Post-Surgery Resting Energy Expenditure

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1 Background

Accurately assessing postoperative metabolic needs is critical for optimizing nutritional support and improving recovery outcomes in cardiac surgery patients. Resting energy expenditure (REE), measured using indirect calorimetry (IC), provides a direct estimate of metabolic demand, yet little is known about how REE changes throughout recovery or how it differs across clinically relevant factors such as obesity status, ventilator use, and hospital location. This study seeks to address these gaps by analyzing 35 repeated REE and REE/kg measurements collected from 11 cardiac surgery patients during their stays in the intensive care unit (ICU) and step-down unit (SDU). By characterizing patterns of energy expenditure across patients and over time, the goal of this analysis is to identify factors associated with increased metabolic demand and to generate insights that can support more tailored and effective postoperative nutritional care.

2 Exploratory Data Analysis

To understand patterns in postoperative metabolic demand and to guide the structure of my final model, I first conducted a detailed exploratory analysis of REE and REE/kg across patients and clinical factors. The distributions of the two outcome variables (Figure 1) and (Figure 2) show substantial heterogeneity, with REE moderately right-skewed and REE/kg more symmetric. This distinction suggests that absolute REE is strongly influenced by body size, while REE/kg provides a more standardized measure of metabolic intensity. The differences in distributional shape help continue analyzing both outcomes in parallel.

A key feature of the dataset is its repeated-measures structure. The REE Trajectories by Patient plot ((Figure 3) displays considerable within-patient correlation and highly individualized recovery profiles, with some patients showing rising REE over time while others decline or fluctuate. The Patient-Specific Mean REE plot (Figure 4) further highlights large between-patient differences in average metabolic demand. Together, these figures provide strong justification for a mixed-effects model with patient-level random intercepts, as failing to account for this structure would underestimate variability and bias inference.

We also explored clinical covariates thought to influence metabolic rate. The boxplots comparing obese and non-obese patients (Figure 5) and (Figure 6) reveal that obese patients have substantially higher REE but lower REE/kg, consistent with known physiological patterns where larger bodies require more calories overall but expend less energy per kilogram. The REE by Ventilator Status plot (Figure 7) shows that ventilated patients exhibit noticeably lower REE than those breathing spontaneously, suggesting ventilator use is an important predictor to include. Finally, the smoothed scatterplots of BMI against both REE and REE/kg (Figure 8) and (Figure 9) show nonlinear associations with BMI, reinforcing the relevance of body composition–related predictors.

3 Model Rationale and Implementation

Taken together, the exploratory analysis shows that an appropriate modeling strategy must:
(1) incorporate patient-level random effects due to strong within-patient correlation (Figure 3) and (Figure 4),
(2) include Obesity, BMI, and Ventilator status as fixed effects due to their clear associations with REE

(Figures 5–9), and
(3) analyze both REE and REE/kg given their distinct distributional behaviors (Figure 1) and (Figure 2).

So this leads to using `lme4::lmer()` for a linear mixed-effects regression framework to characterize the effects of obesity, ventilator use, and clinical setting on postoperative metabolic demand. To assess the importance of individual predictors, nested model comparisons were conducted using Kenward–Roger F-tests implemented in `pbkrtest::KRmodcomp()`. Parallel models were fit for both REE and REE per kilogram (REE/kg) to evaluate whether conclusions changed when adjusting for body size.

Including BMI in the mixed-effects models was not appropriate because BMI does not vary within patients and is highly collinear with obesity status, which was already included as a primary predictor. Since the random intercept captures between-patient differences, adding BMI would offer no additional information and would introduce multicollinearity, making parameter estimates unstable and difficult to interpret. Therefore, excluding BMI does not weaken the analysis and is consistent with both the study objectives and best practices for mixed-model specification.

4 Model Evaluation

A comprehensive set of diagnostic checks indicated that the mixed-effects models were appropriately specified for both REE and REE/kg. The Residuals vs Fitted plots for the REE model (Figure 10, p. 13) and the REE/kg model showed centered residuals with no strong systematic pattern, although mild heteroskedasticity appeared at higher fitted values (Figure 10) and (Figure 15). Normal Q–Q plots for residuals revealed approximate normality with expected deviations in the tails due to the small sample size (Figure 11) and (Figure 12). Q–Q plots of the patient-level random intercepts (Figure 12) and (Figure 17) demonstrated that the random effects were approximately normally distributed, supporting the validity of the random-intercept structure.

Model fit statistics were reported only for the full REE and REE/kg mixed models used for inference. For the REE model, the marginal R^2 (0.456) indicated that the fixed effects explained approximately 46% of the variability in REE, while the conditional R^2 (0.544) showed that including patient-specific random intercepts increased the explained variance to 54% (Table 9). The adjusted ICC (0.163) suggested modest between-patient differences in baseline REE (Table 9). Consistent with the lack of significant predictors, the REE/kg model showed substantially lower marginal and conditional R^2 values and a small ICC, reflecting minimal explainable structure in weight-adjusted metabolic rate (Table 10). This relatively low ICC is expected in metabolic data, where REE varies markedly over short time intervals due to clinical and physiological dynamics. These results support the use of a random-intercept structure while also indicating that within-patient variability remains the dominant source of variation in the dataset.

No major anomalies were evident in the data, although a few minor issues were noted. A small number of patients exhibited unusually high REE values (e.g., >2400 kcal/day), which contributed to increased random-effect variance but did not act as influential outliers. Additionally, mild heteroskedasticity and slight tail deviations were visible in the residual diagnostics, but these patterns are expected given the small sample size and do not indicate serious assumption violations. The strongest structural limitation was the temporal confounding between clinical variables and measurement order, as most “ICU” and “Ventilator” observations occurred early in recovery. However, this reflects the study design rather than data anomalies, and the mixed-effects framework handled this imbalance reasonably well. Overall, no irregularities were detected that would invalidate the modeling approach or materially distort the conclusions.

$$\mathrm{REE}_{ij} = \beta_0 + \beta_{\mathrm{Obese}}\,\mathrm{Obese}_{ij} + \beta_{\mathrm{Vent}}\,\mathrm{Vent}_{ij} + \beta_{\mathrm{Loc}}\,\mathrm{ICU/SDU}_{ij} + b_{0i} + \varepsilon_{ij},$$

$$b_{0i} \sim N(0, \sigma_b^2), \qquad \varepsilon_{ij} \sim N(0, \sigma^2).$$

$$\mathrm{REE/kg}_{ij} = \beta_0 + \beta_{\mathrm{Obese}}\,\mathrm{Obese}_{ij} + \beta_{\mathrm{Vent}}\,\mathrm{Vent}_{ij} + \beta_{\mathrm{Loc}}\,\mathrm{ICU/SDU}_{ij} + b_{0i} + \varepsilon_{ij},$$

$$b_{0i} \sim N(0, \sigma_b^2), \qquad \varepsilon_{ij} \sim N(0, \sigma^2).$$

5 Model results

The mixed-effects model for REE revealed that obesity status and ventilator use were meaningful predictors of total metabolic expenditure. Obese patients exhibited approximately 488 kcal/day higher REE than non-obese patients ($p = 0.011$), consistent with exploratory patterns (Table 1). Ventilated patients showed an estimated 340 kcal/day reduction in REE ($p = 0.048$), reflecting lower metabolic demand under mechanical ventilation (Table 1). ICU vs SDU location demonstrated no detectable association with REE ($p = 0.564$) (Table 1). Kenward–Roger tests confirmed these findings: removing obesity significantly worsened model fit ($p = 0.009$), while removing ventilator status produced borderline evidence of loss of fit ($p = 0.065$), and removing location had no effect ($p = 0.58$) (Table 2) (Table 3) (Table 4). When REE was weight-adjusted, the conclusions changed substantially. In the REE/kg model, none of the predictors were significant, and no nested model comparison indicated loss of fit, consistent with the strong overlap seen in the REE per KG by Obesity Status plot (Table 5). Thus, obesity and ventilator status meaningfully affect total energy expenditure but not energy expenditure per kilogram, indicating that differences in REE are driven by body size rather than intrinsic metabolic rate (Table 6) (Table 7) (Table 8).

In summary, the modeling objectives were fully achieved. Using a properly diagnosed mixed-effects framework, we characterized how REE depends on obesity, ventilator use, and location. I also demonstrated that these conclusions change when REE is weight-adjusted, and verified through residual, random-effect, and predictive diagnostics that the models fit the data appropriately. The final results show that clinically meaningful differences in metabolic demand arise from obesity and ventilator status, but these differences disappear when adjusting for body weight.

6 Shortcomings and Conclusion

This analysis is limited by the small sample size (35 observations across 11 patients), which reduces power and leads to unstable degrees of freedom for between-patient predictors such as obesity. ICU/SDU location and ventilator status are both strongly tied to recovery stage, creating temporal confounding the model cannot fully disentangle. Mild heteroskedasticity and slight non-normality in residuals suggest that model assumptions are only approximately met, and a few high-REE patients may disproportionately influence random-effect estimates. Finally, the lack of additional clinical covariates limits the model's ability to explain variation in metabolic demand. Future work should incorporate larger, more balanced datasets and models that explicitly account for recovery time and more clinical information.

The mixed-effects analysis shows that obesity and ventilator status meaningfully affect total REE, while ICU versus SDU location does not. Obese patients have higher absolute metabolic demand, and ventilated patients exhibit lower REE, but these differences disappear when adjusting for body weight, indicating that metabolic rate per kilogram is stable across groups. Model diagnostics confirmed that linear mixed-effects models were appropriate and adequately captured key features of the data, though a lot remained unexplained within-patient variability. These findings highlight the importance of individualized metabolic monitoring to guide postoperative nutritional support.

Table 1: Fixed Effects for REE Mixed Model

effect	term	estimate	std.error	statistic	df	p.value	conf.low	conf.high
fixed	(Intercept)	1515.986	148.723	10.193	25.811	0.000	1210.172	1821.799
fixed	ObeseObese	488.067	144.437	3.379	7.285	0.011	149.219	826.915
fixed	VentilatorVent	-340.563	165.099	-2.063	28.403	0.048	-678.538	-2.588
fixed	ICUorSDUSDU	89.509	153.558	0.583	29.230	0.564	-224.446	403.463

7 Appendix

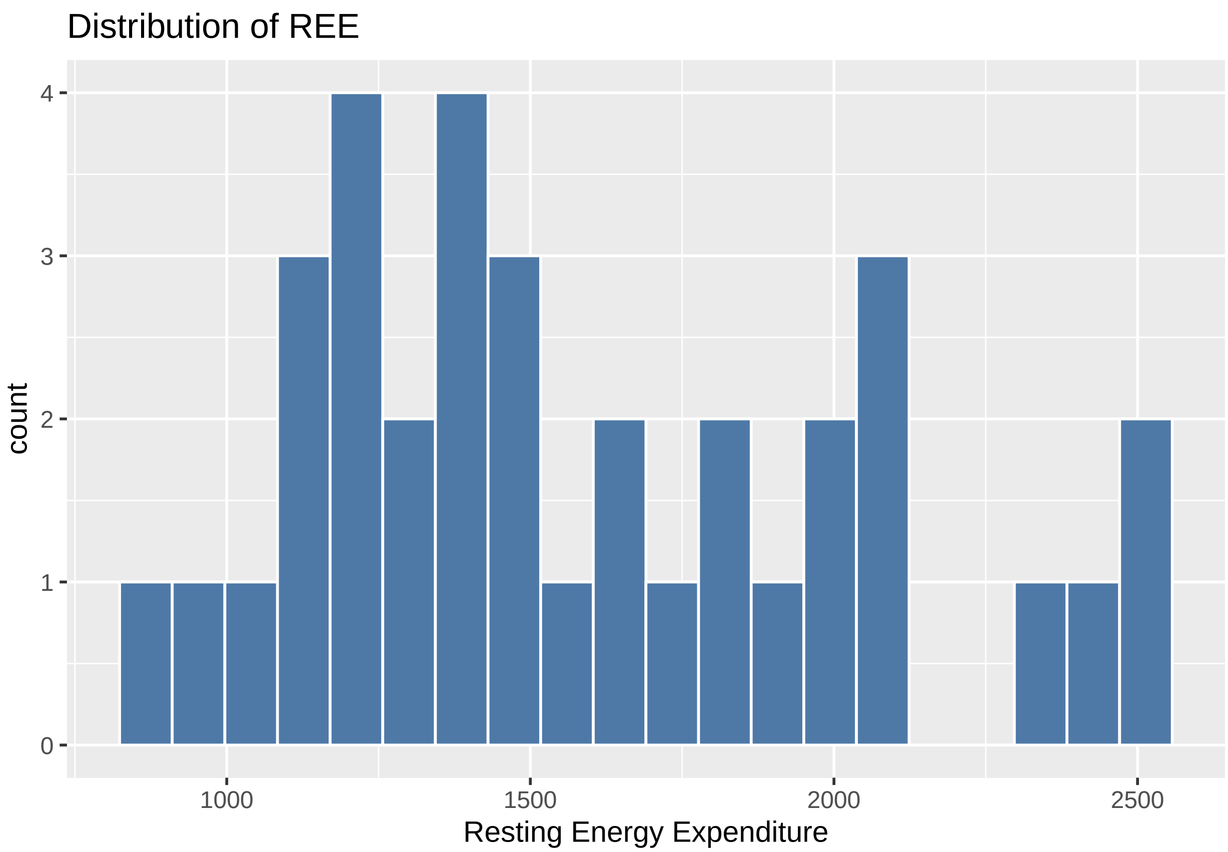


Figure 1: Distribution of REE across patients

7.0.1 Modeling:

```
library(tidyverse)

# build two clean plotting datasets
df_REE <- REE %>%
  mutate(
    Fitted = fitted(model_REE),
    Observed = REE,
    Model = "REE"
  ) %>%
  select(Fitted, Observed, ID, Model)
```

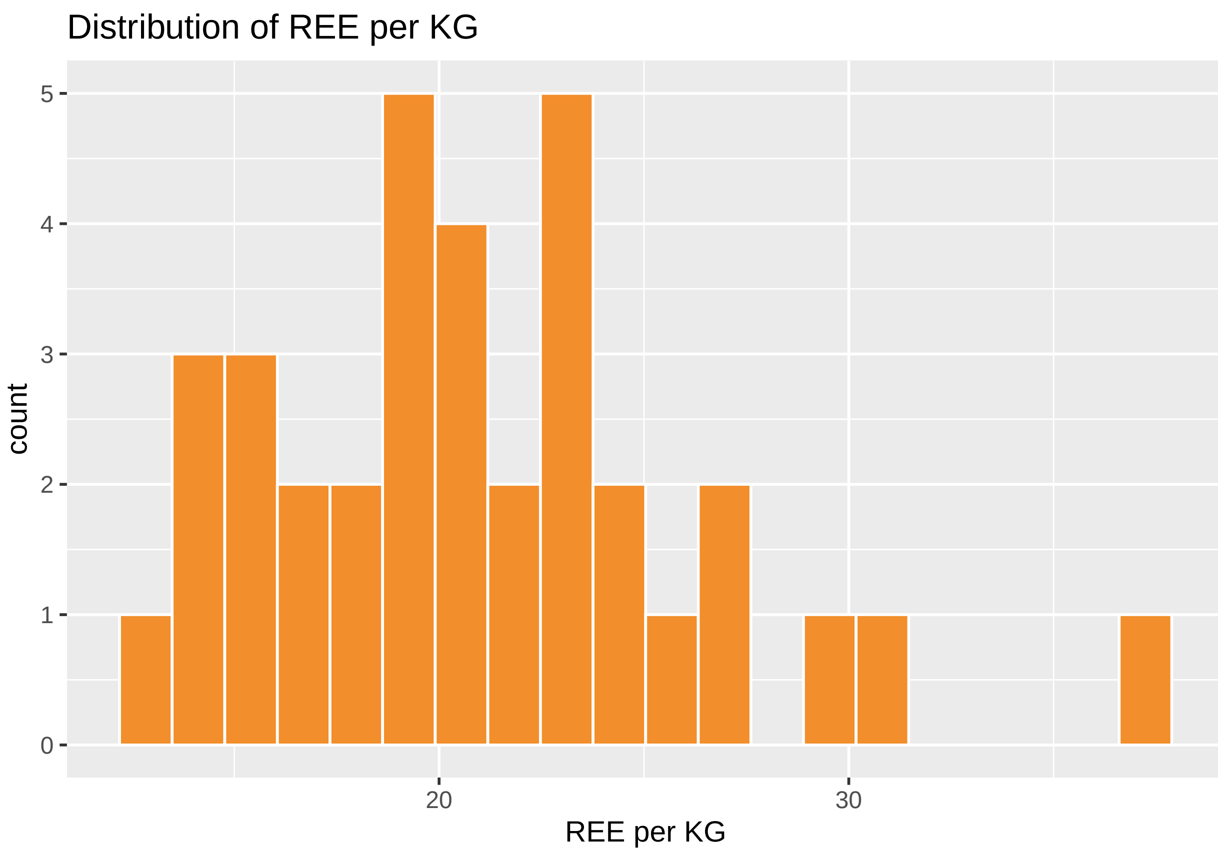


Figure 2: Distribution of REE per KG across patients

Table 2: Kenward–Roger Test Comparing Full Model REE vs. Model without Obesity

type	stat	ndf	ddf	p.value
Ftest	11.164	1	8.4779	0.0094

Table 3: Kenward–Roger Test Comparing Full Model REE vs. Model without Ventilator

type	stat	ndf	ddf	p.value
Ftest	11.164	1	8.4779	0.0094

Table 4: Kenward–Roger Test Comparing Full Model REE vs. Model without ICU/SDU

type	stat	ndf	ddf	p.value
Ftest	11.164	1	8.4779	0.0094

Table 5: Fixed Effects for REE/kg Mixed Model

effect	term	estimate	std.error	statistic	df	p.value	conf.low	conf.high
fixed	(Intercept)	22.074	2.315	9.535	21.722	0.000	17.269	26.878
fixed	ObeseObese	-2.990	2.749	-1.088	8.202	0.308	-9.302	3.322
fixed	VentilatorVent	-2.327	2.374	-0.980	30.524	0.335	-7.172	2.518
fixed	ICUorSDUSDU	1.993	2.057	0.969	26.220	0.341	-2.233	6.218

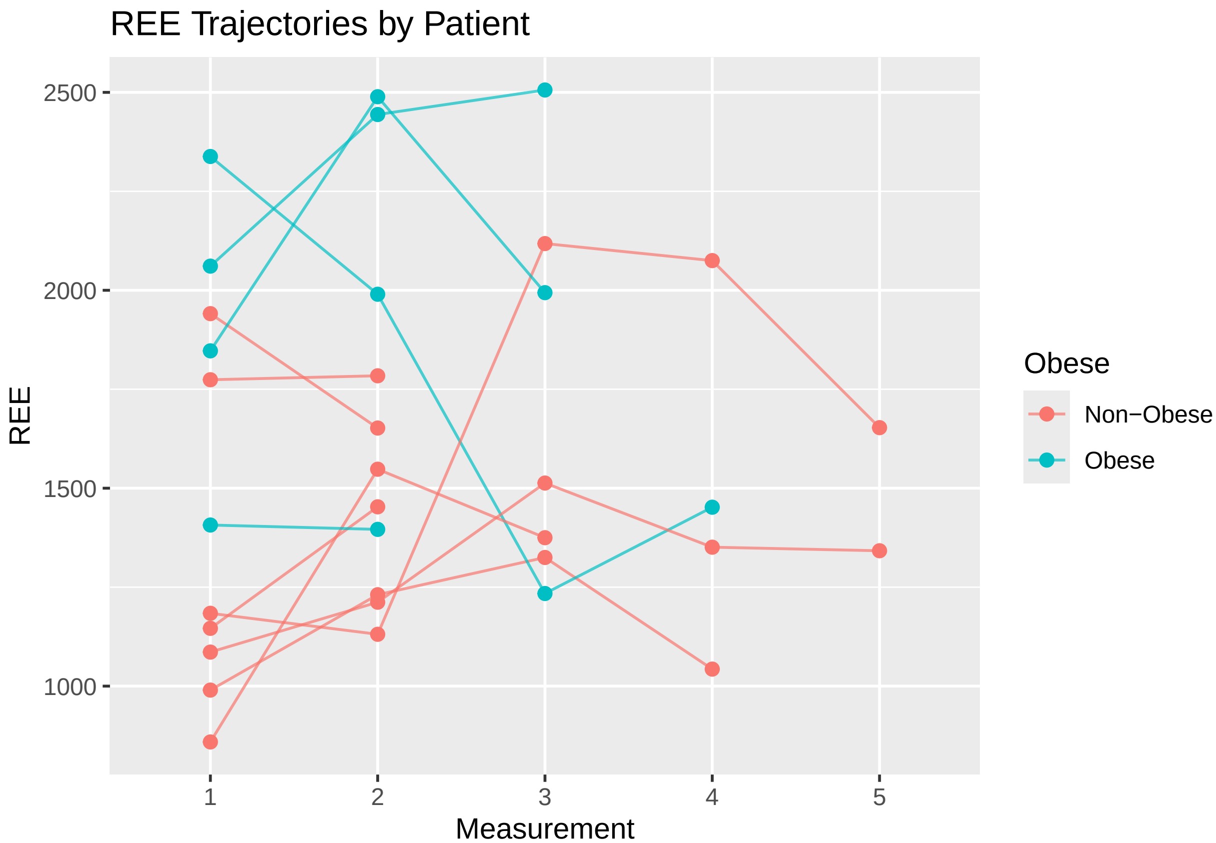


Figure 3: REE by Patient showing within-patient correlation & between-patient variability

Table 6: Kenward–Roger Test Comparing Full Model REE/kg vs. Model without Obesity

type	stat	ndf	ddf	p.value
Ftest	1.1779	1	8.6975	0.307

Table 7: Kenward–Roger Test Comparing Full Model REE/kg vs. Model without Ventilator

type	stat	ndf	ddf	p.value
Ftest	0.8615	1	30.5602	0.3606

Table 8: Kenward–Roger Test Comparing Full Model REE/kg vs. Model without ICU/SDU

type	stat	ndf	ddf	p.value
Ftest	0.8906	1	26.5364	0.3538

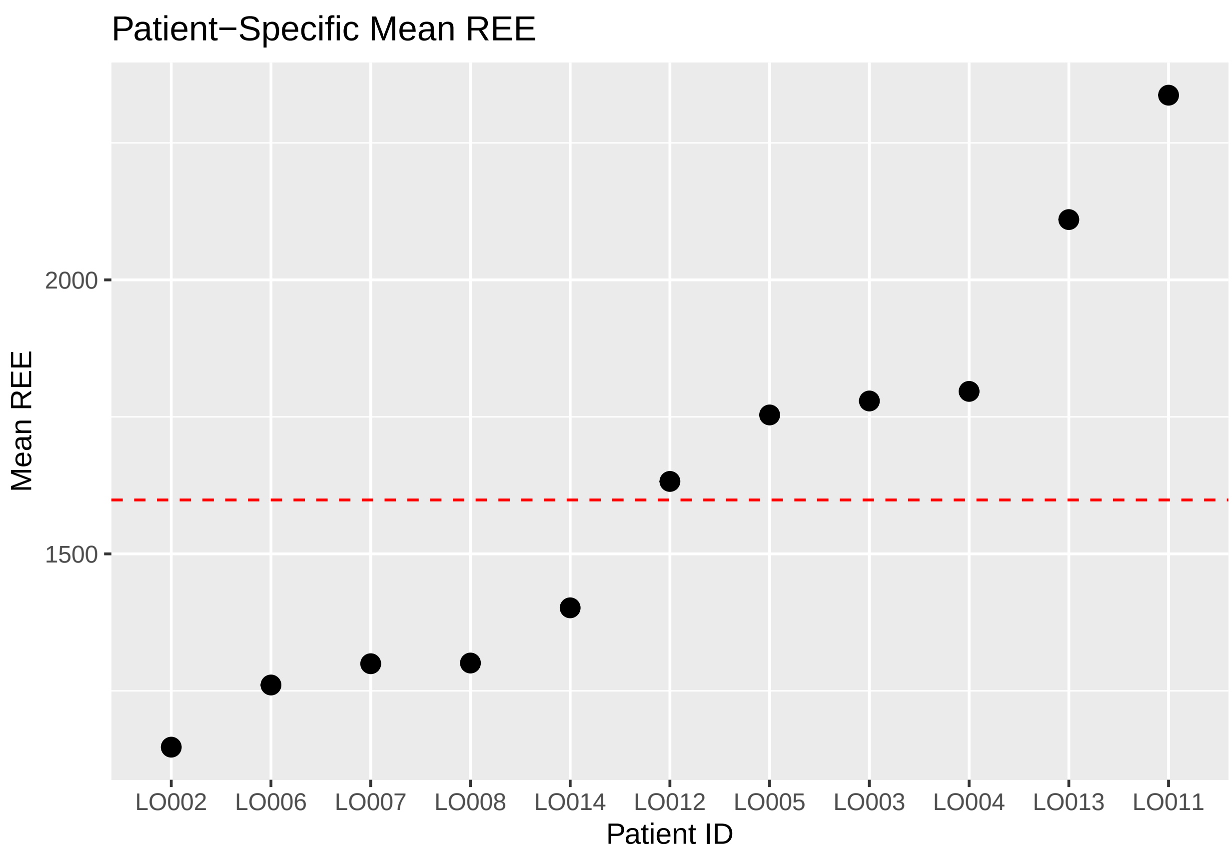


Figure 4: Mean REE by Patient Mean

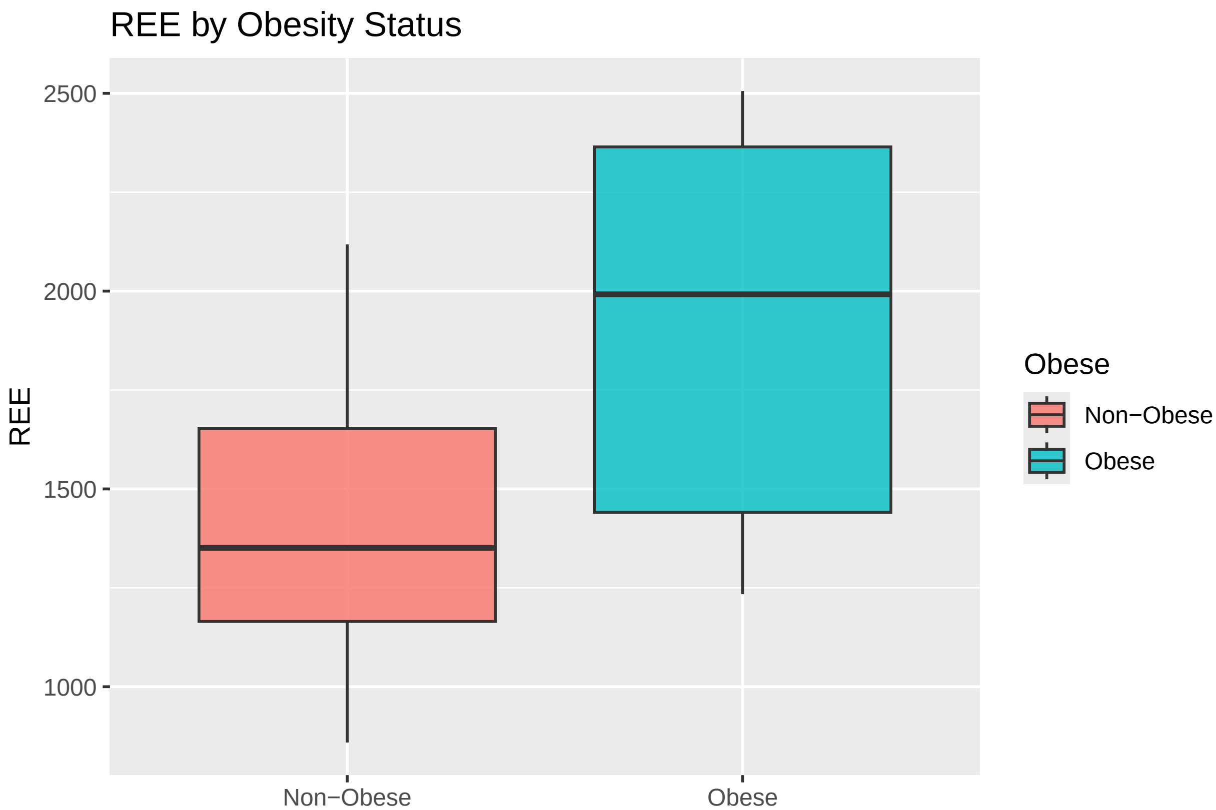


Figure 5: REE by Non-Obese & Obese Patients

Table 9: Model Fit Statistics for Full REE Mixed Model

Metric	Value
Marginal R^2	0.456
Conditional R^2	0.544
Adjusted ICC	0.163
Unadjusted ICC	0.089

Table 10: Model Fit Statistics for Full REE/kg Mixed Model

Metric	Value
Marginal R^2	0.174
Conditional R^2	0.559
Adjusted ICC	0.466
Unadjusted ICC	0.385

```
df_REEkg <- REE %>%
  mutate(
    Fitted = fitted(model_REEkg),
    Observed = REEperKG,
    Model = "REE/kg"
  ) %>%
```

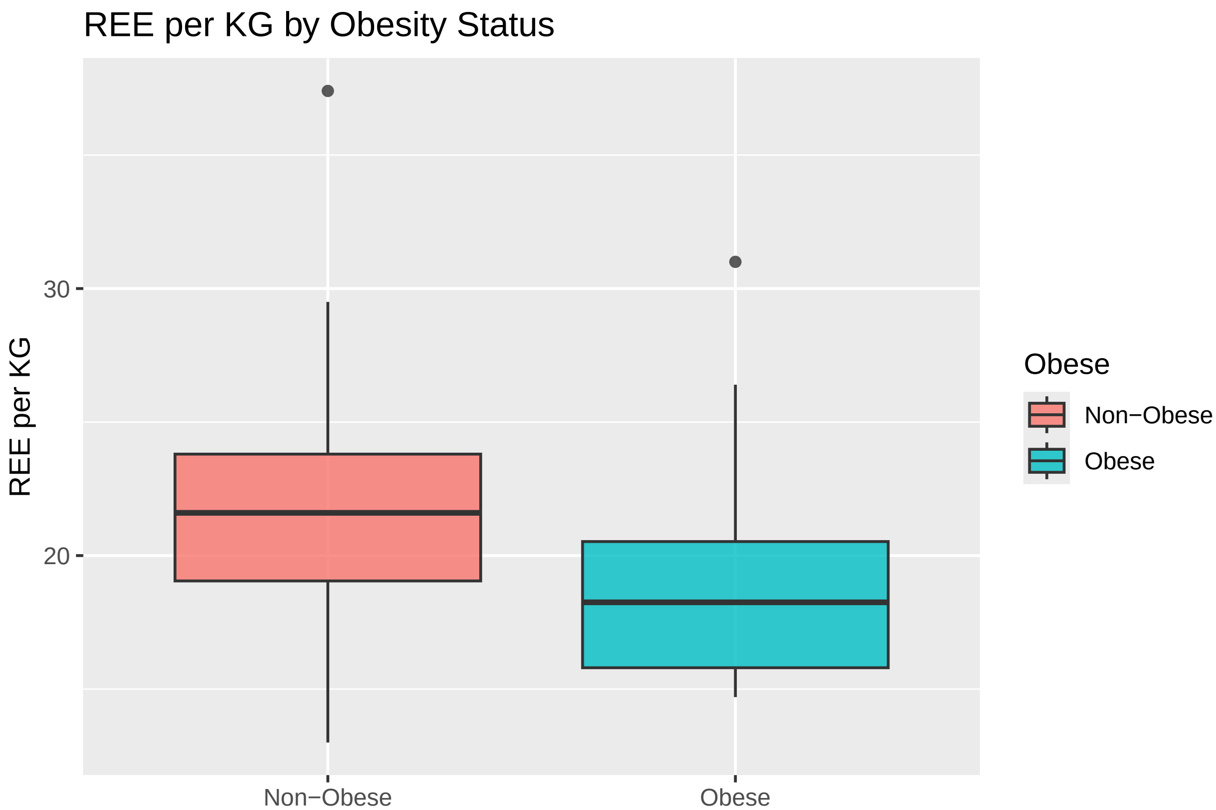


Figure 6: REE per KG by Non-Obese and Obese Patients

```
  select(Fitted, Observed, ID, Model)

# combine
df_plot <- bind_rows(df_REE, df_REEkg)

# final combined plot
ggplot(df_plot, aes(x = Fitted, y = Observed, color = ID)) +
  geom_point(alpha = 0.75, size = 2) +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed", size = 1) +
  facet_wrap(~ Model, scales = "free") +
  labs(
    title = "Observed vs Fitted Values",
    x = "Fitted",
    y = "Observed"
  ) +
  theme_minimal() +
  theme(legend.position = "none")
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

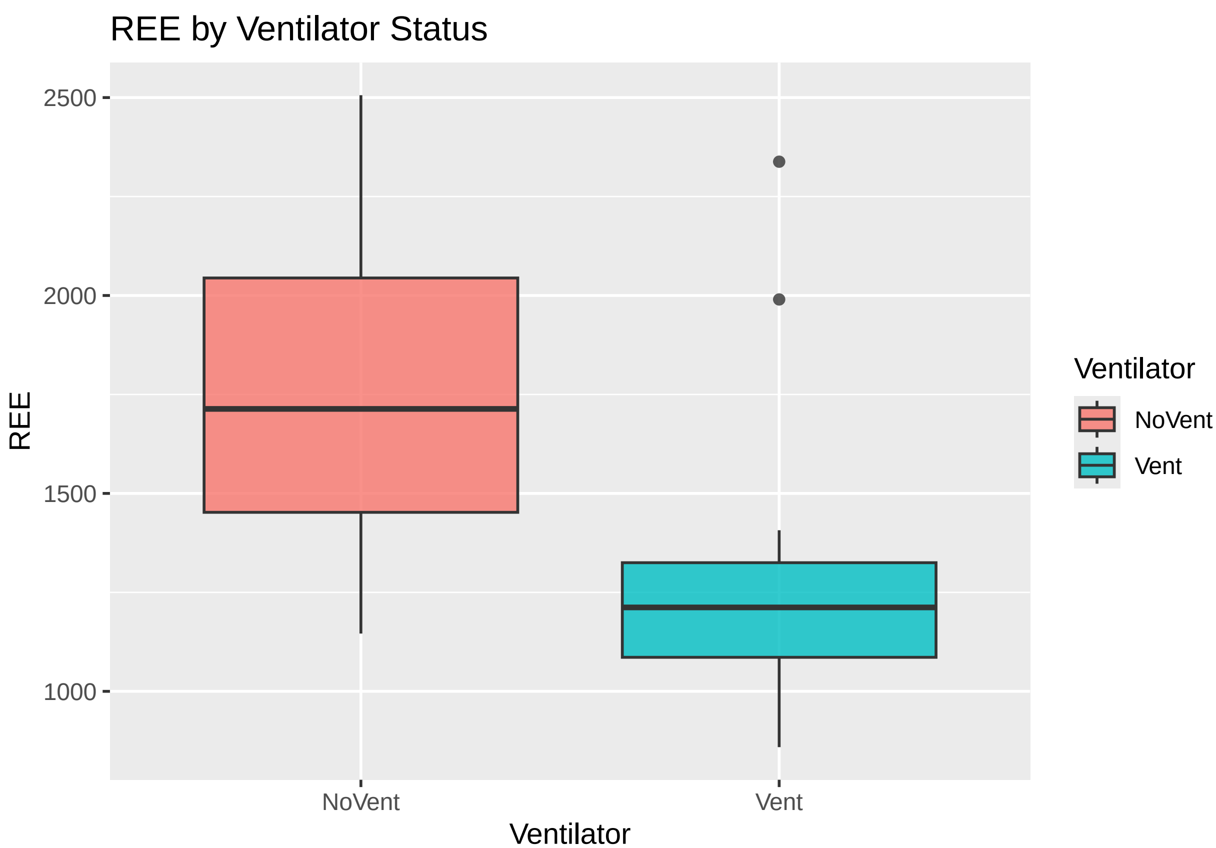


Figure 7: REE by Ventilator Status for Obese and Non-Obese Patients

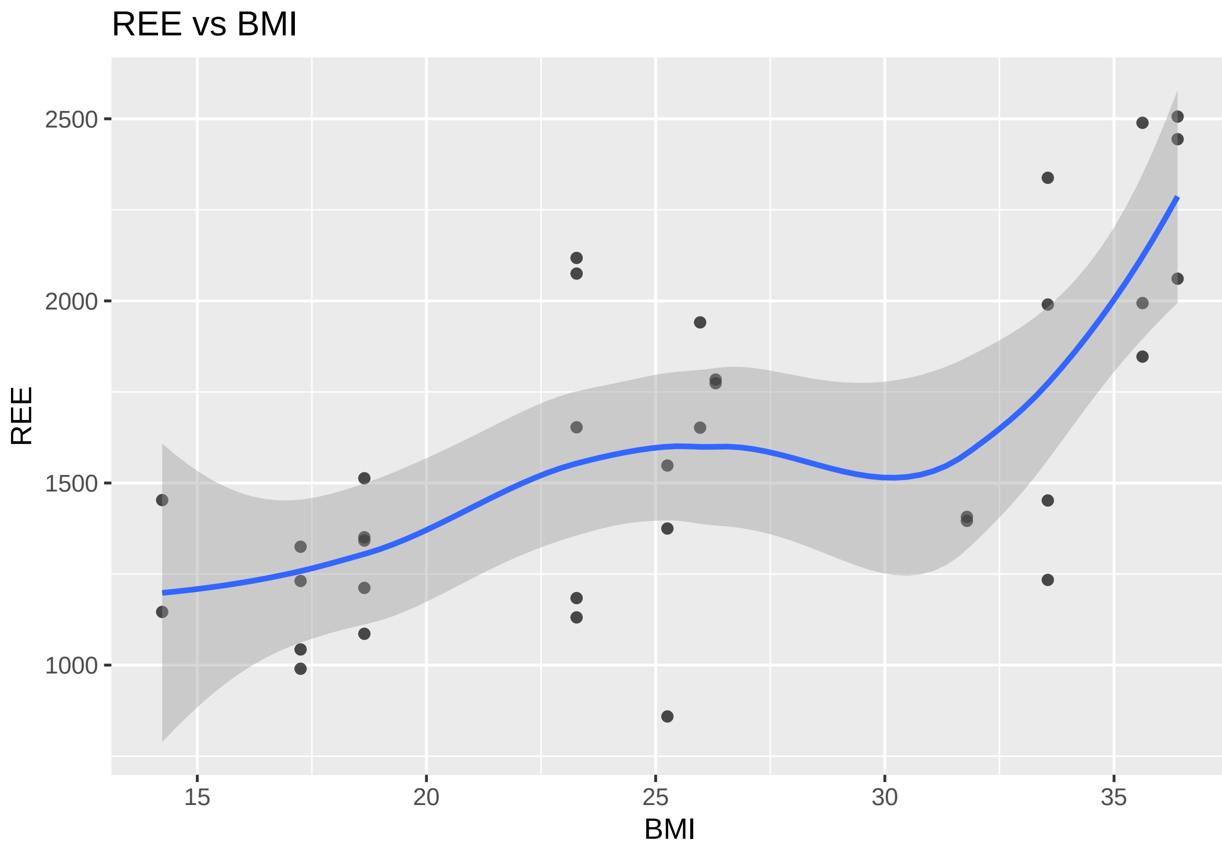


Figure 8: REE vs BMI fit with a LOESS curve

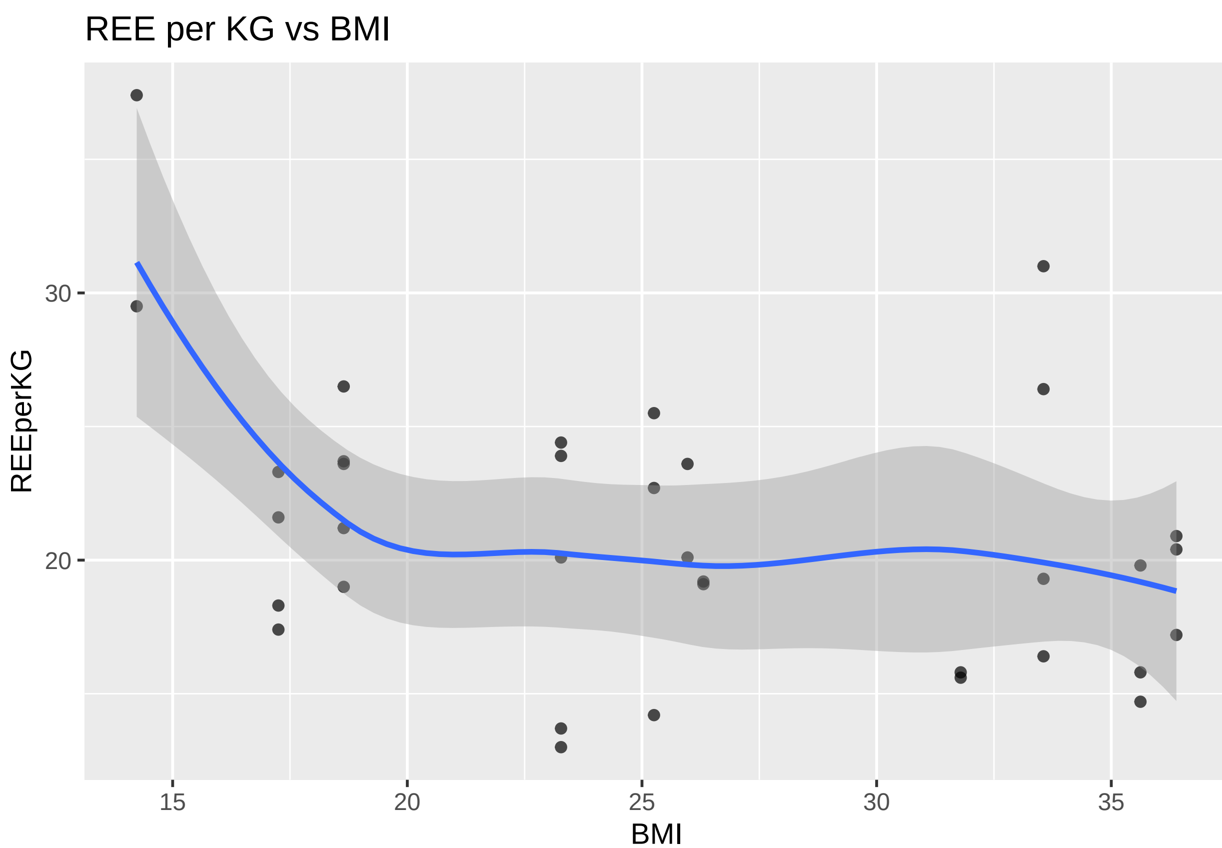


Figure 9: REE per KG vs BMI fit with a LOESS curve

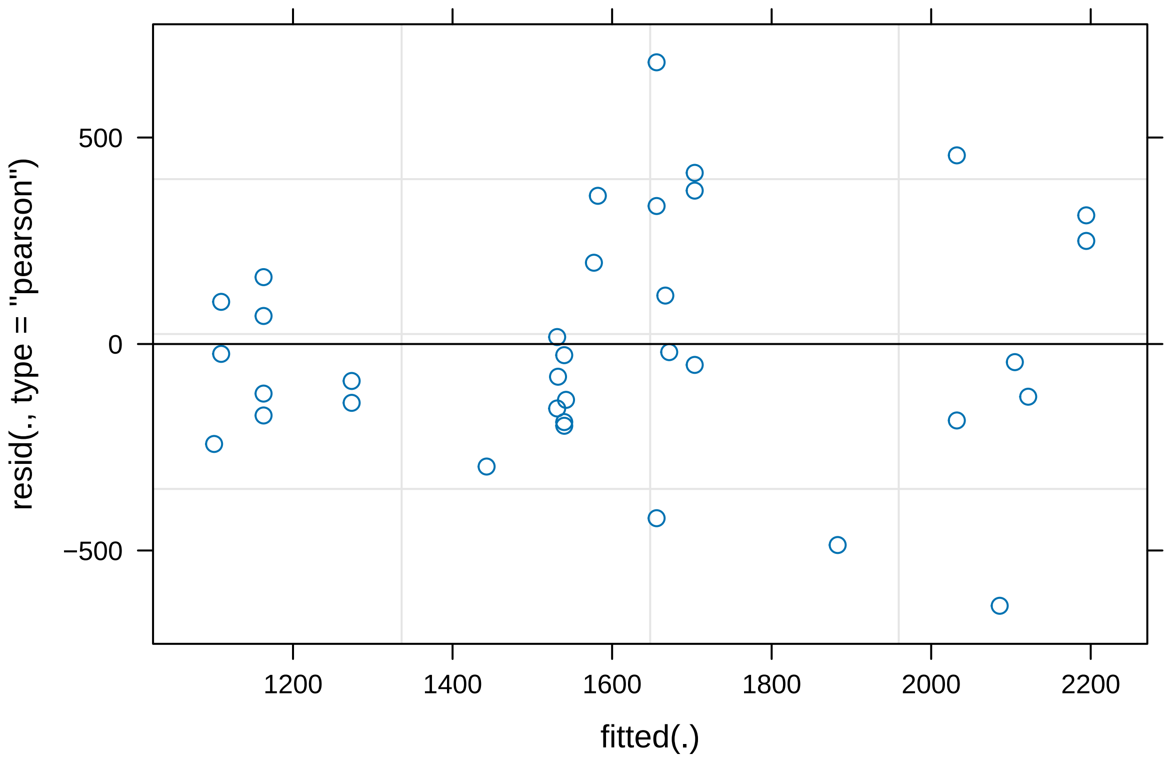


Figure 10: Residuals vs Fitted Plot for full REE model

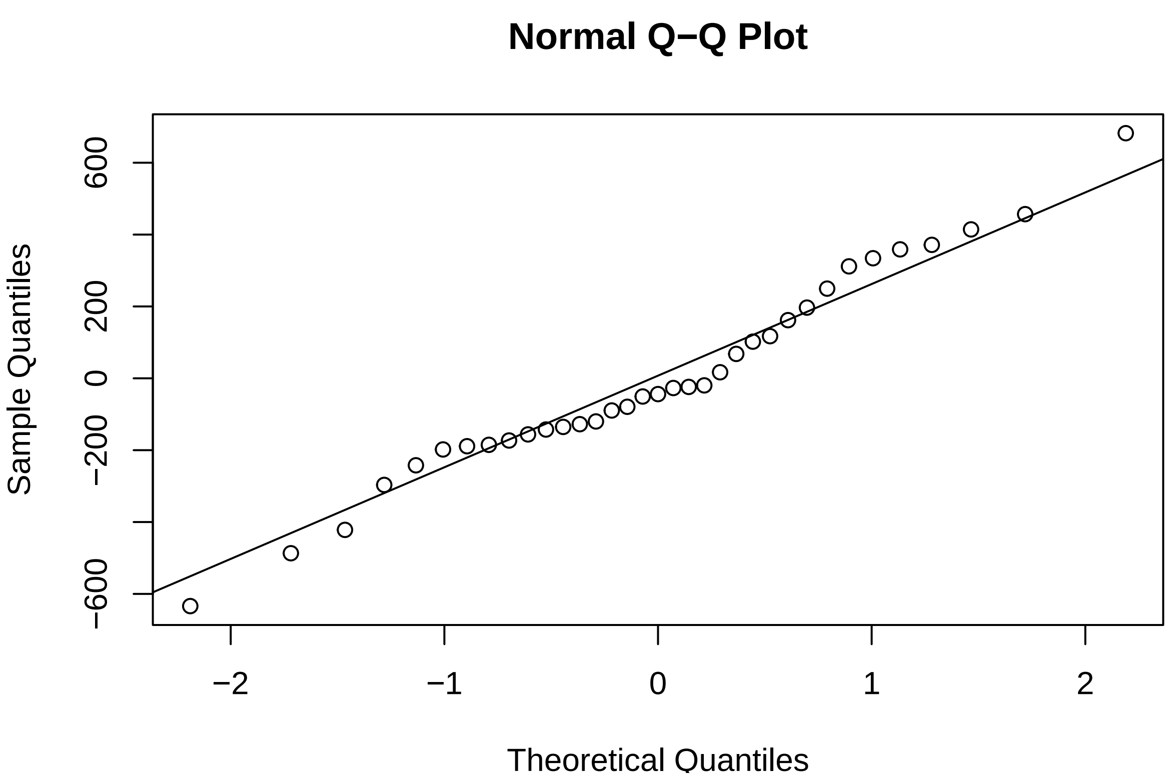


Figure 11: Normal QQ Plot for full REE model

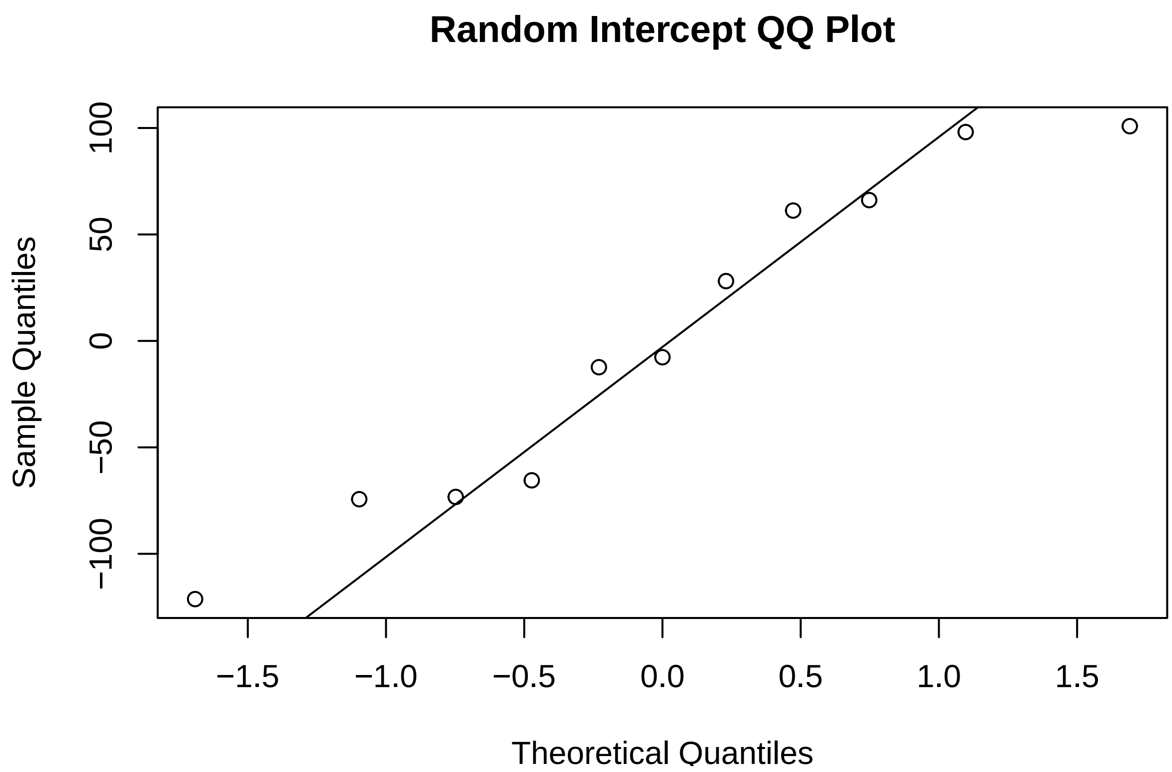


Figure 12: Random Intercept QQ Plot for full REE model

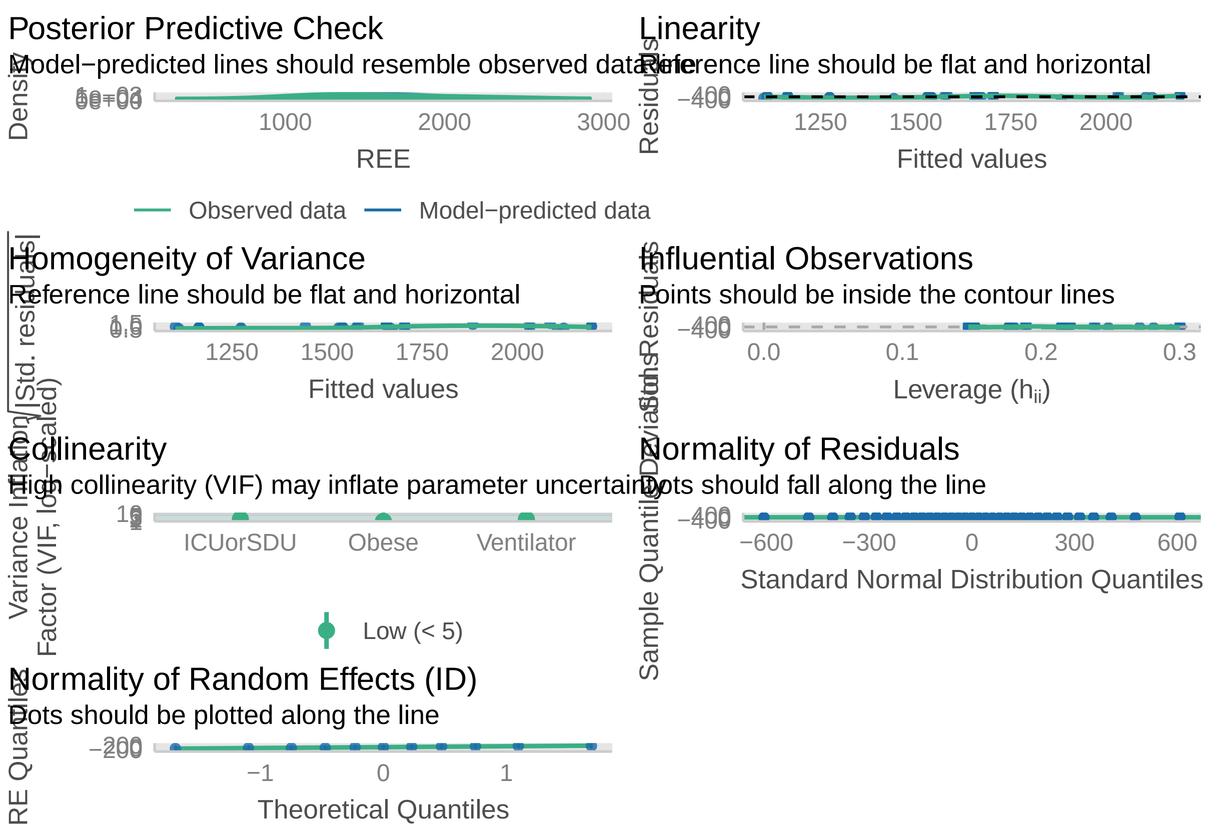


Figure 13: KR Test Full Model vs. Model without ICU/SDU

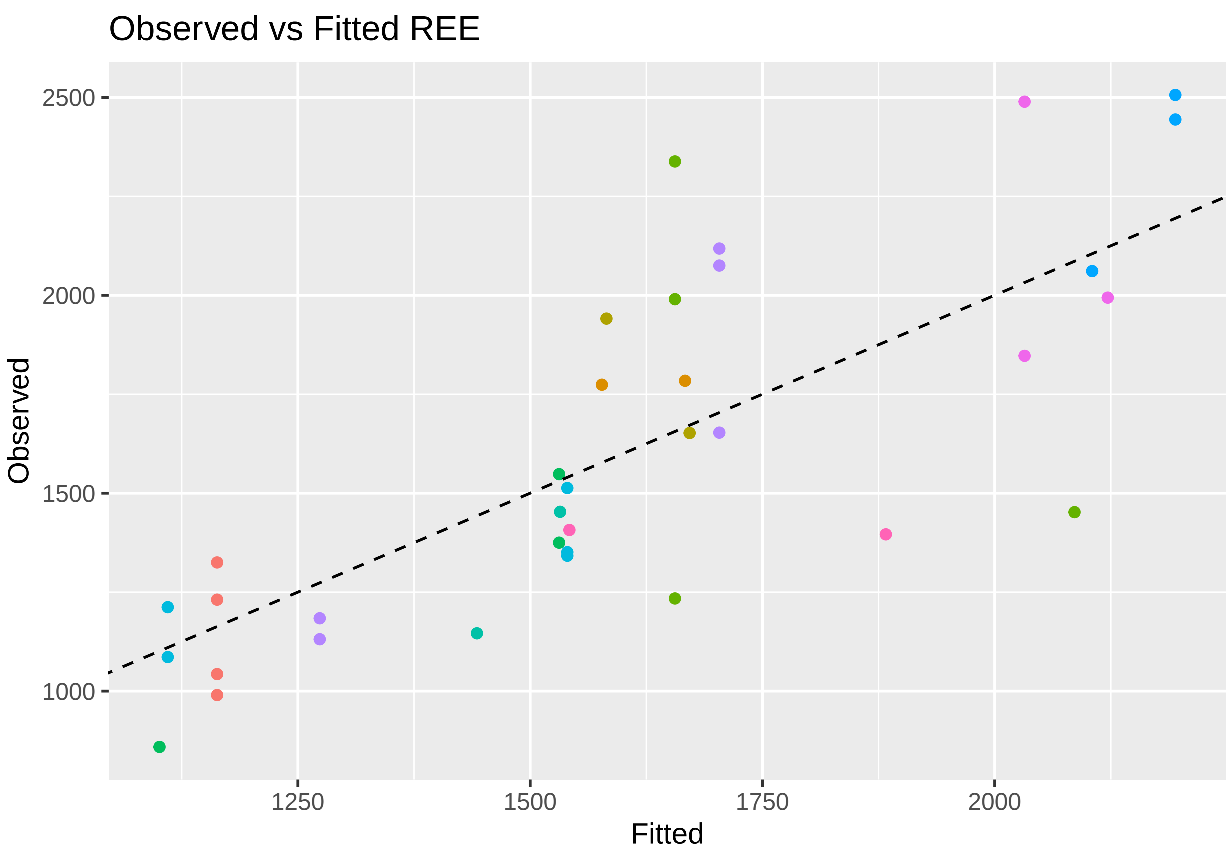


Figure 14: Observed vs Fitted REE by Patient ID

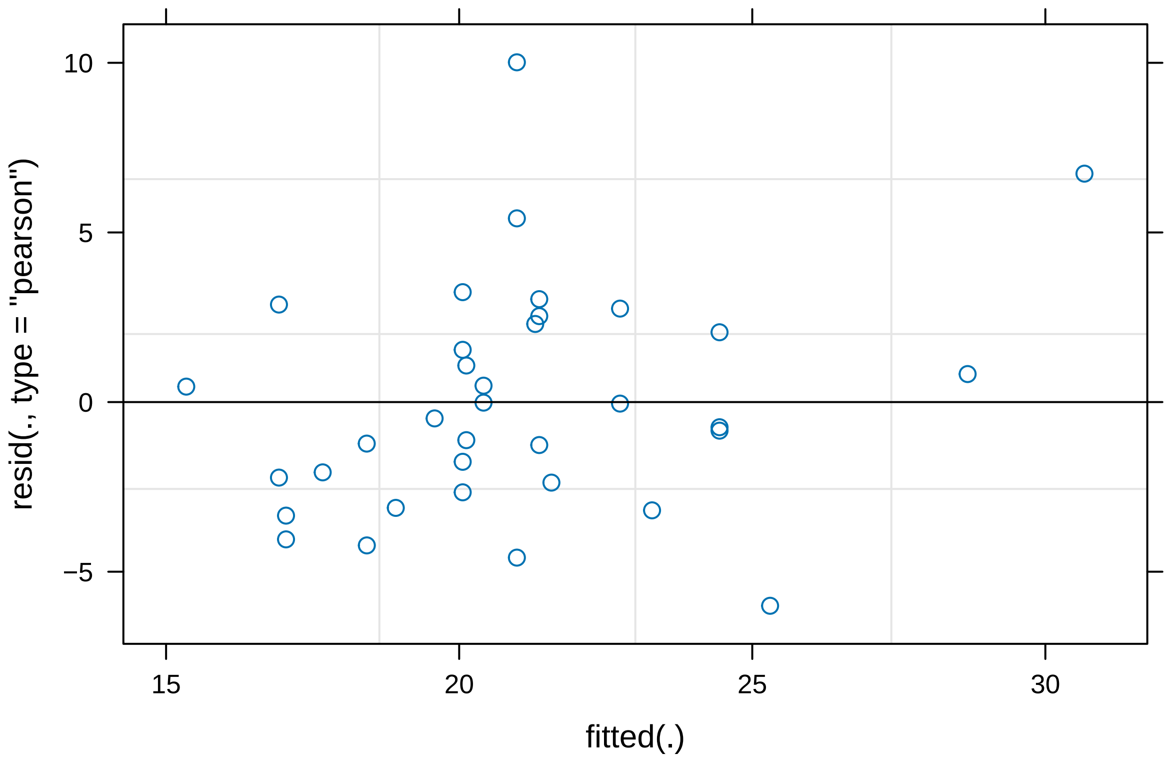


Figure 15: Residual Plot for REE per KG model

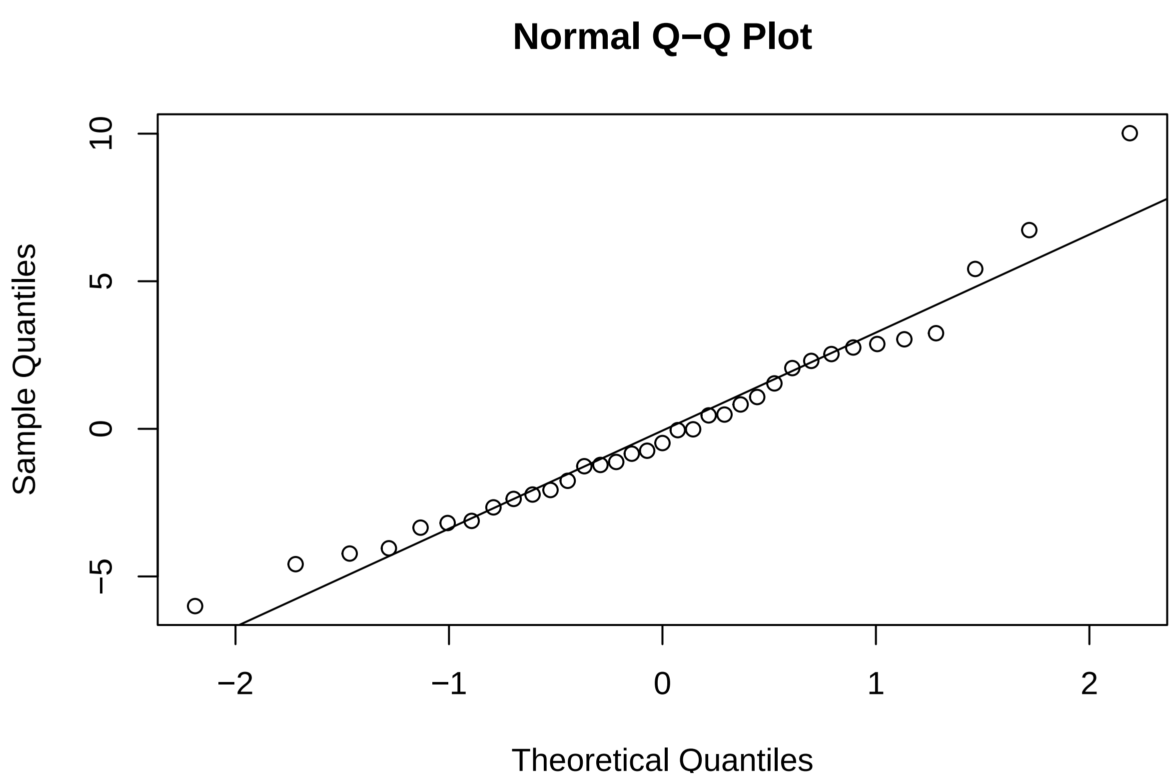


Figure 16: QQ Plot for REE per KG model

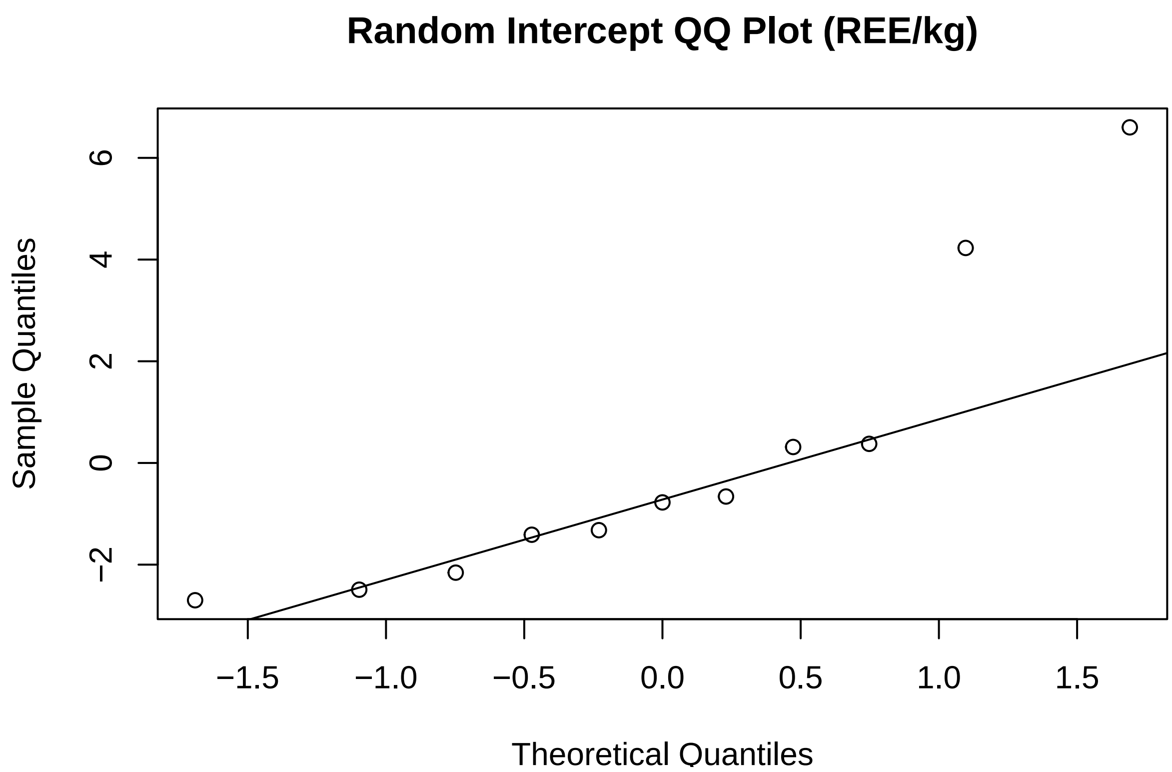
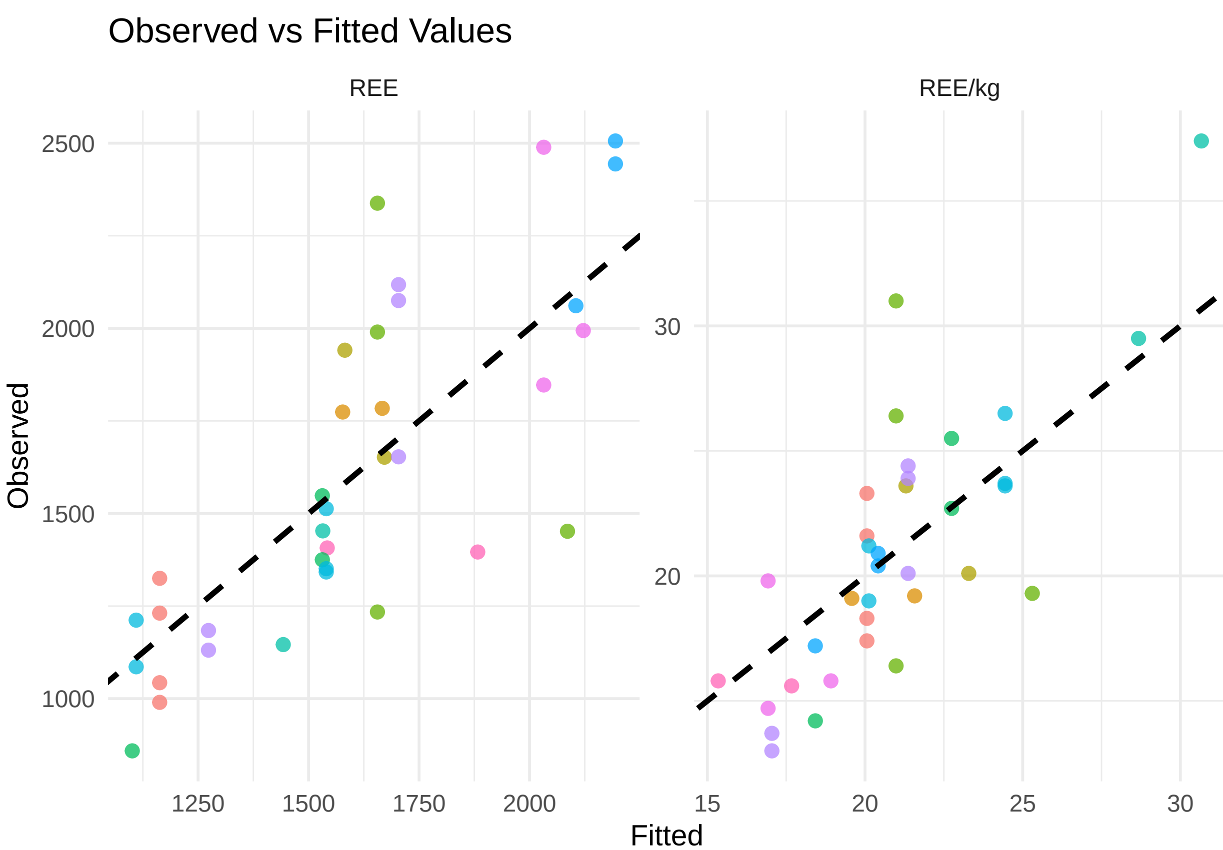


Figure 17: Random Intercept QQ Plot for REE per KG model



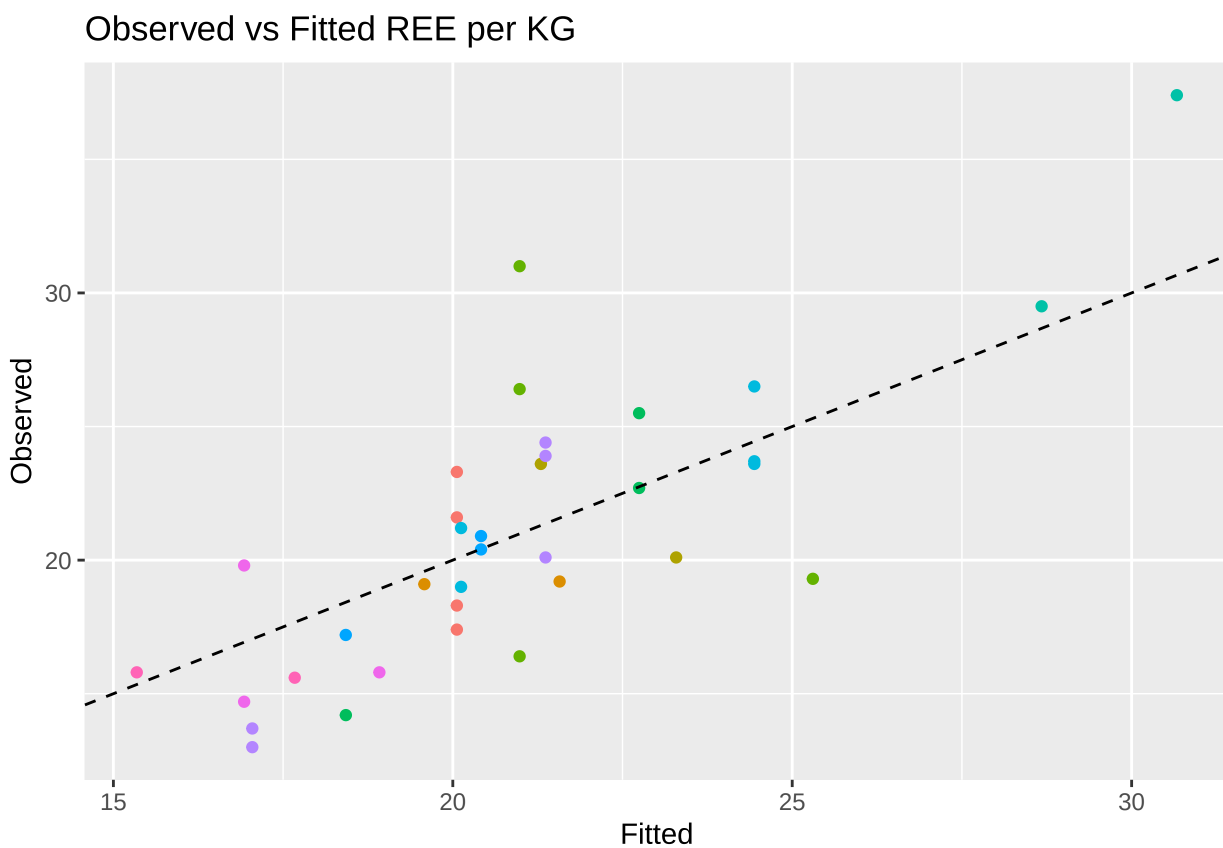


Figure 18: bserved vs Fitted REE per KG by Patient ID