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Supplementary material – Cross validation results of using presented models to predict high resource demand days (HRDs)

High-severity wildfire potential – associating meteorology, climate, resource demand and wildfire activity with preparedness levels

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Results

Cross validation of *high resource demand models*

The absolute and relative ability of the models to predict future high resource demand days (HRDs) is assessed using cross validation with RMSE as a measure of performance. At the National scale, RMSE is lowest in the information-rich model (0.23) and saturated model (0.43), and highest in the meteo-only model (0.51). At the Northwest scale, the RMSE is again lowest in the information-rich model (0.26) and saturated model (0.31), and highest in the meteo-only model (0.32) (Fig. S1).

The relative ability of the models to predict HRD days (i.e., preparedness level four or five) varies by geographic scale and data scenario. At the National scale, only information-rich models outperform the naïve model on average. Nearly all of the folds (32 of 35) of the simulation result in a lower RMSE in the information-rich model than in the naïve model, and the RMSE is on average 21 % smaller in the former than in the latter. The conditional expected difference in RMSE is -24 % in folds favoring the information-rich model and is +9 % in folds favoring the naïve model. Although the saturated model outperforms the naïve model for a majority of folds (23 of 35), the RMSE is expected to be 1 % larger in the former than in the latter. The conditional expected difference in RMSE is -22 % in folds favoring the saturated model and is +43 % in folds favoring the naïve model. The meteo-only models exhibit lower skill than the saturated models. The meteo-only models outperform the naïve model for approximately half of the folds (17 of 35), but still the RMSE is expected to be 31 % larger in the meteo-models. The conditional expected difference in RMSE is -9% in folds favoring the meteo-only model but is +68% in folds favoring the naïve model.

At the Northwest scale, only the information-rich models outperform the naïve model on average. In the majority of the folds (28 out of 35) the information-rich model has a smaller RMSE than the naïve model, and on average the RMSE is 12% smaller in the information-rich model. The conditional expected difference in RMSE is -18% in folds favoring the information-rich model but is +11% in folds favoring the naïve model. The meteo-only model to outperforms the naïve model in a majority of folds (23 out of 35). The meteo-only model has a smaller RMSE than the naïve model in these folds but, on average, the RMSE is 2% larger in the meteo-only model. The conditional expected difference in RMSE is -4% in folds favoring the meteo-only model but is +12% in folds favoring the naïve model. The saturated model performs even worse than the meteo-only model. Only 11 out of 35 folds favor the saturated model, and the RMSE is 20% larger in the saturated model than in the naïve model. The conditional expected difference in RMSE is -14 % in folds favoring the saturated model but is +36 % in folds favoring the naïve model. (Fig. S2).

Fig. S1. Histogram of simulation results for preparedness level models under saturated, information-rich, and meteo-only scenarios for National and Northwest scales. The distribution of raw RMSEs produced by the resampling procedure is represented with a histogram (across the 35 folds), while the average is indicated by a black dot.

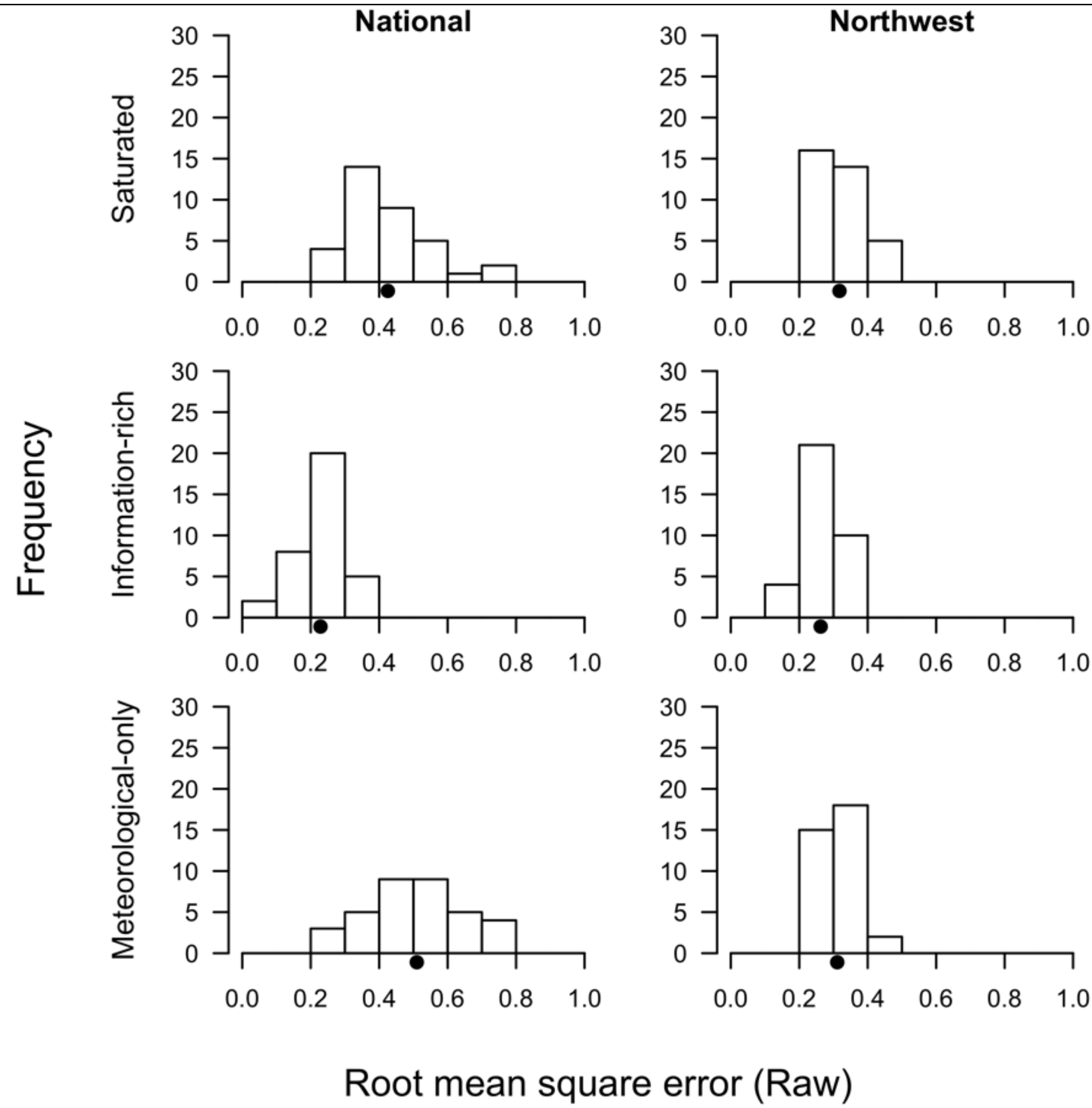
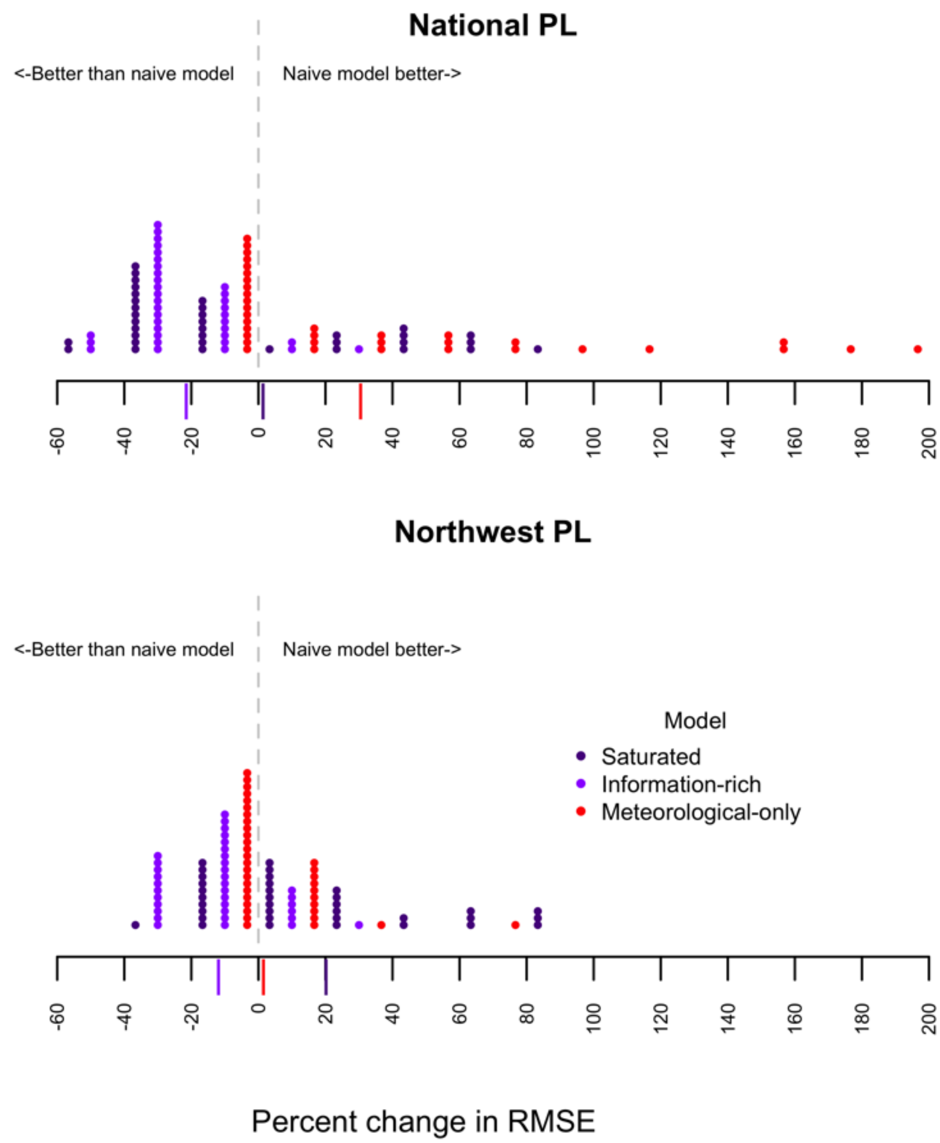


Fig. S2. Simulation results for logit models predicting days with high-resource demand. The dot plots represent the distribution of the percent difference in root mean square error between each model and the naïve model. Vertical lines below the x-axis indicate the mean percent change in root mean squared error across the simulation. Note: relative location of dot stacks within the x-axis bins is simply for graphical convenience.



Regression Diagnostics

The variance inflation factor (VIF) is used to measure the severity of multicollinearity. The car package is used to calculate the VIF for each model coefficient. Values above five are typically associated with high multicollinearity.

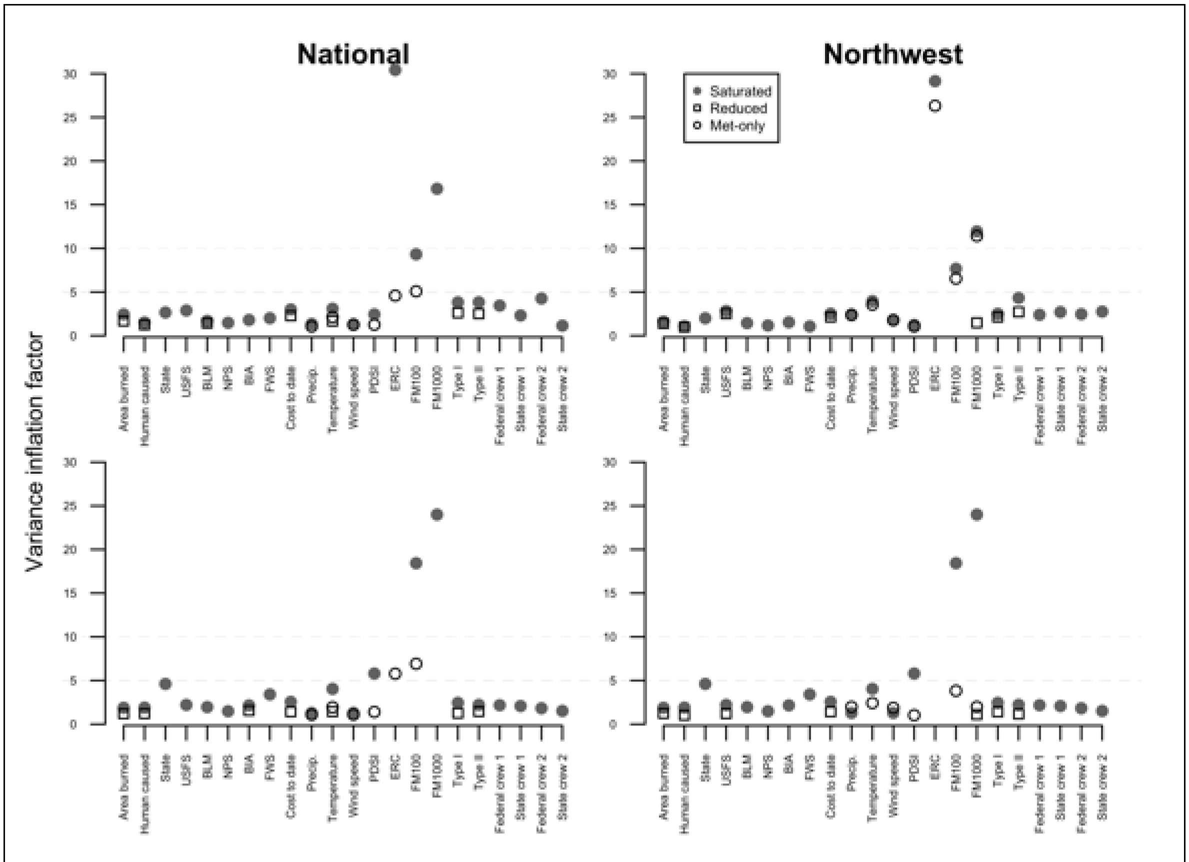


Figure S3. Variance inflation factors for 12 models (2 regions x 3 model classes x 2 responses).

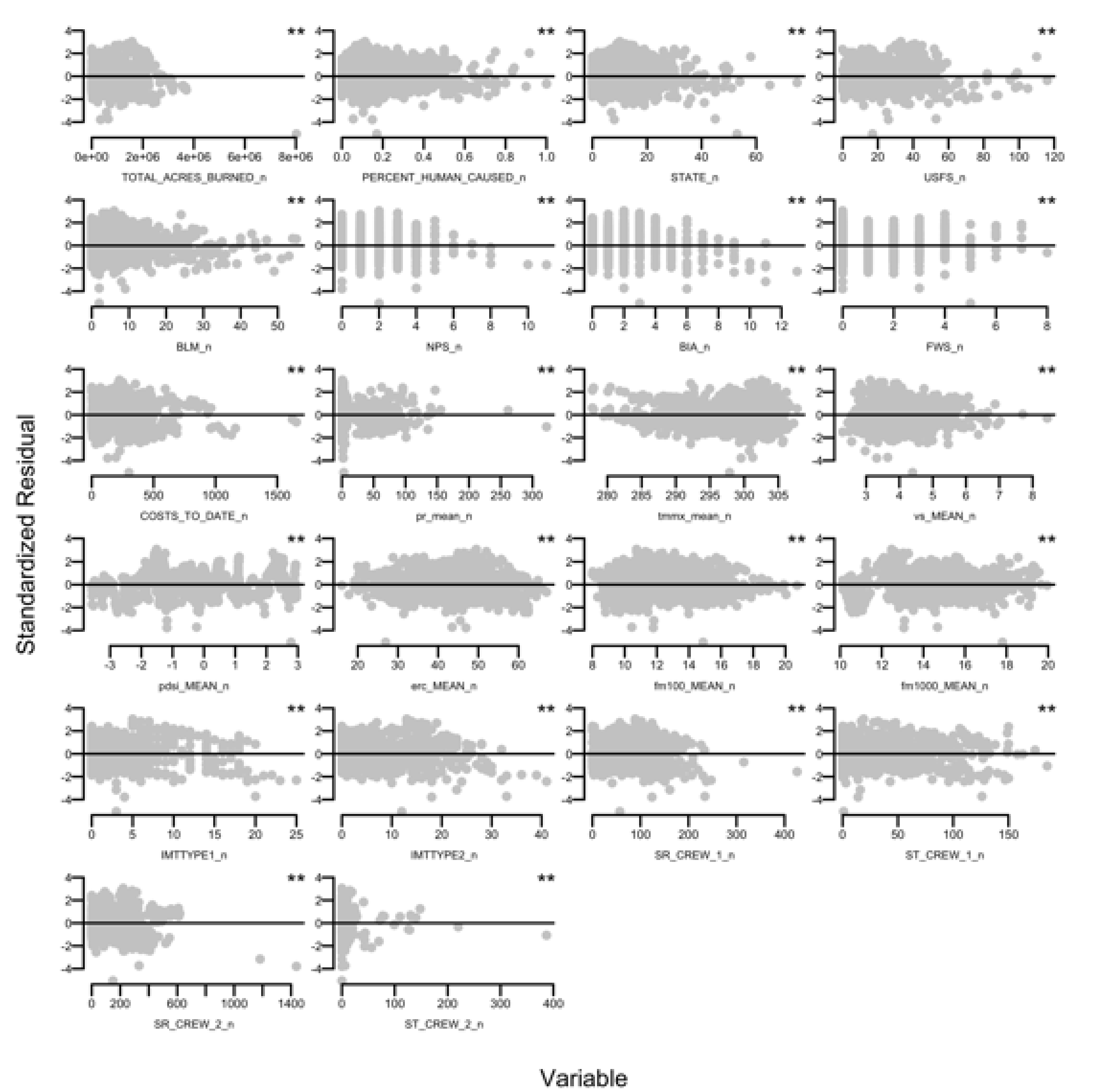


Figure S4. Residuals of national linear full model.

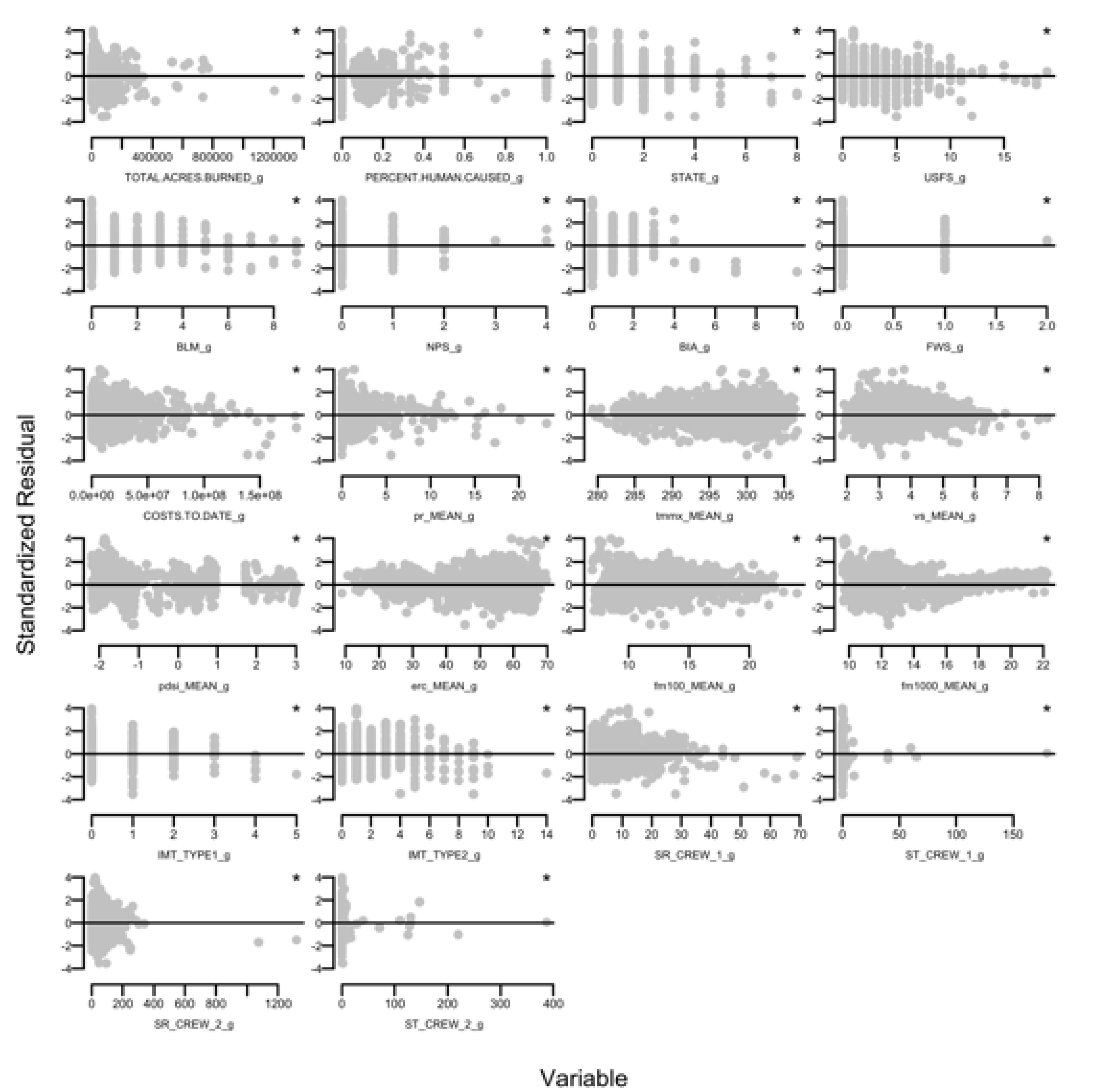


Figure S5. Residuals of Northwest linear full model.

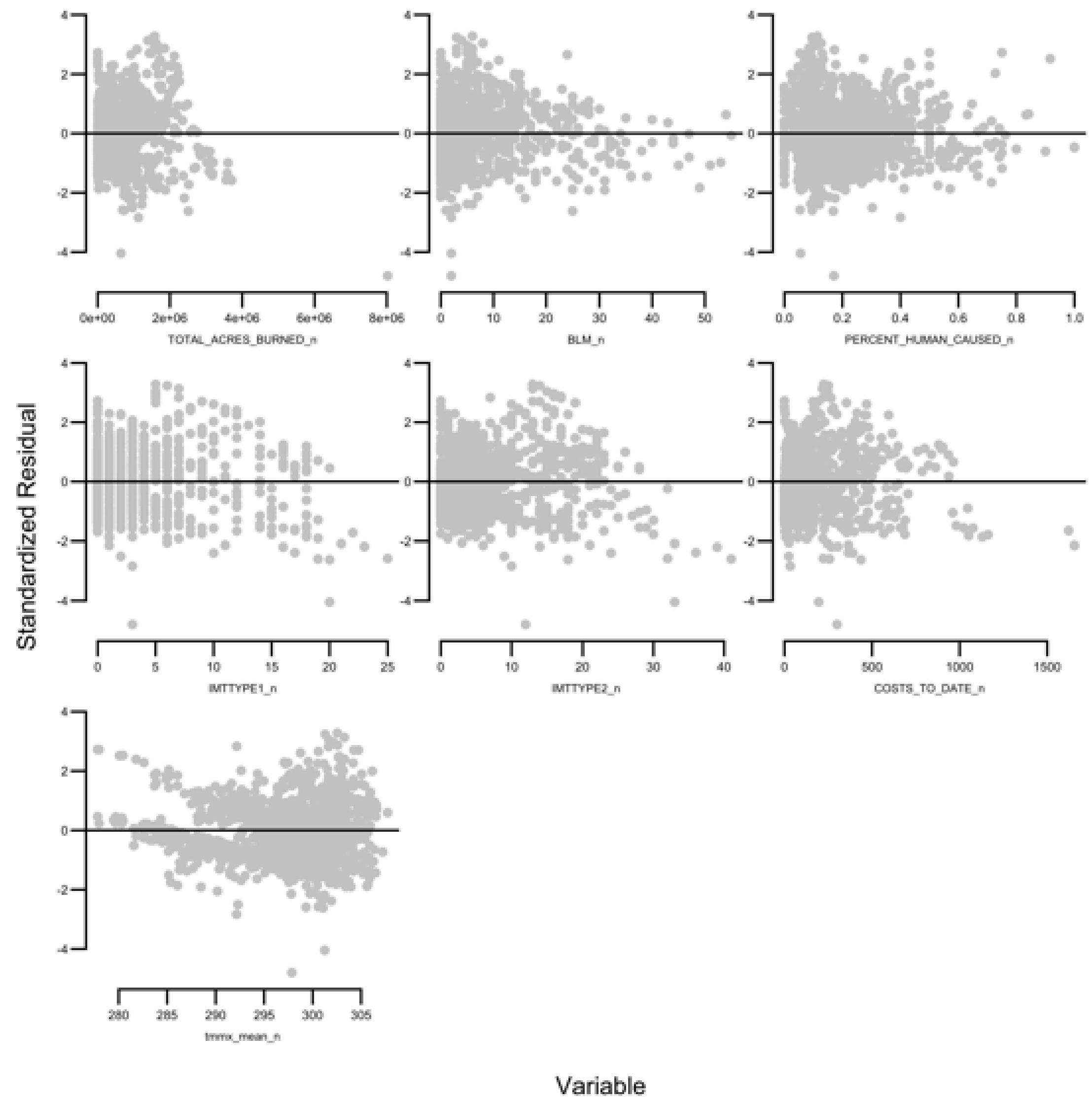


Figure S6. Residuals of National linear reduced model.

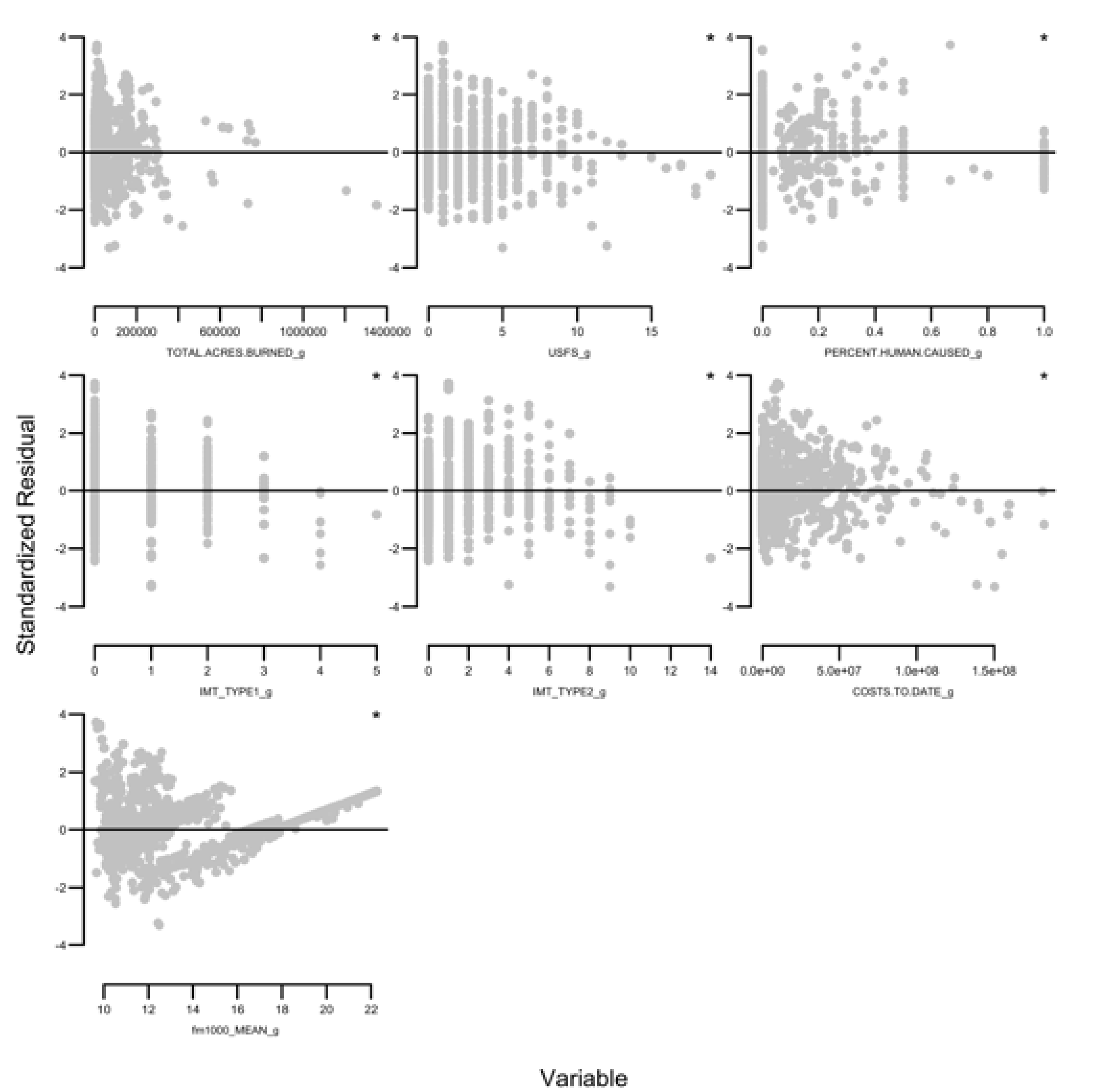


Figure S7. Residuals of Northwest linear reduced model**.**

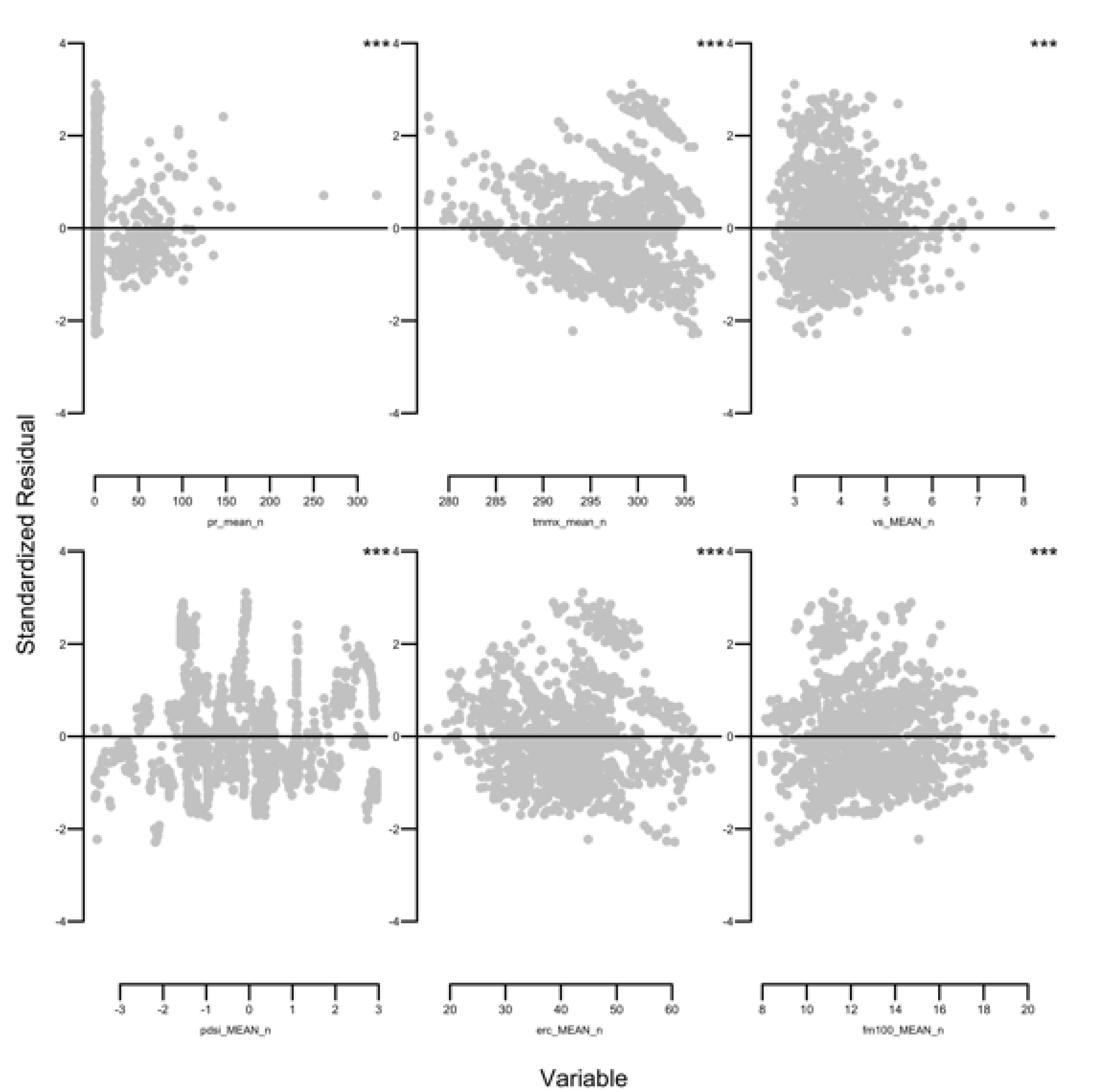


Figure S8. Residuals of National linear met-only model.

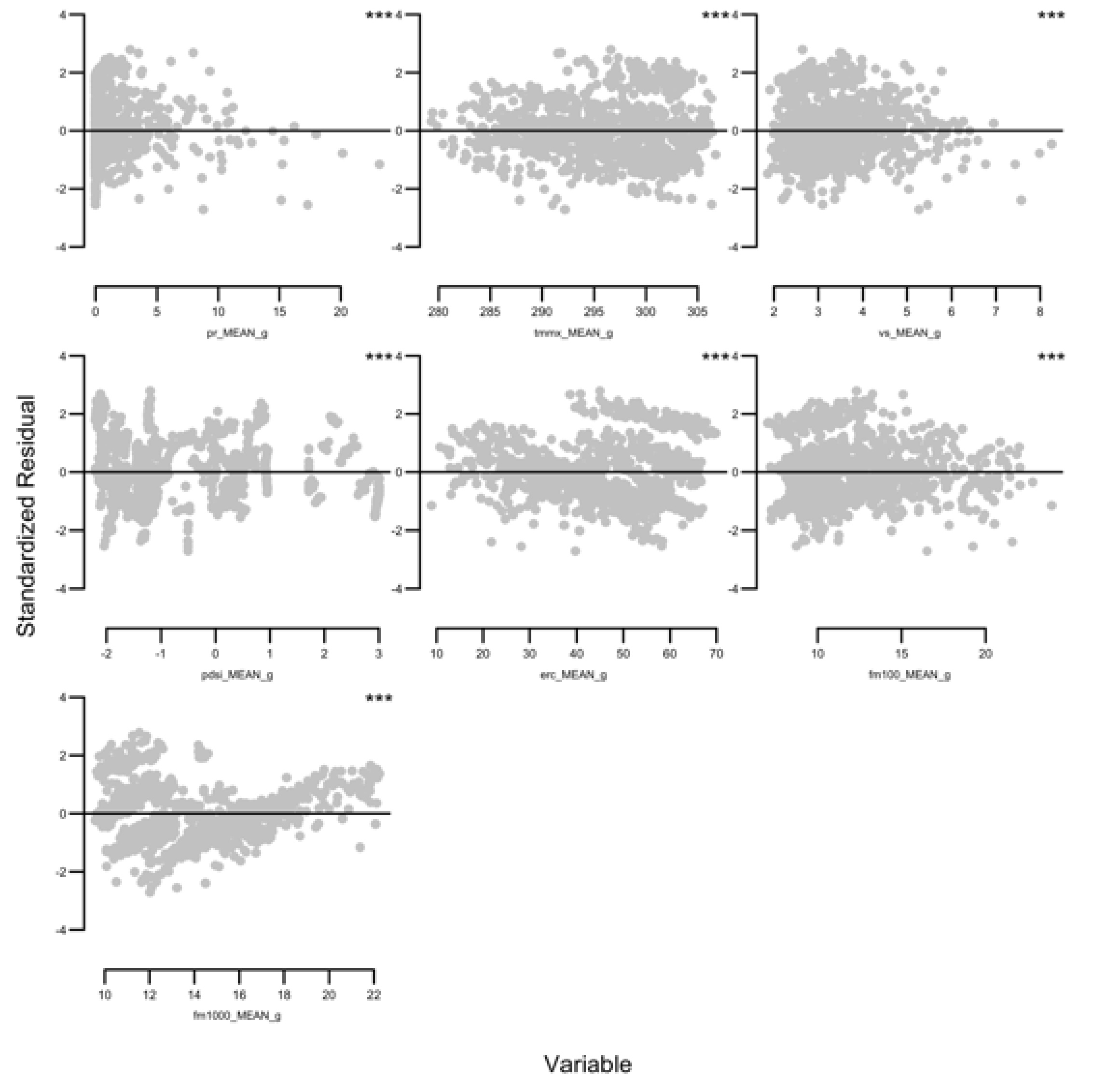


Figure S9. Residuals of Northwest linear met-only model.

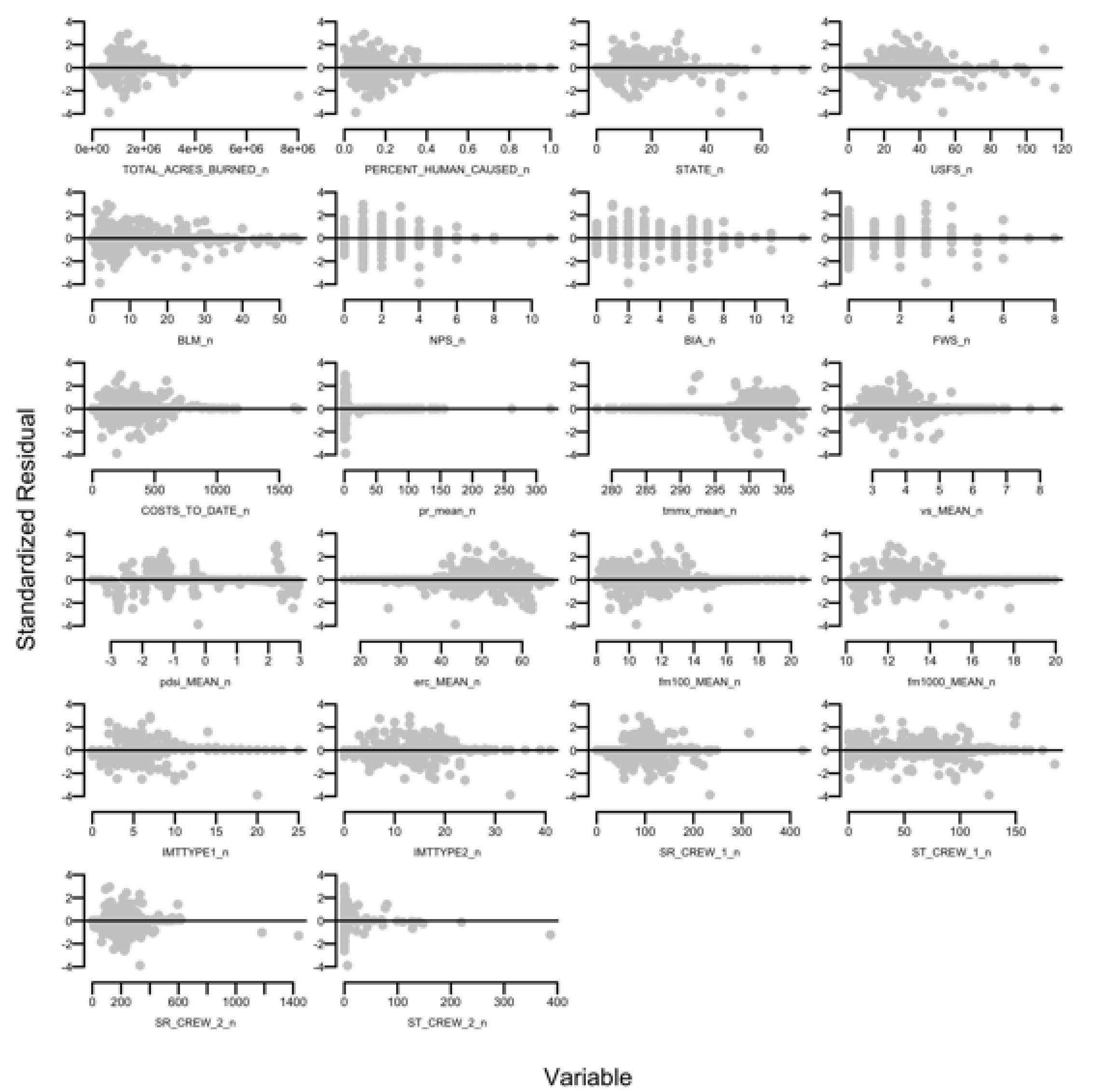


Figure S10. Residuals of National logit full model.

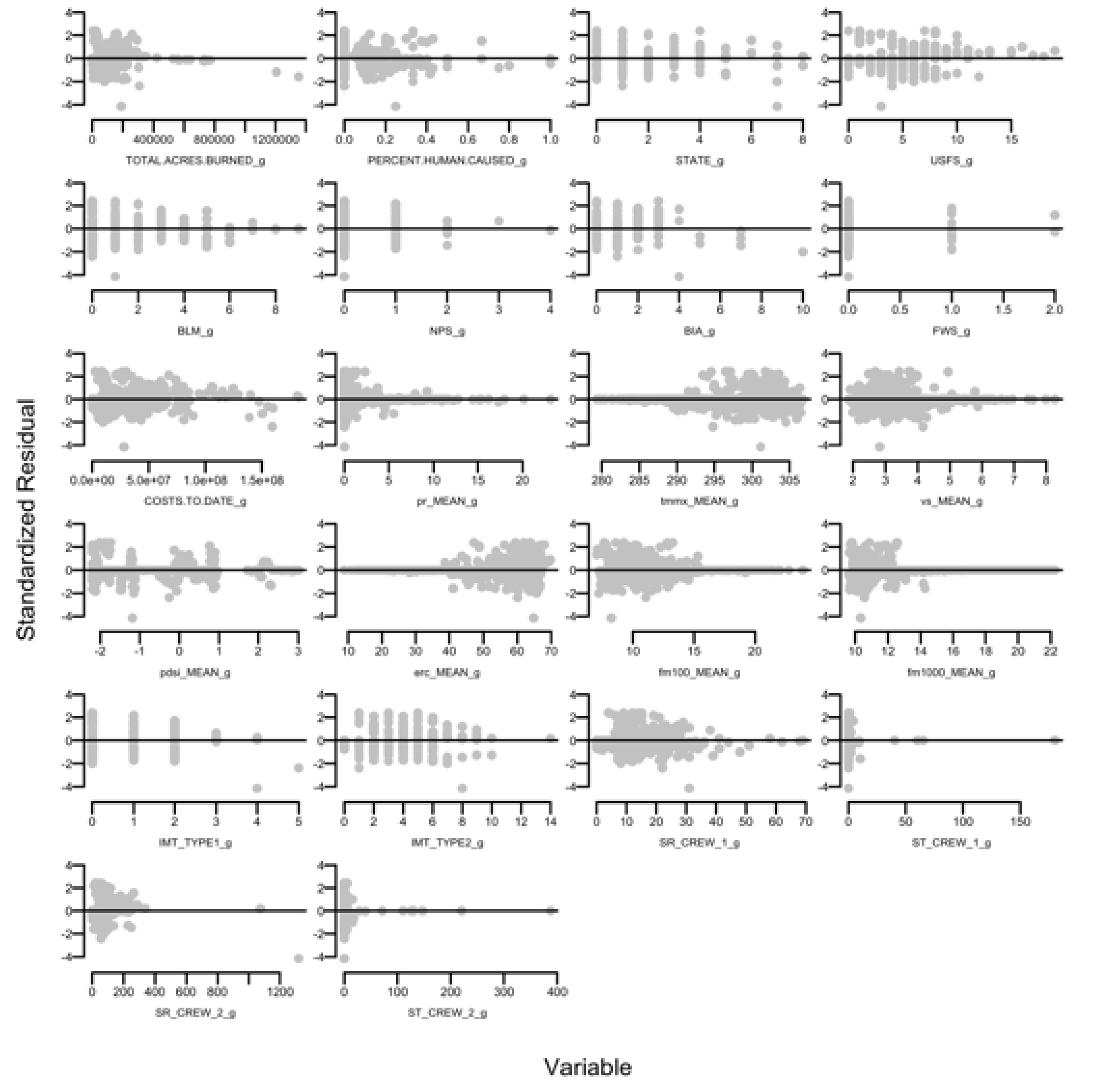


Figure S11. Residuals of Northwest logit reduced model.

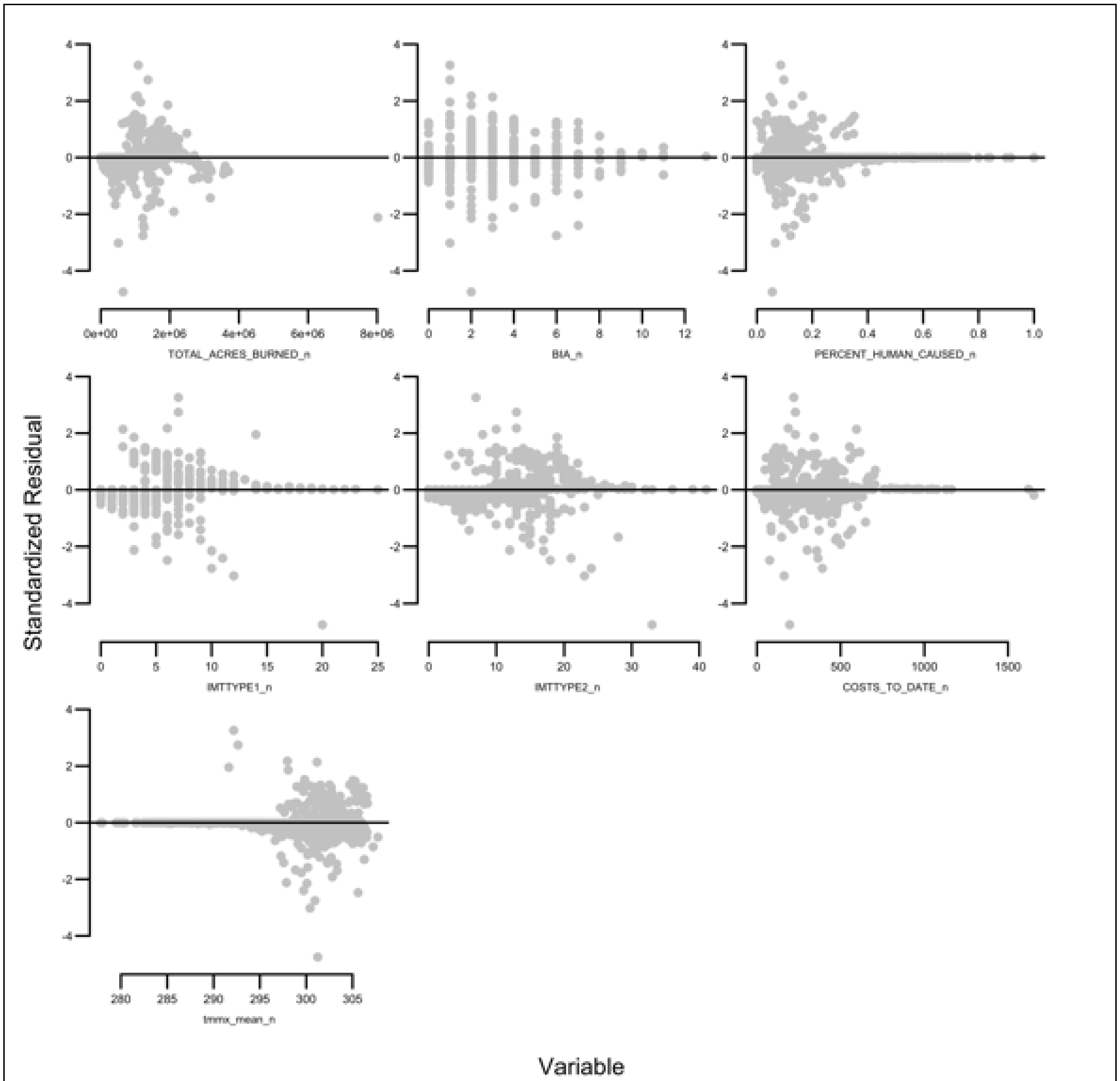


Figure S12. Residuals of National logit reduced model.

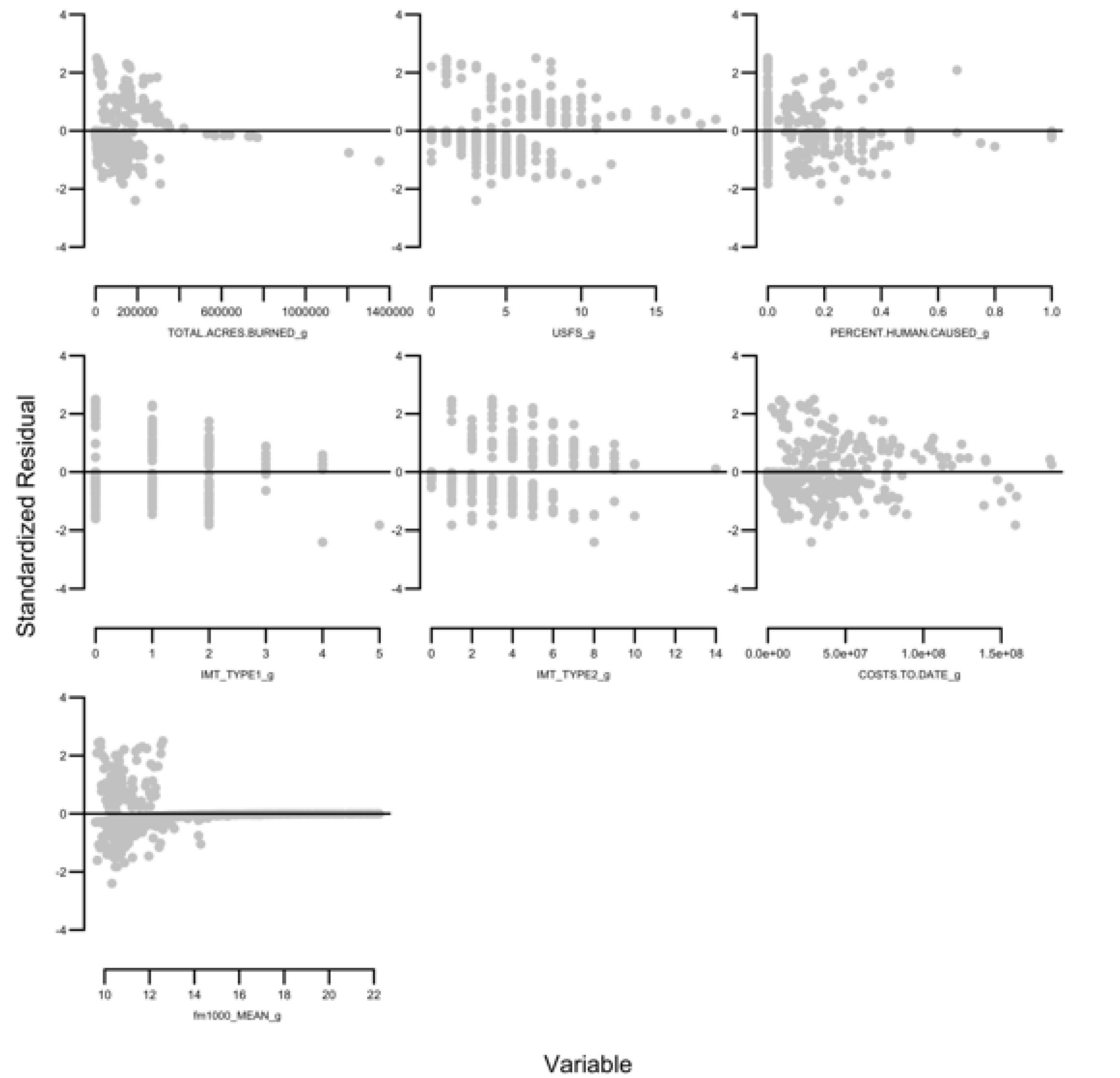


Figure S13. Residuals of Northwest logit reduced model.

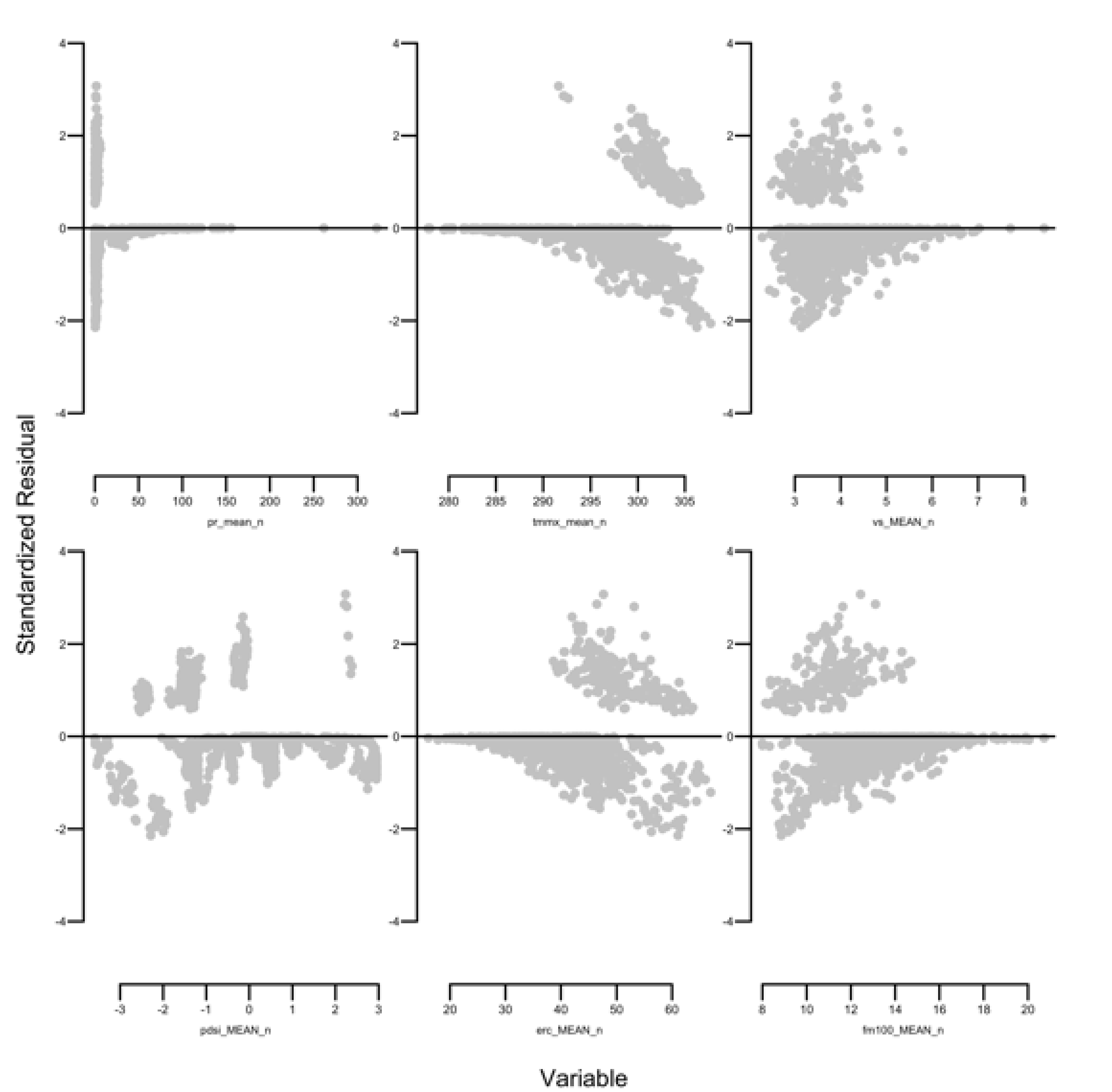


Figure S14. Residuals of National logit met-only model.

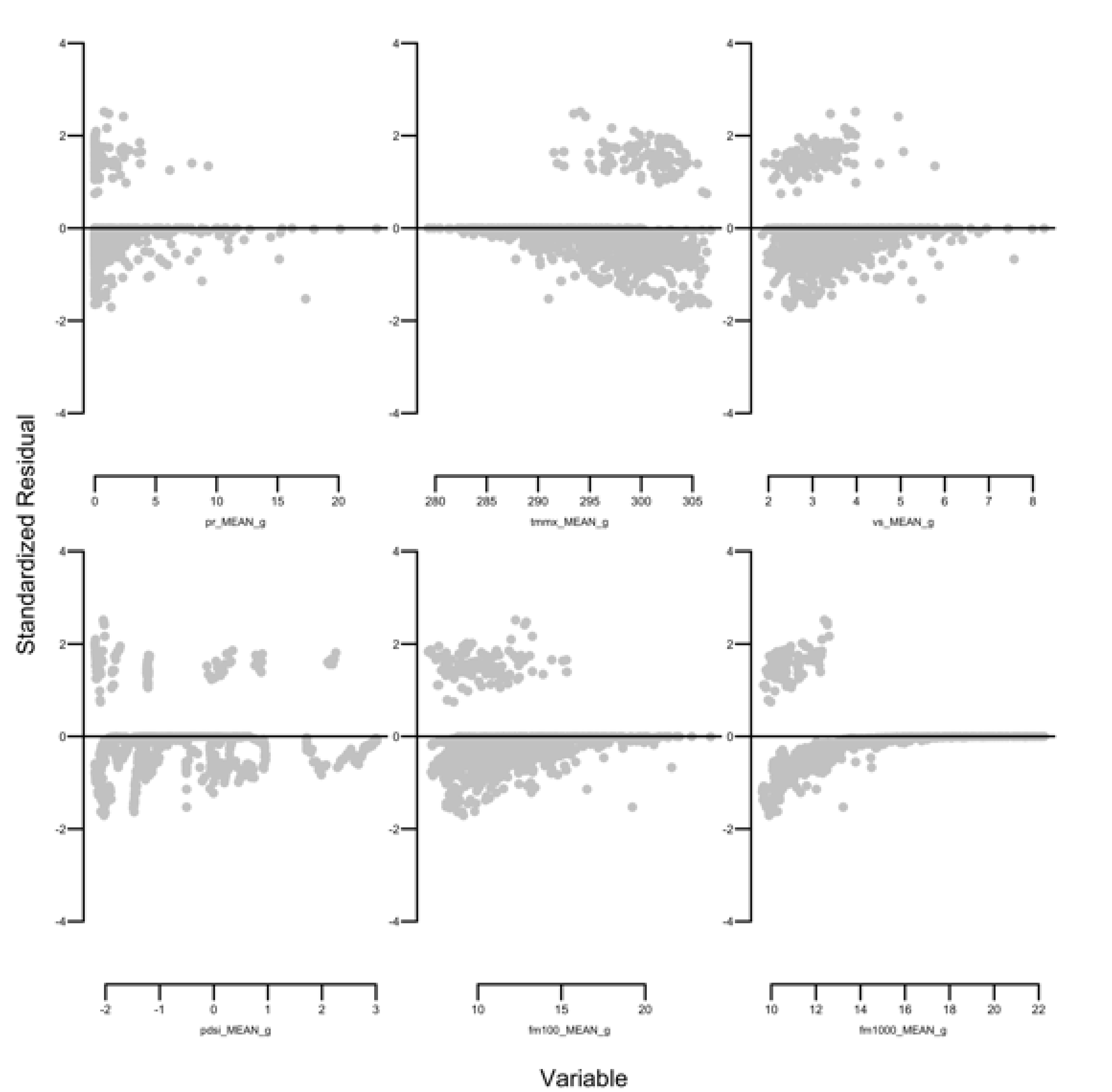


Figure S15. Residuals of Northwest logit met-only model.