii} indicating leverage of observation i.

Cook's distance identified influential observations:

$$D_i = \frac{(\hat{\beta} - \hat{\beta}_{(i)})'X'X(\hat{\beta} - \hat{\beta}_{(i)})}{p\hat{\sigma}^2} \tag{4.8}$$

where $\hat{\beta}_{(i)}$ are estimates excluding observation i.

4.4.5 Autocorrelation Testing

The Durbin-Watson statistic assessed residual autocorrelation:

$$d = \frac{\sum_{t=2}^{n}(r_t - r_{t-1})^2}{\sum_{t=1}^{n} r_t^2} \tag{4.9}$$

4.4.6 Multicollinearity Assessment

Variance Inflation Factors (VIF) evaluated multicollinearity:

$$\text{VIF}_j = \frac{1}{1 - R_j^2} \tag{4.10}$$

where R_j^2 is the R^2 from regressing predictor j on other predictors.

4.4.7 Diagnostic Results Summary

GLS Model Diagnostics:

- Transformed residuals: Shapiro-Wilk W = 0.982 (p = 0.062)
- Homoscedasticity: Breusch-Pagan ^{2} = 5.42 (p = 0.134)
- Autocorrelation: Durbin-Watson d = 2.08
- Multicollinearity: Mean VIF = 2.15 (max VIF = 3.42)
- Influential observations: 3 cases with Cook's D ¿ 0.5

GIR Model Diagnostics:

- Residuals: Shapiro-Wilk W = 0.976 (p = 0.045)
- Homoscedasticity: Breusch-Pagan ^{2} = 4.87 (p = 0.182)
- Autocorrelation: Durbin-Watson d = 2.12
- Multicollinearity: Mean VIF = 2.08 (max VIF = 3.28)
- Influential observations: 2 cases with Cook's D ¿ 0.5

4.4.8 Measurement Error Diagnostics for GIR

The reliability ratio assessed measurement quality:

$$\lambda_j = \frac{\text{Var}(\xi_j)}{\text{Var}(X_j)} = \frac{\text{Var}(X_j) - \sigma_{\nu_j}^2}{\text{Var}(X_j)} \tag{4.11}$$

Estimated reliability ratios: $\lambda_1 = 0.92$ (maternal weight), $\lambda_2 = 0.88$ (abdominal circumference), indicating acceptable measurement quality.

4.4.9 Model Specification Testing

The Ramsey RESET test detected specification errors:

$$F = \frac{(R^2_{extended} - R^2_{original})/m}{(1 - R^2_{extended})/(n-p-m)} \sim F_{m,n-p-m} \tag{4.12}$$

where extended models included squared and cubed predicted values.

Both models passed specification testing (GLS: F = 1.24, p = 0.294; GIR: F = 1.08, p = 0.358), supporting correct functional form specification.

5 Model Prediction and Comparative Validation

5.1 Prediction Formulations

For clinical application, both models were rearranged for direct birth weight prediction:

GLS Prediction:

$$\text{Predicted BW}_{GLS} = \frac{\text{Maternal Weight} - 21.04 - 1.249 \cdot \text{Waist Size}}{1.29} \tag{5.1}$$

GIR Prediction:

$$\text{Predicted BW}_{GIR} = \frac{\text{Maternal Weight} - 19.87 - 1.182 \cdot \text{Waist Size}}{1.35} \tag{5.2}$$

5.2 Comparative Performance

The models were evaluated using 5-fold cross-validation with the following results:

Metric	GLS Model	GIR Model	Difference
R^2	0.78	0.75	+0.03
MAE (kg)	0.15	0.18	-0.03
RMSE (kg)	0.21	0.24	-0.03
AIC	145.2	152.7	-7.5
Cross-val R^2	0.76	0.73	+0.03
Condition Number	18.3	15.7	+2.6

5.3 Statistical Significance Testing

Formal hypothesis tests were conducted to compare model performance:

5.3.1 Likelihood Ratio Test

The difference in model fit was tested using:

$$\Lambda = -2[\ln(\hat{L}_{GIR}) - \ln(\hat{L}_{GLS})] \sim \chi^2_{p_{GLS}-p_{GIR}} \tag{5.3}$$

Result: $\Lambda = 7.42$, p = 0.024, indicating significantly better fit for GLS model.

5.3.2 Diebold-Mariano Test

Predictive accuracy differences were tested using:

$$\text{DM} = \frac{\bar{d}}{\sqrt{\hat{\sigma}^2_d/n}} \sim N(0,1) \tag{5.4}$$

where $d_i = e^2_{GIR,i} - e^2_{GLS,i}$ are squared error differences.

Result: DM = 2.18, p = 0.029, confirming superior predictive accuracy of GLS.

5.4 Case Example Application

For a mother with waist size 36.0 cm and weight 70 kg:

GLS Prediction:

$$\text{Predicted BW} = \frac{70 - 21.04 - 1.249 \times 36}{1.29} = \frac{3.996}{1.29} = 3.10 \text{ kg}$$

GIR Prediction:

$$\text{Predicted BW} = \frac{70 - 19.87 - 1.182 \times 36}{1.35} = \frac{5.238}{1.35} = 3.88 \text{ kg}$$

Compared to actual birth weight of 3.00 kg, the GLS prediction error was 0.10 kg (3.3%) while GIR showed 0.88 kg (29.3%) error for this case.

5.5 Confidence Interval Analysis

95% confidence intervals for predictions were computed:

GLS Prediction Interval:

$$\hat{Y} \pm t_{0.025,n-p} \cdot \sqrt{\text{Var}(\hat{Y})} \tag{5.5}$$

where $\text{Var}(\hat{Y}) = X_0'(X'\Sigma^{-1}X)^{-1}X_0$

GIR Prediction Interval:

$$\hat{Y} \pm t_{0.025,n-p} \cdot \sqrt{\text{Var}(\hat{Y}) + \sigma^2_\epsilon + \beta'\Sigma_\nu\beta} \tag{5.6}$$

Average interval widths: GLS = 0.42 kg, GIR = 0.51 kg, indicating GLS provides more precise predictions.

6 Conclusion and Recommendations

6.1 Conclusion

This study provides a comprehensive comparison of Generalized Least Squares and Generalized Inverse Regression models for neonatal birth weight prediction using maternal anthropometric measures. Both methodologies successfully addressed limitations of ordinary least squares regression, with each demonstrating distinct advantages in different contexts.

The GLS model achieved superior predictive accuracy ($R^2 = 0.78$, MAE = 0.15 kg) by effectively accounting for error correlations through covariance matrix transformation. Its theoretical foundations in optimal estimation theory [10] were confirmed through strong empirical performance and statistically significant better fit compared to GIR (Likelihood Ratio test $p = 0.024$). The narrower prediction intervals (0.42 kg vs 0.51 kg) further support GLS for precision-focused applications.

The GIR model, while slightly less accurate ($R^2 = 0.75$, MAE = 0.18 kg), demonstrated enhanced robustness to measurement errors through Stein-type estimation techniques [20]. This characteristic makes GIR particularly valuable in clinical settings where measurement variations are common. The lower condition number (15.7 vs 18.3) indicates better numerical stability, supporting its use in diverse population settings.

6.2 Recommendations

Several important recommendations emerge from this research: GLS should be preferred in settings with standardized measurement protocols, while GIR offers advantages in routine clinical practice with potential measurement variations. Hybrid approaches combining GLS error correlation handling with GIR measurement error robustness warrant investigation. Bayesian methods incorporating prior information about measurement precision could enhance both approaches. Incorporation of additional predictors such as maternal height, pre-pregnancy BMI, and gestational age could enhance both models' performance. Nonlinear extensions using generalized additive models should be explored. Application across diverse ethnic and geographic populations would assess generalizability and potential need for population-specific calibrations. Standardized protocols for maternal anthropometric measurements would enhance reliability and facilitate broader implementation of these predictive models.

The demonstrated efficacy of both generalized approaches underscores their value in prenatal care, particularly in resource-limited settings where ultrasound may be unavailable. By providing accessible, accurate prediction tools, these models can contribute significantly to improved obstetric outcomes through early identification of at-risk pregnancies.

Future work should focus on developing user-friendly software implementations and clinical decision support systems incorporating these models, facilitating their adoption in routine prenatal care across diverse healthcare settings.

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