

Downscaling Groundwater Storage Data in China to a 1-km Resolution Using Machine Learning Methods

Jianxin Zhang ^{1,2,3}, Kai Liu ^{1,2,3,*} and Ming Wang ^{1,2,3}

¹ *State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal*

University, 100875 Beijing, China

² *Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal*

University, Beijing 100875, China

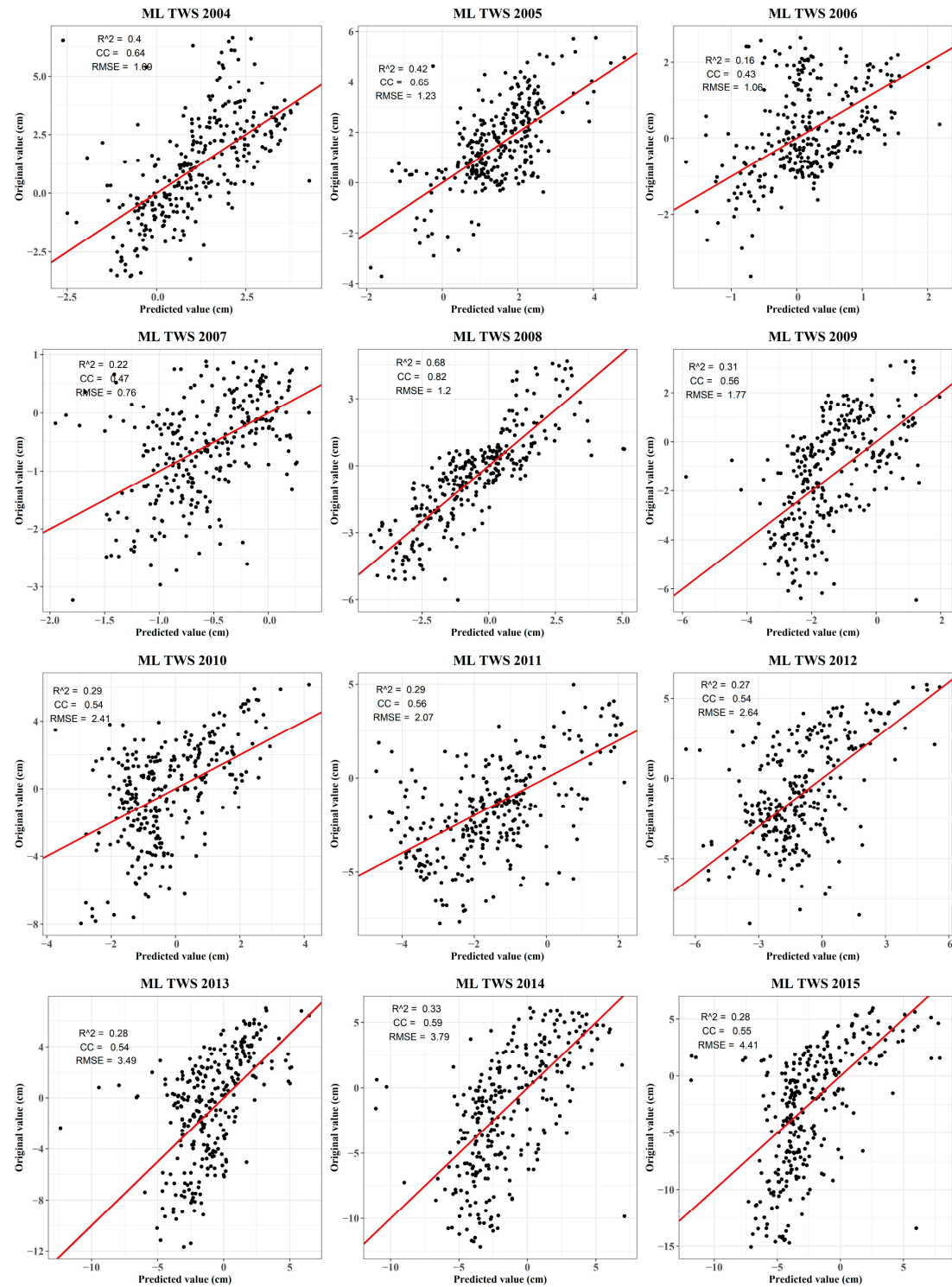
³ *Academy of Disaster Reduction and Emergency Managemen, Beijing 100875, China*

* Address correspondence to Kai Liu, State Key Laboratory of Earth Surface Processes and Resource Ecology,

Beijing Normal University, #19 Xijiekou Wai Ave., Beijing 100875, China; liukai@bnu.edu.cn

Before performing machine learning methods, we have tried multiple linear (ML) regression methods. Figures S1 and S2 give the scatter plots and the accuracy metrics for each year based on numerical variables. We found that the R^2 ranged from 0.16–0.68 for TWS and 0.09–0.46 for GLDAS. The correlation coefficient (CC)

ranged from 0.43–0.82 for TWS and 0.30–0.68 for GLDAS, whilst the RMSE ranged from 0.76–5.41 for TWS and 1.00–2.98 for GLDAS. The accuracy of the ML models in each year is low except 2008, and it can not be used for downscaling.



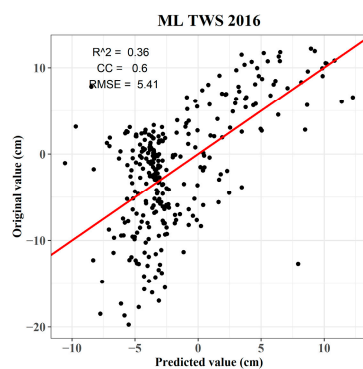
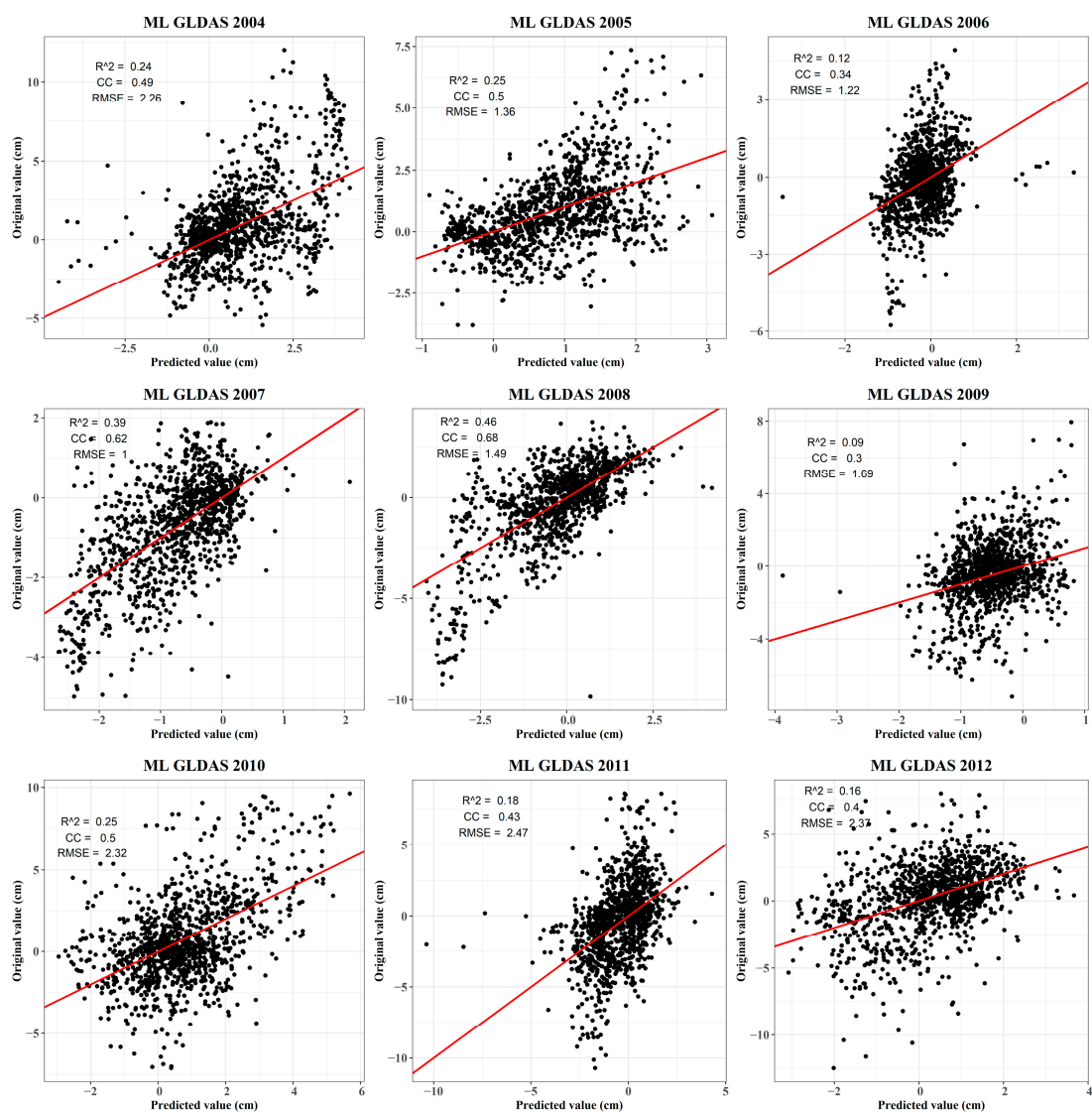


Figure S1. Scatterplots and regression fits of the testing dataset of TWS using multiple linear regression and the original dataset from 2004-2016.



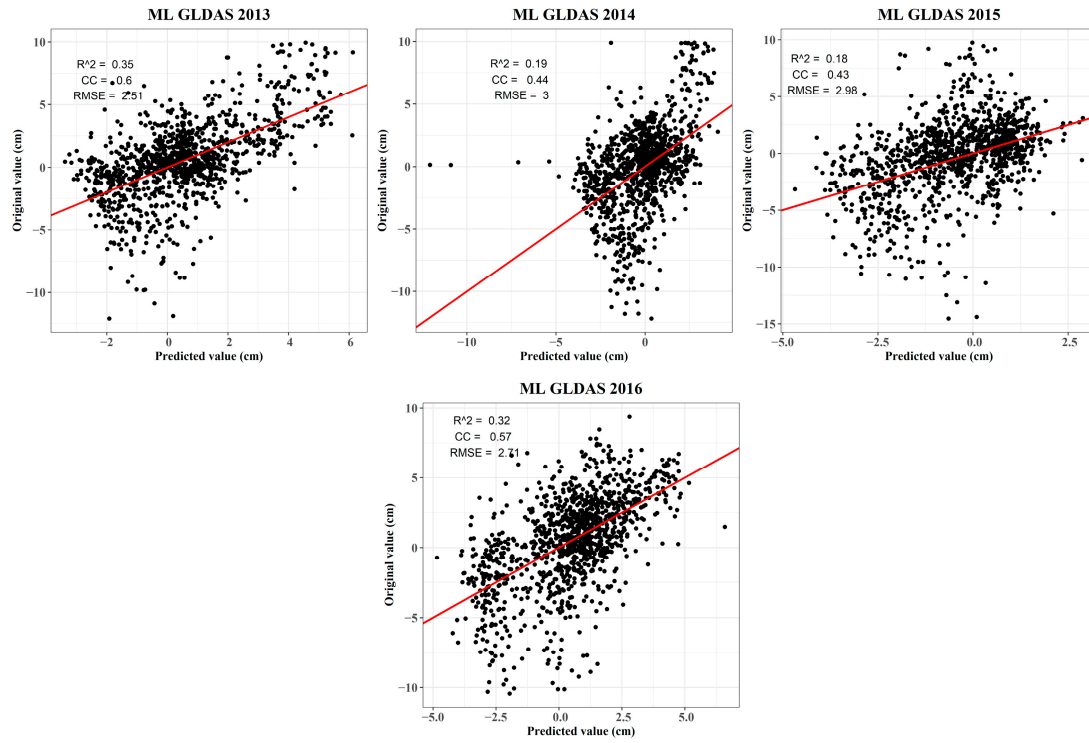


Figure S2. Scatterplots and regression fits of the testing dataset of GLDAS using multiple linear regression and the original dataset from 2004-2016.

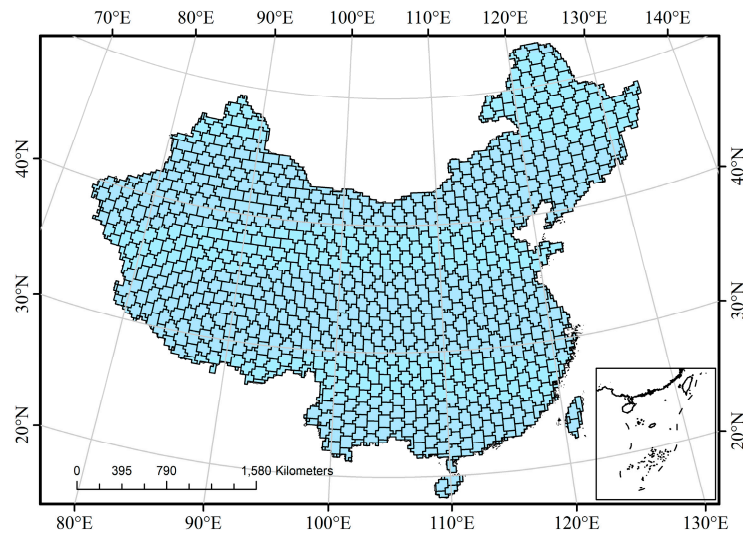
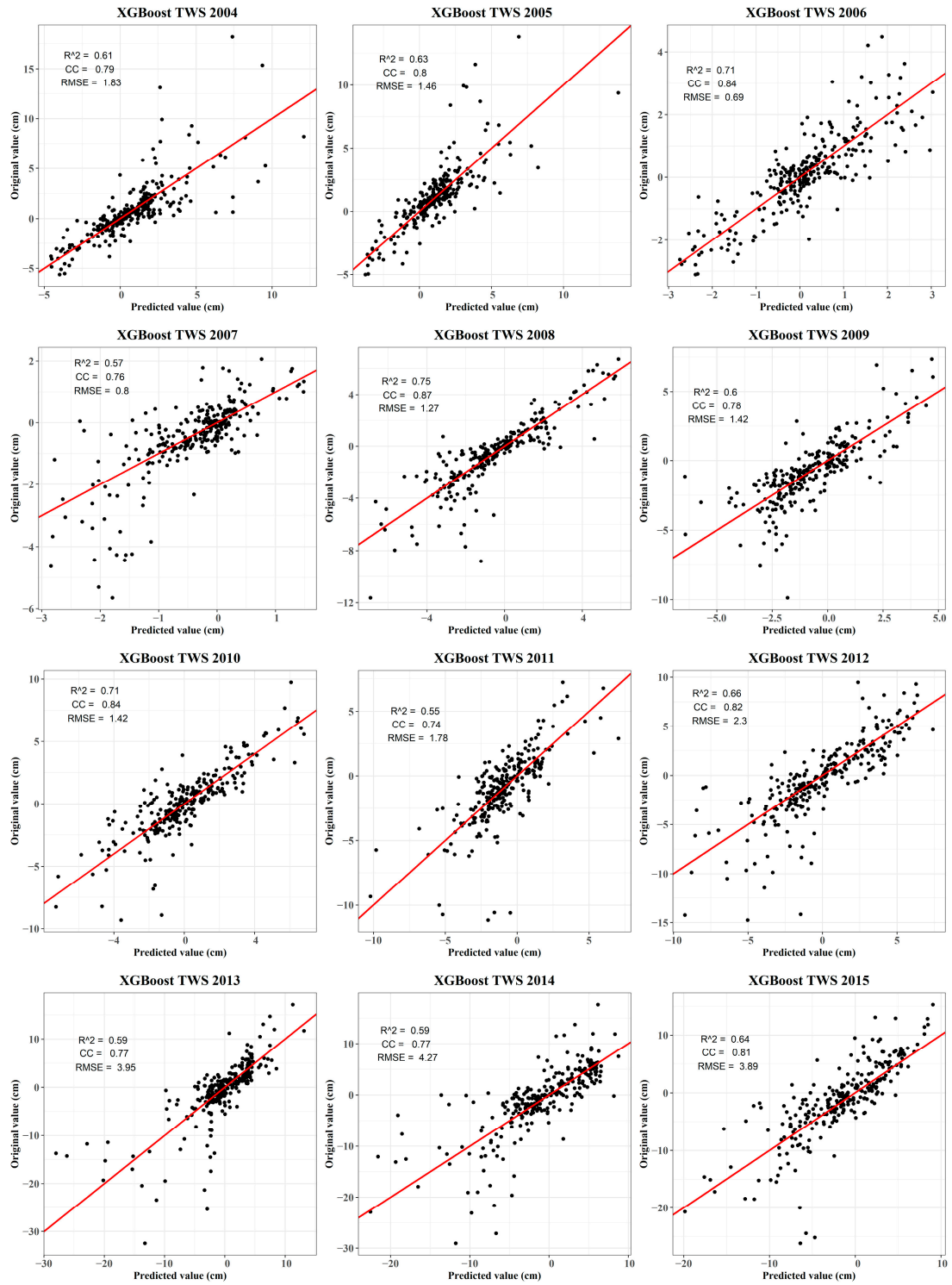


Figure S3 The spatial distribution of 906 clusters using mean shift clustering analysis based on monthly CSR-MS TWS.



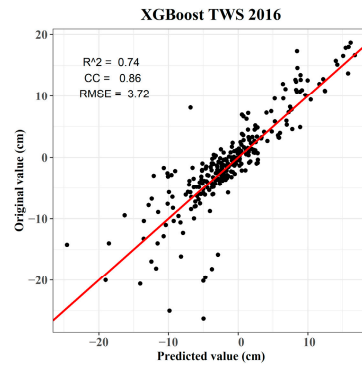
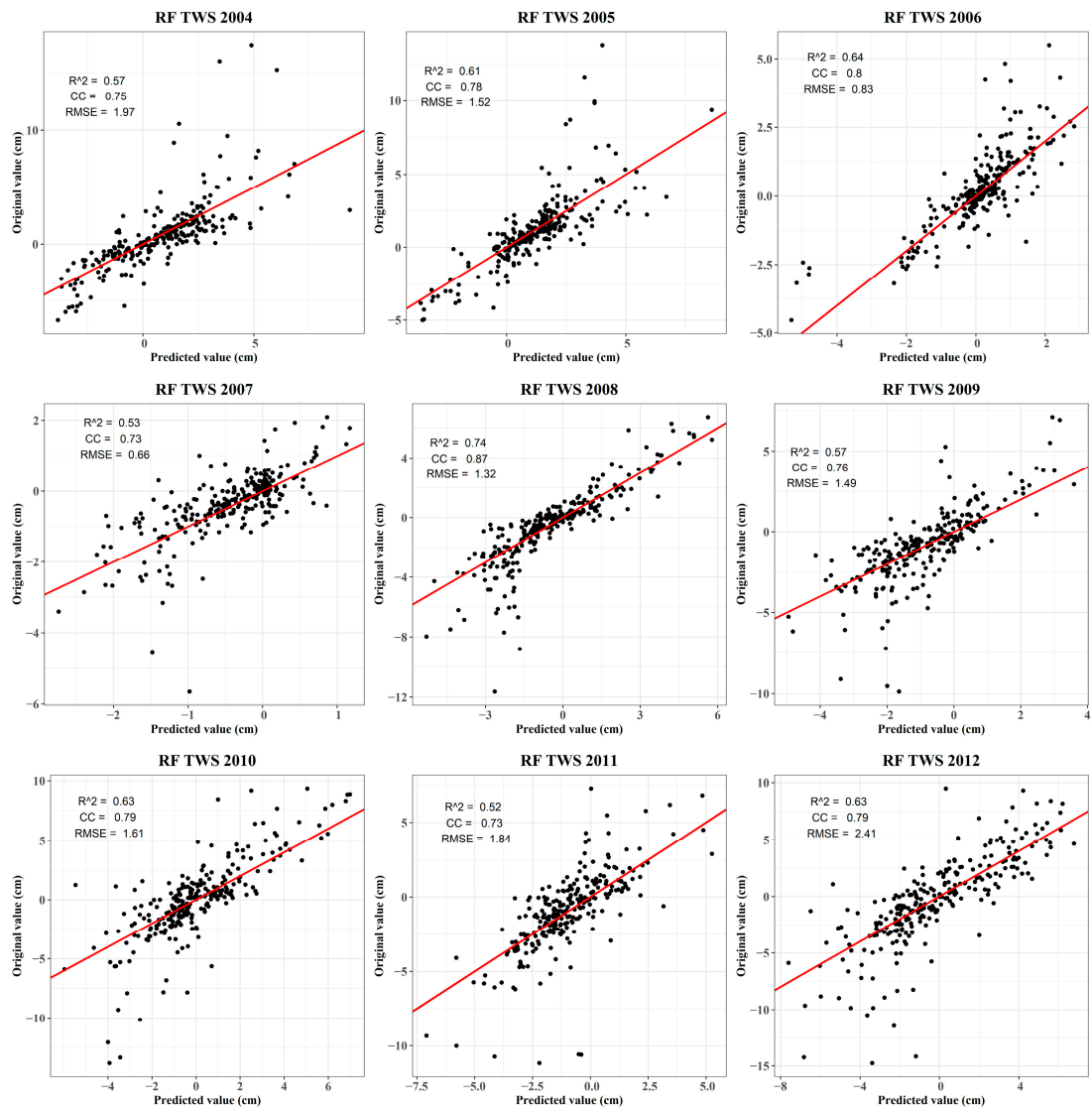


Figure S4 Scatterplots and regression fits of the testing dataset of TWS using XGBoost and the original dataset for 2004–2016 based on CSR-MS 906 clusters analysis.



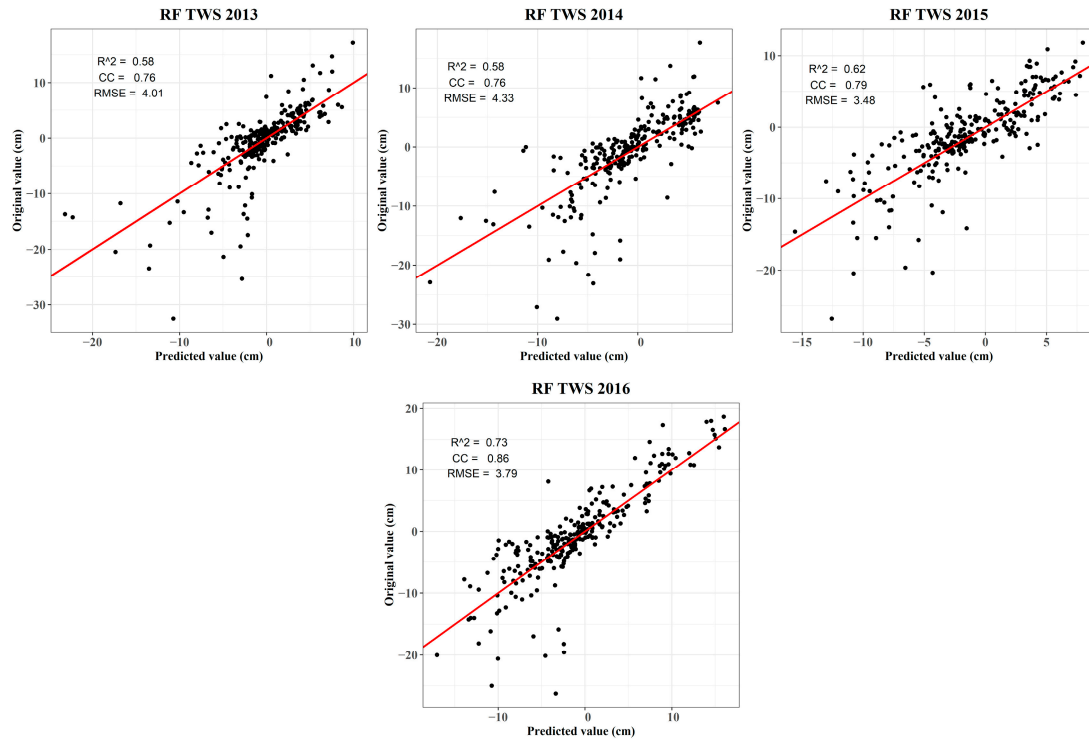
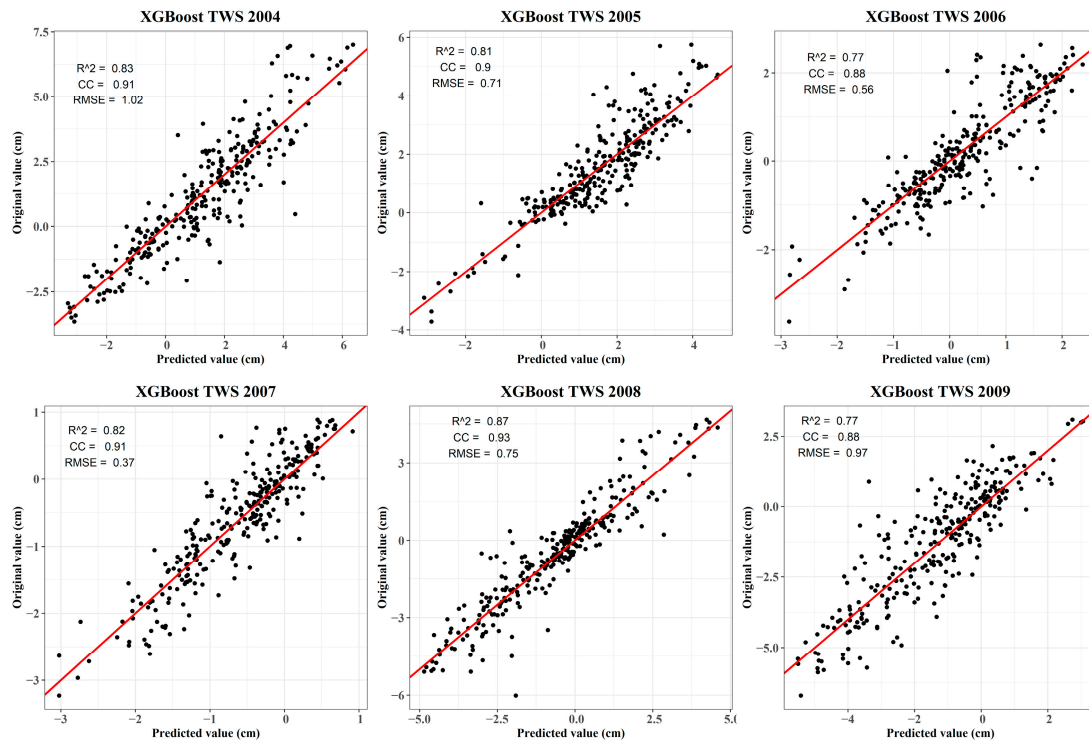


Figure S5 Scatterplots and regression fits of the testing dataset of TWS using RF and the original dataset for 2004–2016 based on CSR-MS 906 clusters analysis.

Figures S6–S13 give scatterplots and variable importance measures for TWS and GLDAS based on RF and XGBoost methods using CSR TELLUS GRACE data for 2004–2016.



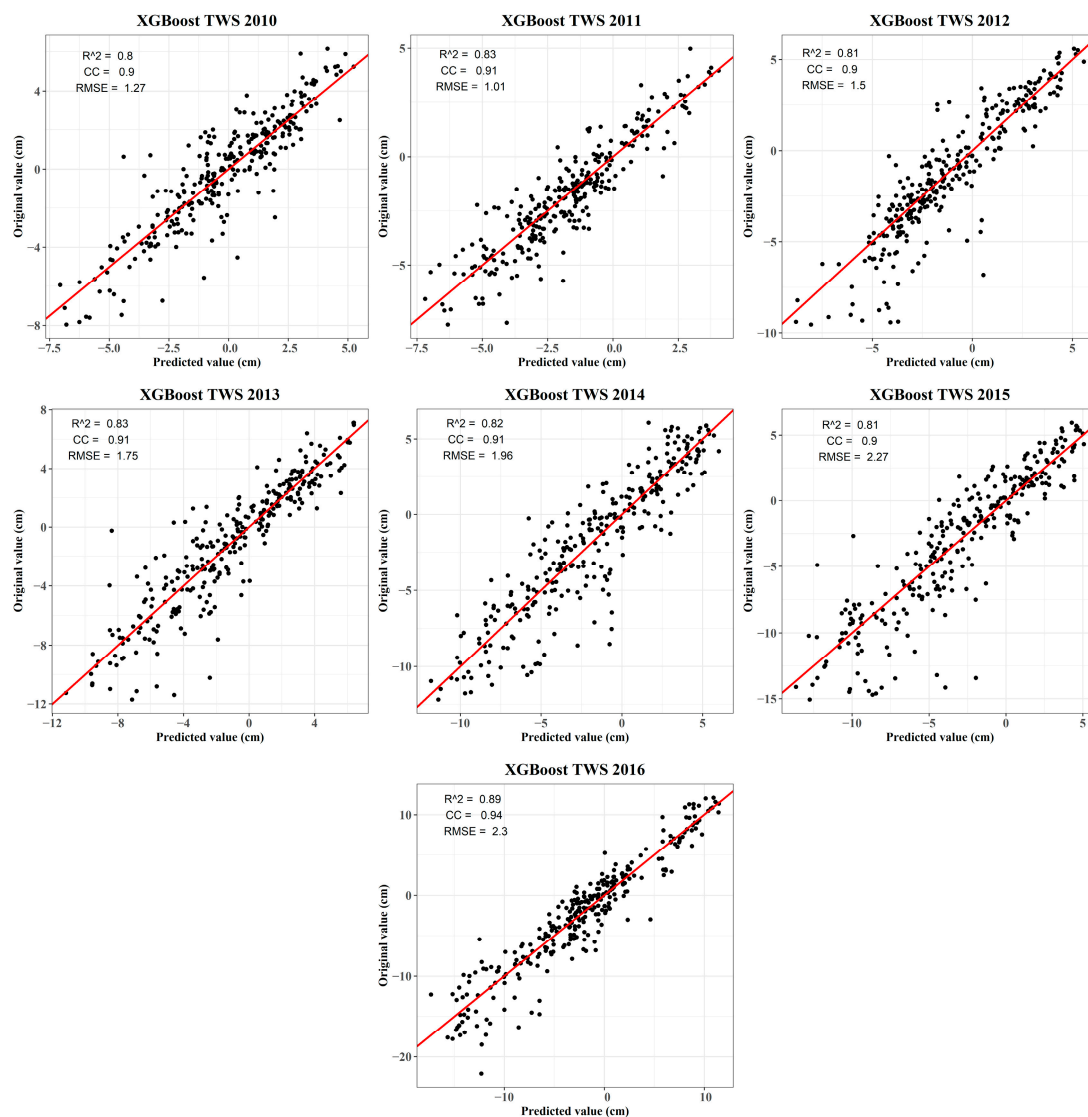
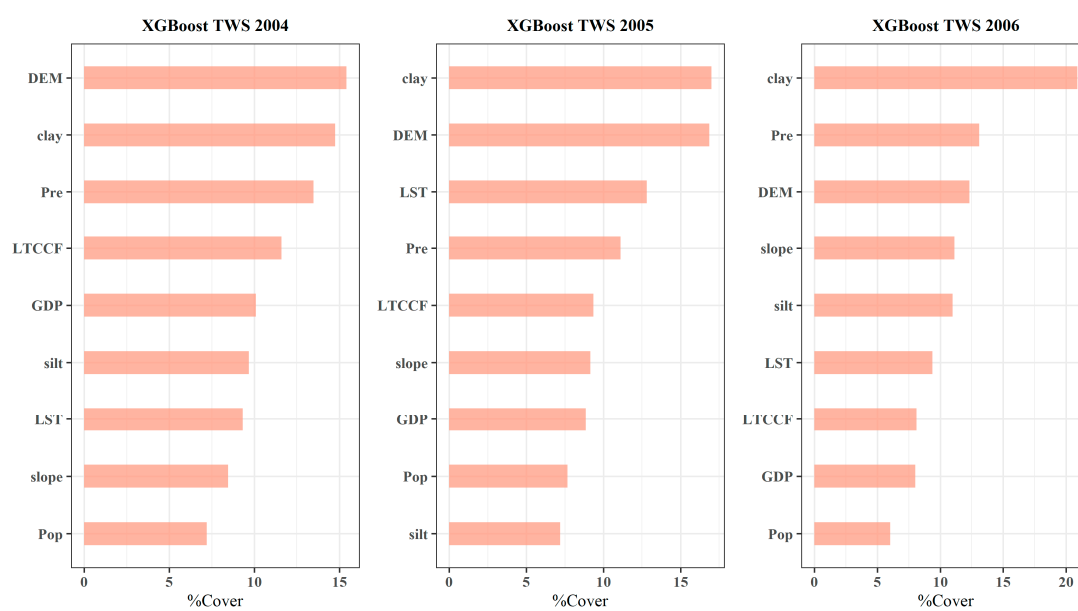


Figure S6 Scatterplots and regression fits of the testing dataset of TWS using XGBoost method.



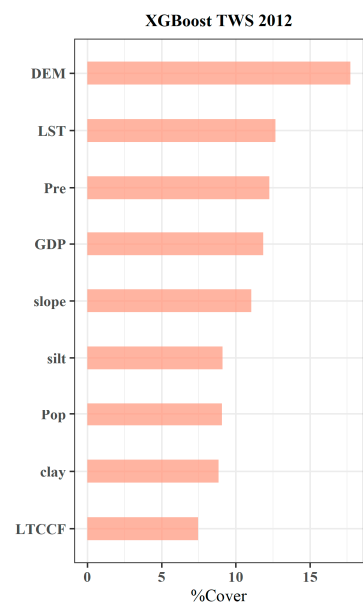
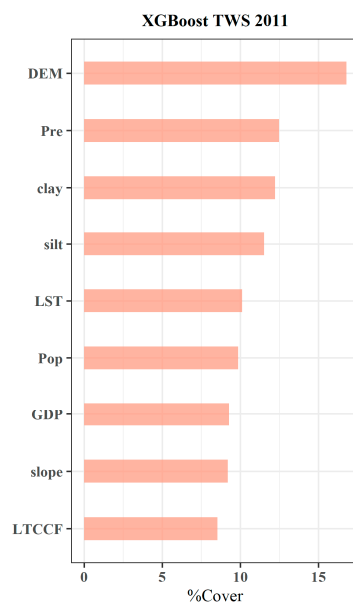
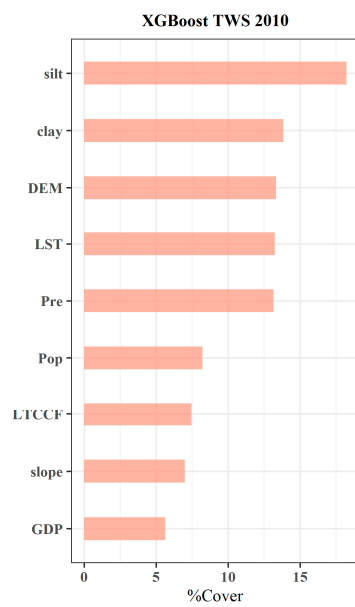
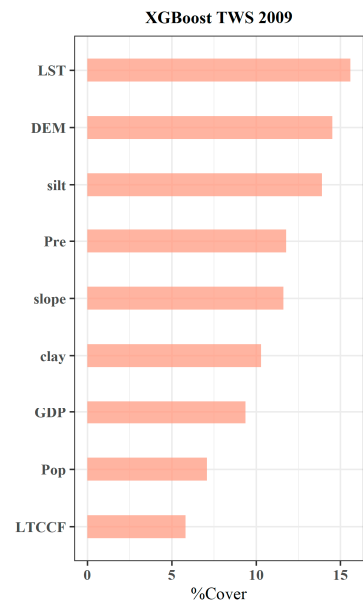
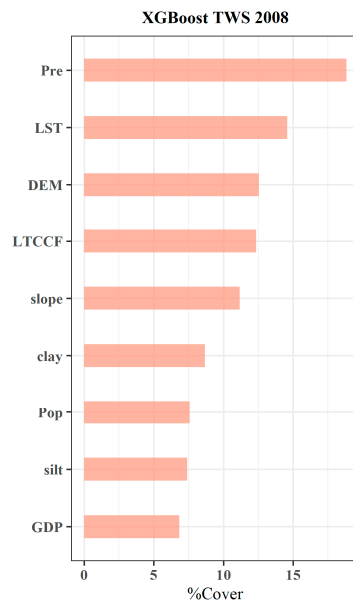
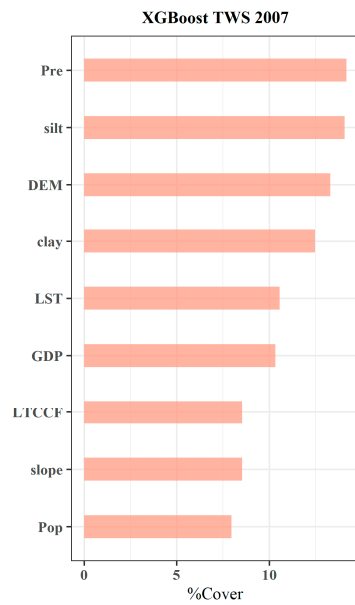
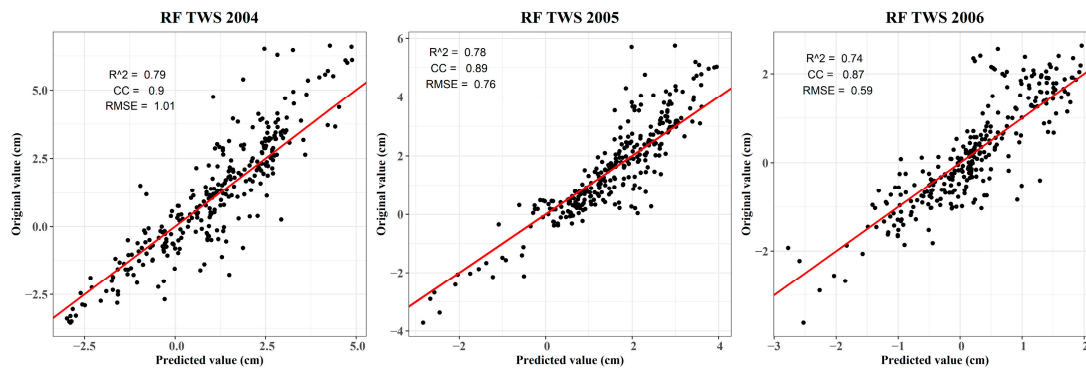




Figure S7 Plots of the variable importance measure (Cover metric of the number of observation related to this feature (%Cover)) for the XGBoost-modeled TWS from 2004-2016.



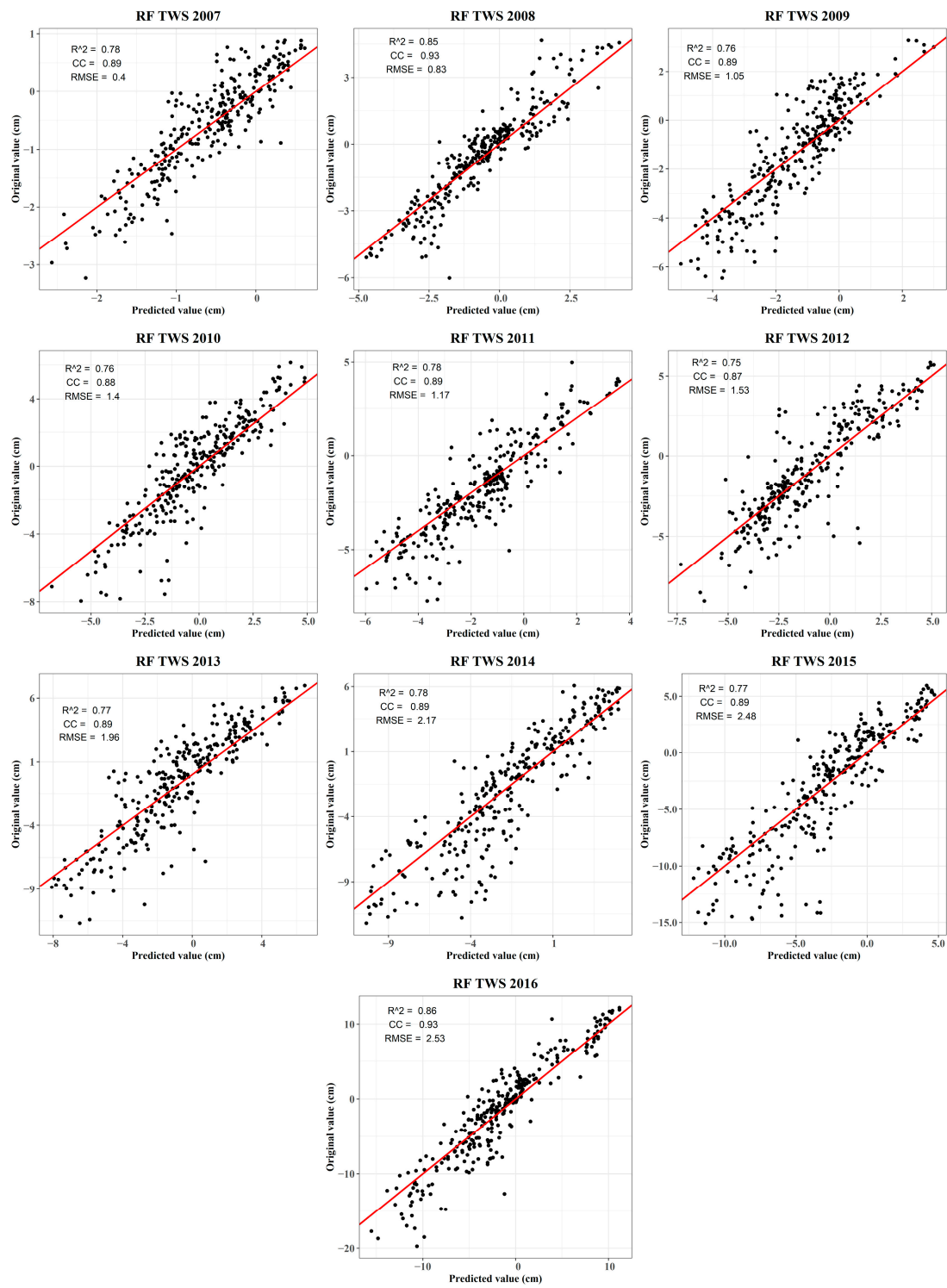
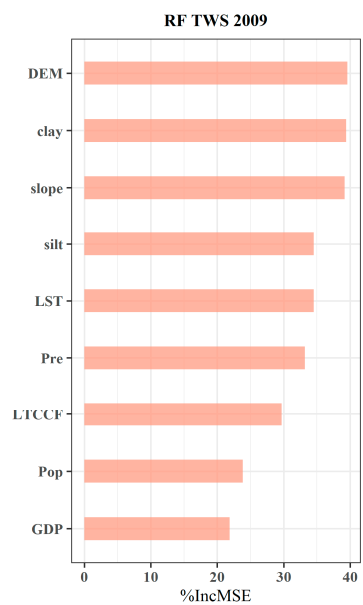
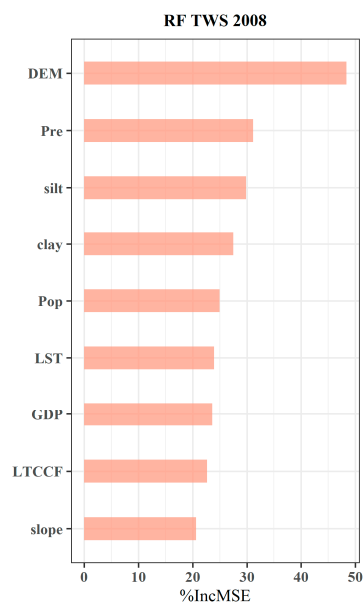
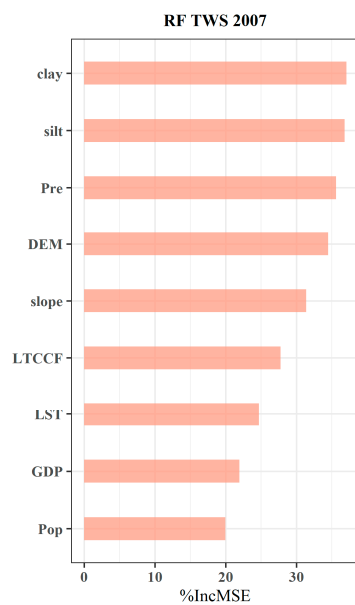
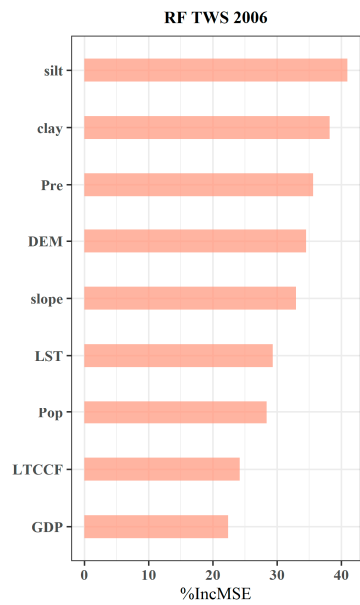
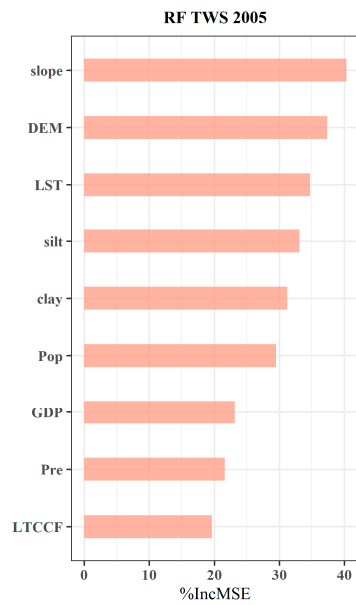
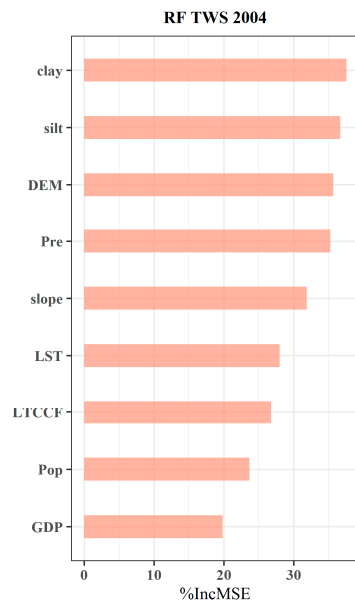


Figure S8 Scatterplots and regression fits of the testing dataset of TWS using RF method.





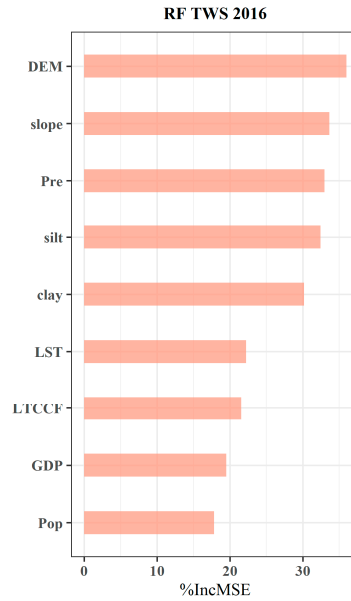
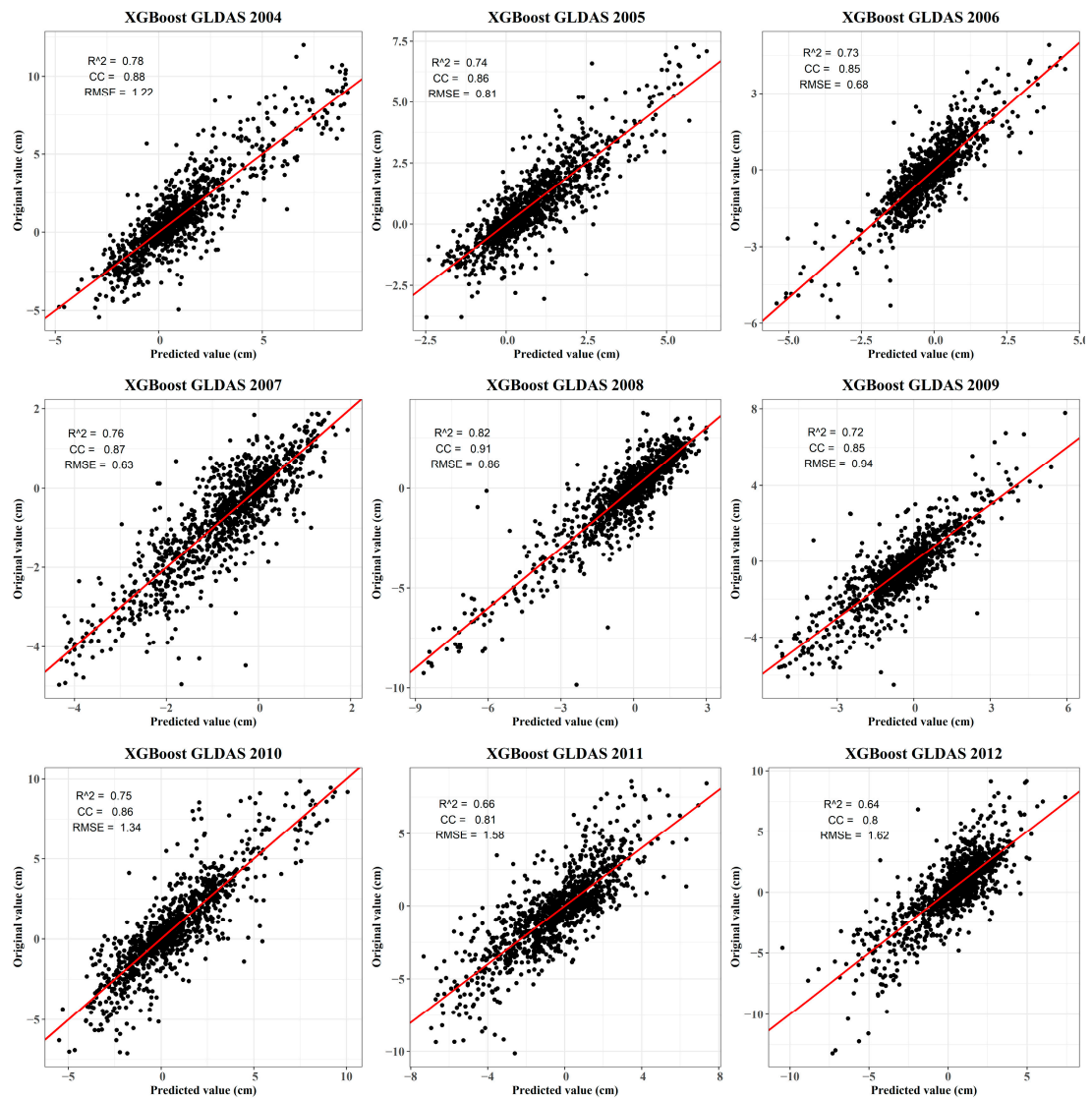


Figure S9 Plots of the variable importance measure (increase in the mean square error (%IncMSE)) for the RF-modeled TWS from 2004-2016.



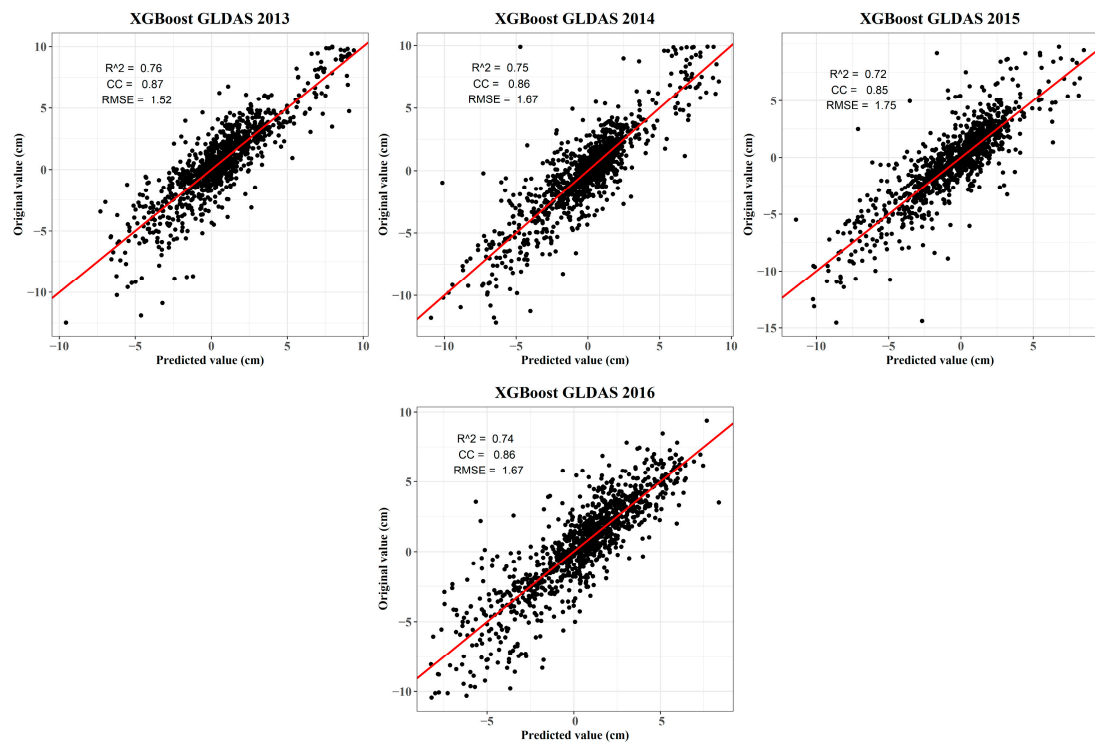
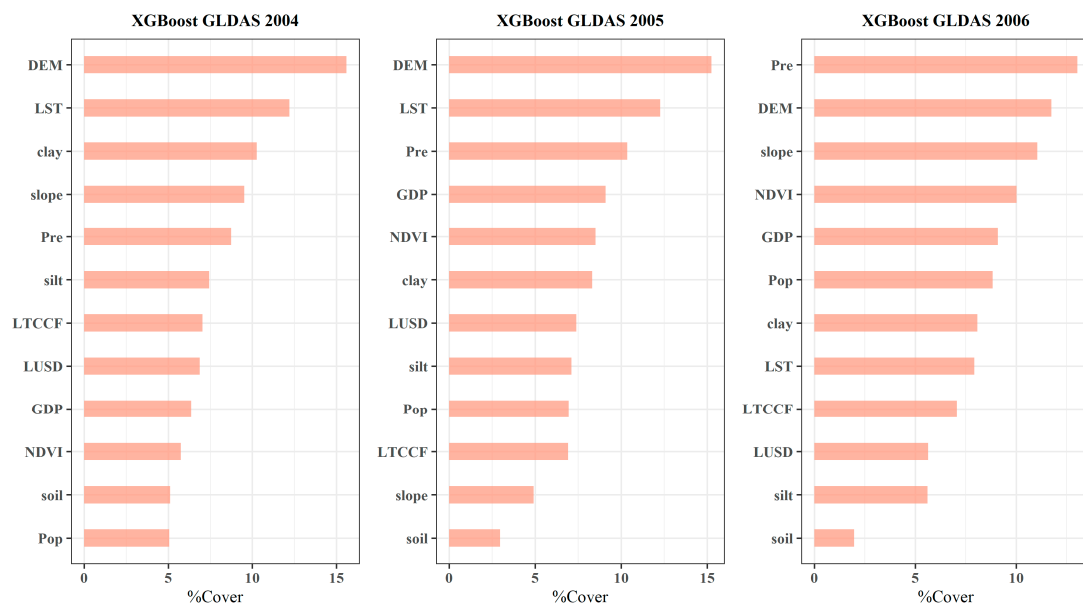


Figure S10 Scatterplots and regression fits of testing dataset of GLDAS using XGBoost method.



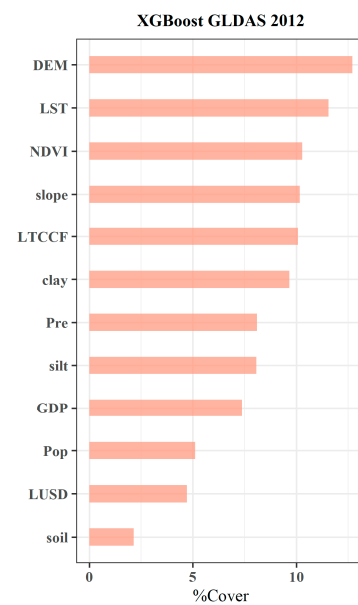
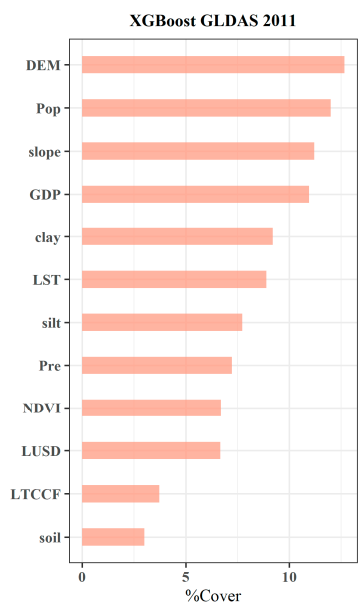
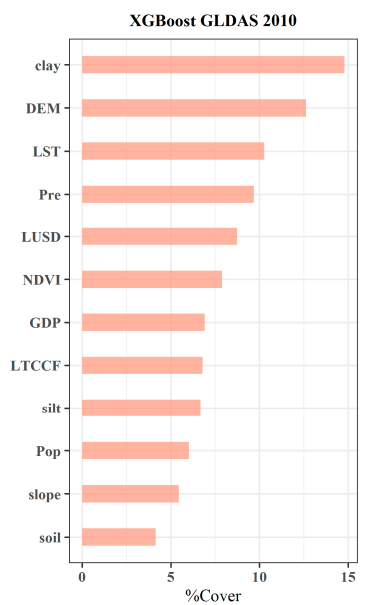
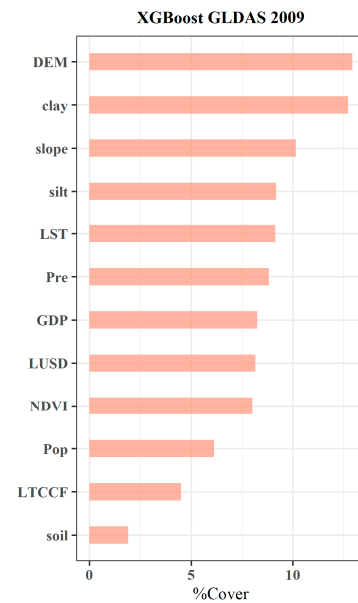
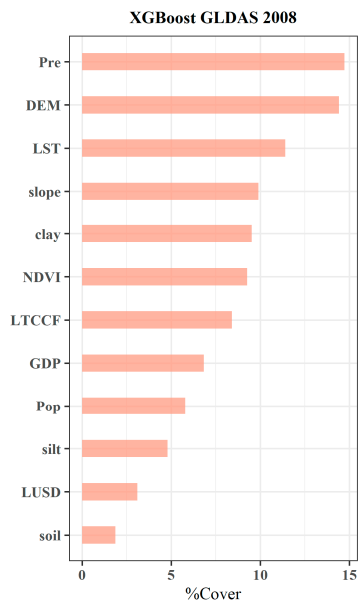
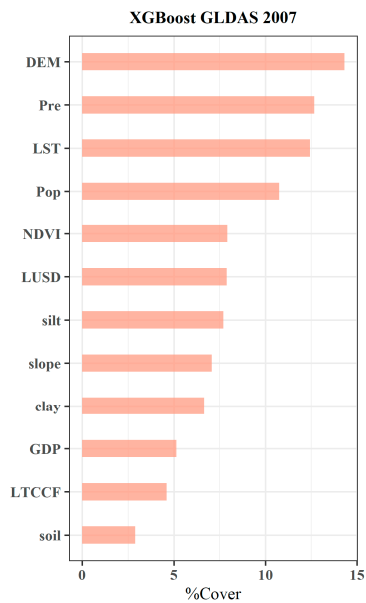
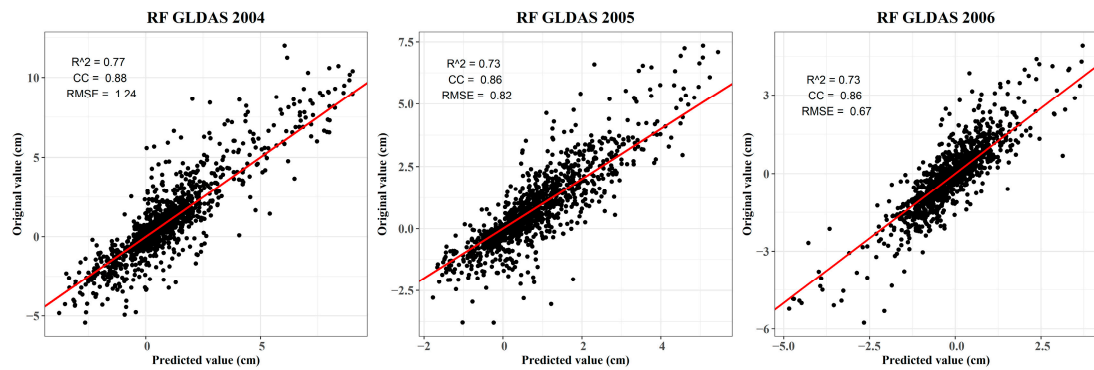




Figure S11 Plots of the variable importance measure (Cover metric of the number of observation related to this feature (%Cover)) for the XGBoost-modeled GLDAS from 2004-2016.



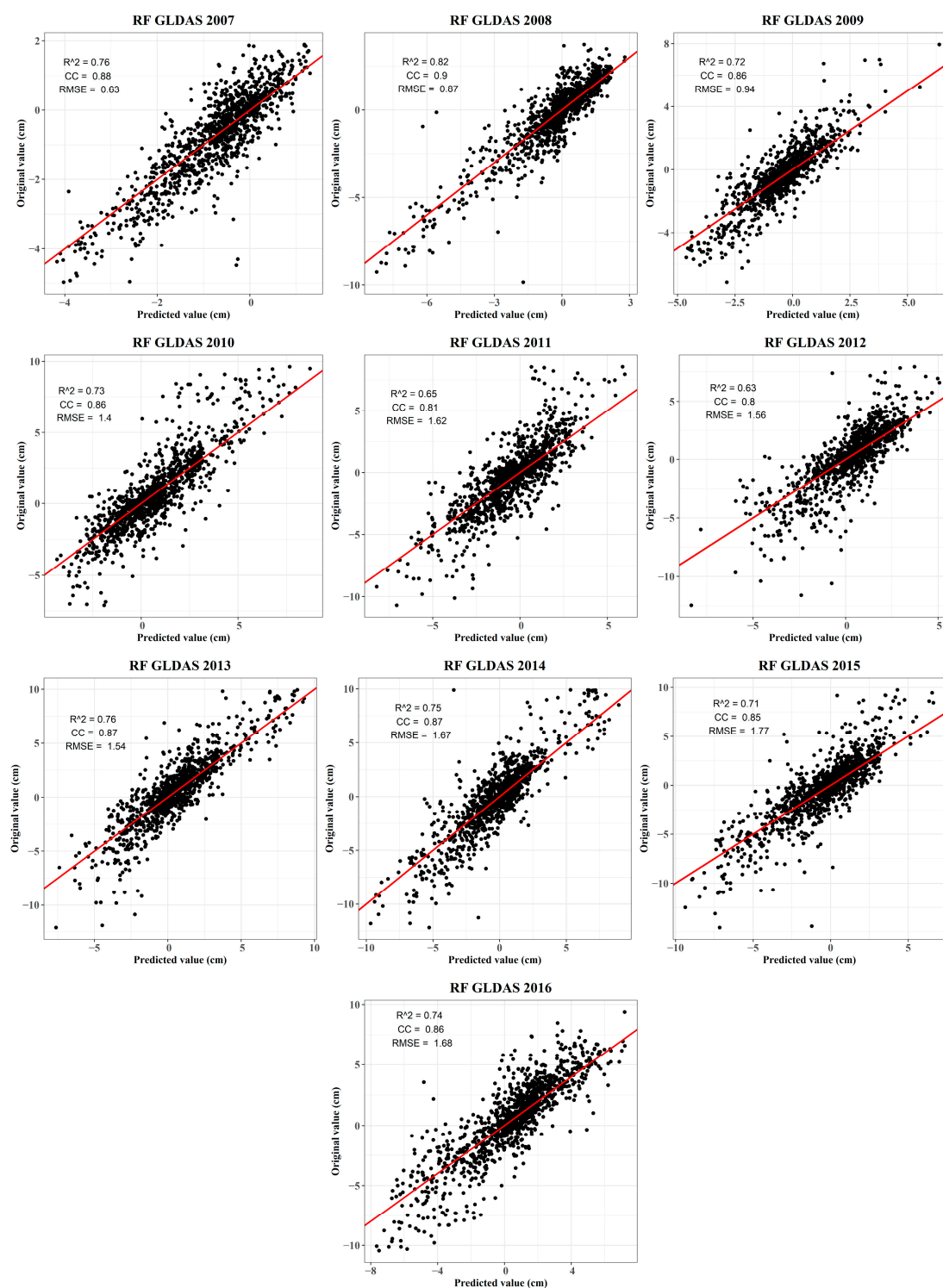
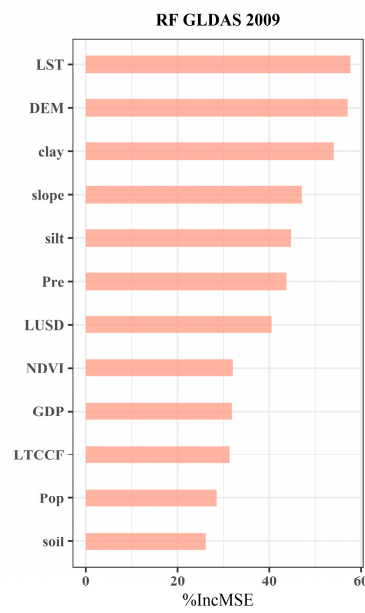
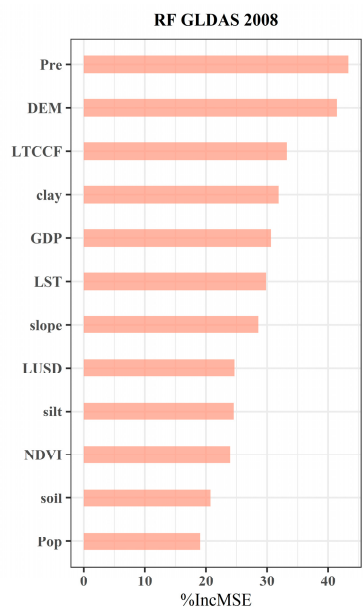
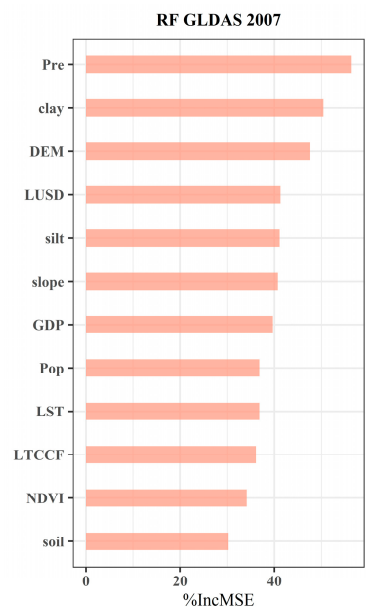
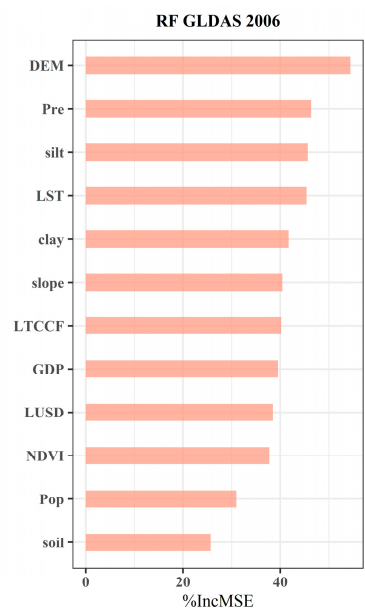
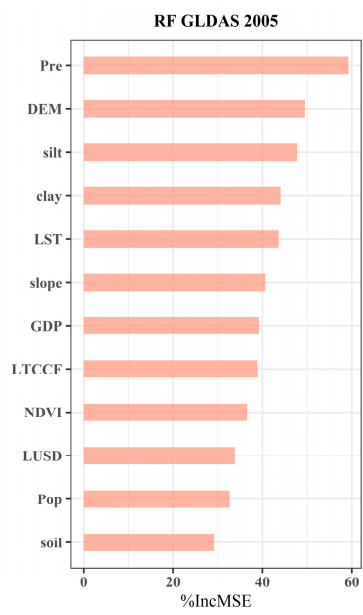
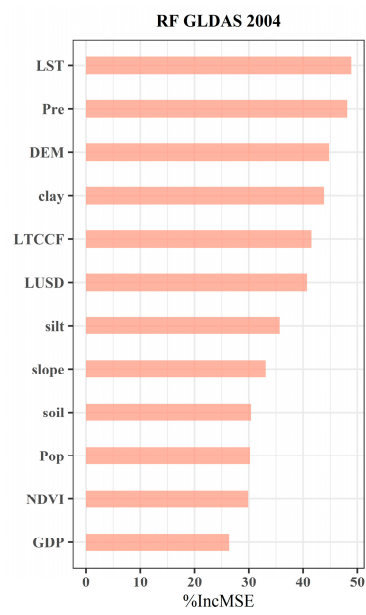
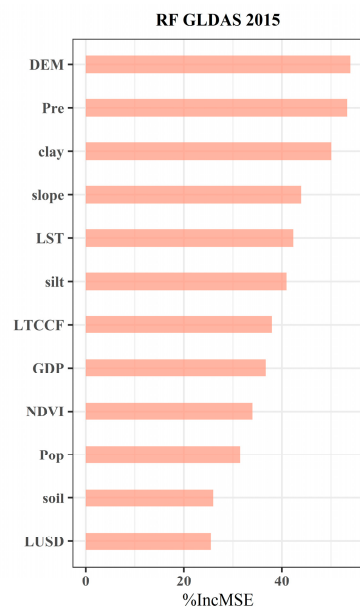
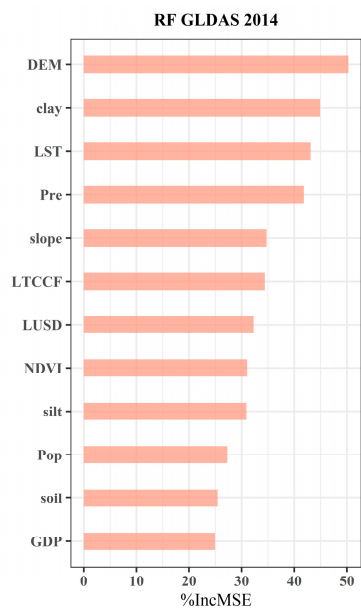
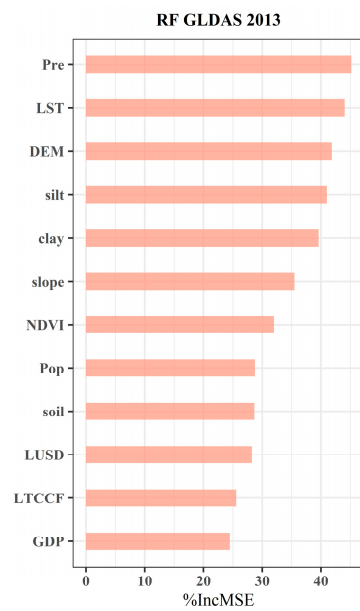
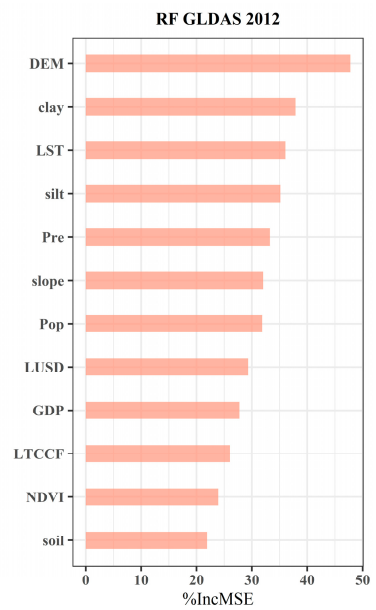
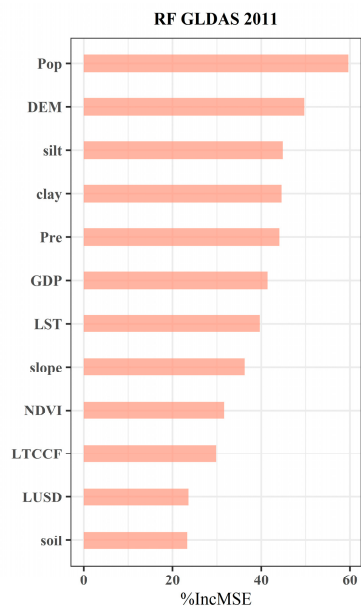
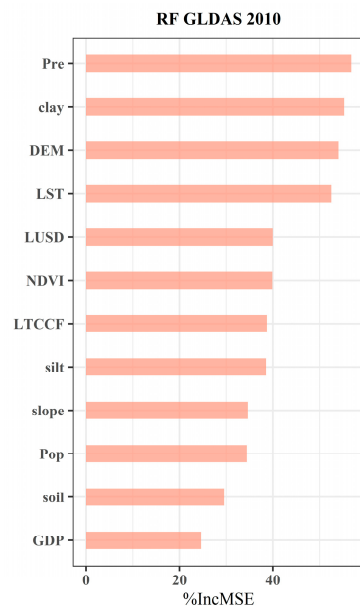


Figure S12 Scatterplots and regression fits of the testing dataset of GLDAS using RF method.





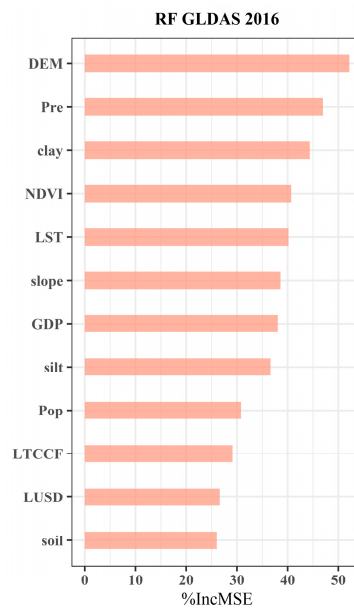


Figure S13 Plots of the variable importance measure (increase in the mean square error (%IncMSE)) for the RF-modeled GLDAS from 2004-2016.