## Linear Multi-task Learning for Predicting Soil Properties Using Field Spectroscopy

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Figure S1. Sparsity (the number of non-zero elements) of the block-sparse matrix  $W_b$  (1), the elementwise sparse matrix  $W_e$  (2), and the combined regression coefficients matrix W (3) of the model generated from linear multi-task learning for predicting available nitrogen (a), available phosphorous (b), available potassium (c), water content (d), pH (e), electrical conductivity (f), and organic matter (g).



Figure S2. Used features (non-zero items in the transpose of the block-sparse matrix  $W_b$  (a), the elementwise sparse matrix  $W_e$  (b) and the combined regression coefficients matrix W (c)) of linear multi-task learning models with  $\lambda_b = 40$  and  $\lambda_e = 10$ .