Improvement of Soil Properties Maps using an Iterative Residual Correction Method

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Short Summary

Accurate soil information is vital. This study developed a method to improve existing probabilistic soil maps — spatially continuous maps providing prior estimates — by correcting their probability distributions as new soil data emerges. By iteratively adjusting previous predictions, the method increases both accuracy and certainty of soil maps. Its application in California enhanced predictions for several soil properties. This method can be further used for more soil properties and regions.

Abstract

Accurate mapping of soil properties is vital for many applications, yet existing models for digital soil maps often underestimate their spatial variability or prediction uncertainties,

which introduces risk for applications such as irrigation and drainage management. This study introduces an approach — iterative residual correction (IRC) — to update existing probabilistic soil maps when new soil observations become available. We demonstrated its application for enhanced soil mapping performance using a Californian case study. To implement this, we first generate prior probabilistic soil property maps using a pruned hierarchical Random Forest (pHRF) method. These prior estimates are then refined by integrating additional soil profile data and iteratively adjusting residuals of distribution of soil properties (reducing differences between observations and prior predictions) pixel by pixel. For this purpose, we employed Random Forest regressors to gradually adjust the soil property distributions and incrementally correct prior bias. Updated soil maps were evaluated over California and at 1-km resolution to test the methodology, using additional soil observations from the World Soil Information Service, the Soil Characterization Database, the University of California Riverside, and the United States Department of Agriculture Agricultural Research Service. Posterior soil texture predictions achieved an RMSE below 10%, a 7% reduction over priors. RMSE and spatial representation for soil organic matter and bulk density also improved. Furthermore, the method reduced prediction uncertainties (narrower prediction intervals compared to the priors) and enforced physical constraints on soil property bounds. Looking forward, this IRC method offers a scalable pathway to improve existing probabilistic soil maps, providing a strategy for the evolution of digital soil products as new soil observations emerge.

1 Introduction

Soils play an important role in regulating Earth's water, energy, and nutrient cycles (Vereecken et al., 2016). Soil maps guide agricultural practices, ecosystem management, hydraulic modeling, and climate studies, such as crop modeling, flood risk assessment, groundwater management, and climate change (Vereecken et al., 2022). The importance of soil maps has increased with the advent of precision agriculture, including site-specific seeding, irrigation, and fertilization recommendations that intrinsically depend on high-resolution soil properties (Jiang et al., 2011; Li et al., 2019; Mueller et al., 2001; Ortuani et al., 2016). However, the accuracy and reliability of these management actions heavily depend on the quality of soil maps as a critical decision-making input. Traditional soil surveys involve field observations, laboratory analyses, and expert interpretation, but are labor-intensive and expensive (Grunwald et al., 2011; Rossiter et al., 2022; Soil Survey Staff et al., 2023). These limitations have driven the development of digital soil mapping (DSM) techniques. DSM leverages decades of soil data collection and sharing, establishing quantitative models to generate georeferenced soil maps (McBratney et al., 2003).

Digital soil maps are typically derived from existing soil surveys, geostatistical models, machine learning, or hybrid approaches. Soil survey-based soil mapping method, which use low, high, and representative values to describe soil property distributions for each soil component (Soil Survey Staff et al., 2023). The method typically approximates each soil component as a triangular distribution (Chaney et al., 2016; Soil survey staff, 2023), potentially oversimplifying multi-modal distributions of soil properties in some cases

(Haghverdi et al., 2020; Nussbaum et al., 2023). Additionally, estimating soil properties from synthetic sampling within a map unit could create artificial spatial patterns, adding noises into the mapping results (Chaney et al., 2019). Developments such as Latin-hypercube sampling and landscape adaptive covariance functions have improved the representation of spatial patterns of soil properties (Minasny and McBratney, 2006). Yet, soil survey-based approaches remain valuable particularly in areas where soil profile data is limited (Nauman et al., 2024). Geostatistical models often require presumed parameterization and are constrained by stationarity assumptions, which is difficult to apply in areas with insufficient field knowledge (Oliver and Webster, 2014). To address these challenges, non-parametric models, such as Random Forest, trained with hybridized soil data that combine soil surveys with georeferenced soil profiles show potentials in improving soil mapping, particularly for large-scale maps (Chaney et al., 2019; Nauman et al., 2024).

Map of soil properties have been observed with bias compared to field observations in certain areas due to many factors (Hengl et al., 2017; Powers et al., 2011). At the measurement level, sampling methods may favor certain landscape positions or soil conditions, causing a clustered representation (Ramcharan et al., 2018). In areas with coarse sampling density, models trained on unrepresentative data are likely to deviate from actual observations (Sharififar et al., 2019). Commonly used DSM models can show bias. For example, Random Forest classifier favors the majority class (Chen et al., 2004), and Random Forest regressors struggle to capture extreme values (Nauman et al., 2024).

Furthermore, certain areas may not be fully captured by the DSM model and the selected feature space, such as areas with complex glacial pattern, parent material transitions, and alluvial processes (unaddressed problem in SOLUS; SoilGrids 2.0; (Nauman et al., 2024; Poggio et al., 2021)). Model-based solutions include using ensemble models to enhance accuracy compared to a single model (Sylvain et al., 2021). Post-processing methods, such as regression kriging and bias-corrected decision trees, can also be used (Hengl et al., 2004). Yet, kriging-based methods have limitations in areas with high spatial heterogeneity and abrupt transitions, where stationary assumptions do not meet. Non-parametric models can be used for bias correction that overcome the limitation of making presumed distributions.

Quantifying uncertainties in DSM is important for its practical applications (Schmidinger and Heuvelink, 2023). DSM products represent soil properties as multi-dimensional matrices showing vertical and horizontal soil variation (Vereecken et al., 2022), with each pixel containing weighted possible values and their prediction uncertainties. These uncertainties can be represented either as continuous values through prediction intervals or as discrete classifications with associated class probabilities (Chaney et al., 2016, 2019; Hengl et al., 2017; Ramcharan et al., 2018). Common quantification approaches include geostatistical techniques like kriging, where the nugget term accounts for measurement errors while kriging variance reflects spatial uncertainty patterns (Chilès and Delfiner, 2012; Takoutsing et al., 2022), and machine learning methods such as Quantile Random Forest (QRF) which generates probability distributions from decision tree outputs

using values of soil properties (Poggio et al., 2021; Shi et al., 2024). For discrete classifications, uncertainty derives from soil raster probabilities during soil taxa classification (Chaney et al., 2016; Odgers et al., 2015). Given the data-driven nature of DSM and frequent limitations in soil profile availability, integrating multiple qualified data sources improves the amount of soil data and reduce prediction uncertainties (Nauman et al., 2024), particularly in regions where predictions must rely more heavily on legacy soil data.

In this study, we present a hybrid DSM approach combining pruned Hierarchical Random Forest (pHRF) with iterative residual correction (IRC) method (Xu et al., 2025). The pHRF method leverages the National Cooperative Soil Survey (NCSS) soil survey data and georeferenced soil taxa information to generate prior distributions, while additional soil profiles correct biases in prior predictions. This method builds on development in previous research while addressing specific limitations. Sylvain et al. (2021) applied XGBoost (sequential decision trees) and ensemble models to correct deterministic soil property maps, demonstrating reduced bias for many soil properties (Sylvain et al., 2021). Zhang et al. (2010) introduced a bias-correction technique with Random Forest models to mitigate their tendency to regress toward mean values, though not in DSM contexts (Zhang and Lu, 2012). Our approach extends these concepts by probabilistically updating posterior distributions at each location through an iterative correction process that continues until convergence across vertical intervals. Vertical correlations are maintained through layer-by-layer residual correction, which preserves inter-layer correlations while dynamically

optimizing the feature space at each correction step. Unlike methods requiring distributional assumptions, our non-parametric framework adapts to diverse landscapes and data scenarios. The models implement residual correction by minimizing the differences between priors and new observations to adjust posterior distributions, with the entire process continuing until property variations stabilize between different iterations. This method aims to improve the accuracy and reliability of soil property maps, supporting decision-making in relevant applications.

2 Methods

This study introduces a hybrid framework for digital soil mapping (DSM) that updates existing probabilistic soil property maps using newly collected soil observations. The framework combines prior soil property estimates with an iterative residual correction (IRC) method. The IRC method integrates additional georeferenced soil profiles (soil observations not used to train prior soil maps) and employs non-parametric models to adjust the distribution of prior estimates, thereby correcting biases in the prior soil maps.

The following sections first describe the general residual correction framework (Section 2.1). To illustrate the method concretely, we then provide a worked example using one randomly selected soil column to demonstrate how the feature space is constructed and updated across two consecutive iterations (Section 2.1.1). Building on this example, we detail the key components of the IRC method: the iterative update of feature space (Section 2.1.2), the convergence criteria for residual correction (Section 2.1.3), and the

process for updating posterior soil properties with physical constraints (Section 2.1.4). Finally, we present the California case study (Section 2.2), describing the soil datasets used (Section 2.2.1) and the implementation details for applying the IRC method over California (Section 2.2.2).

2.1 Iterative Residual Correction Framework for DSM

Residual correction is implemented to address underestimated soil property variation in prior maps (tendency to underestimate high values and overestimate low values, smoothing out soil variation across landscape). The overall workflow of the IRC method consists of three components: (1) prior map generation (Figure 1a), (2) residual preparation (Figure 1b), and (3) iterative correction (Figure 1c).

First, probabilistic prior soil property maps are generated or retrieve probabilistic soil property maps from an existing DSM product as the prior soil maps (Figure 1a). These maps represent the initial estimates of soil properties and their associated uncertainties. Second, a residual preparation step is carried out to enable correction using new soil profile observations (Figure 1b). The preparation involves four key steps: (1) adding additional soil profiles from new field measurements or databases; (2) spatially aligning these profiles with the corresponding pixels in the prior soil maps using geographic coordinates; (3) vertically aligning observations with prior predictions at matching depth intervals; and (4) calculating residuals depth by depth as the difference between observed values and prior predictions. During this stage, the feature space for residual modeling is

176 also prepared, consisting of static environmental covariates (which remain fixed
177 throughout iterations) and dynamic soil covariates (which are updated iteratively). Detailed
178 construction of the feature space is described in Section 2.1.1.
179
180 Finally, iterative residual correction is performed to update soil property estimates across
181 depths (Figure 1c). During each iteration, the model predicts residuals for one depth layer
182 at a time, with the layer selected randomly. A Random Forest regressor is trained to learn
183 the relationship between residuals and the feature space at sampled locations, then
184 interpolates residual corrections across the study area. Predicted residuals are added to
185 the prior (or previous iteration's) estimates to generate updated soil property values. After
186 each update, convergence is evaluated for the modeling depth by comparing the median
187 difference between the current residuals and those from the previous iteration. Once this
188 change falls below a predefined threshold, that depth is considered converged and
189 excluded from subsequent updates. The algorithm then focuses on the remaining
190 “unconverged” depths, until convergence is achieved across all layers. After convergence
191 is verified for all depths, the final corrected residuals are added to the prior estimates to
192 update the posterior distributions of soil properties.
193

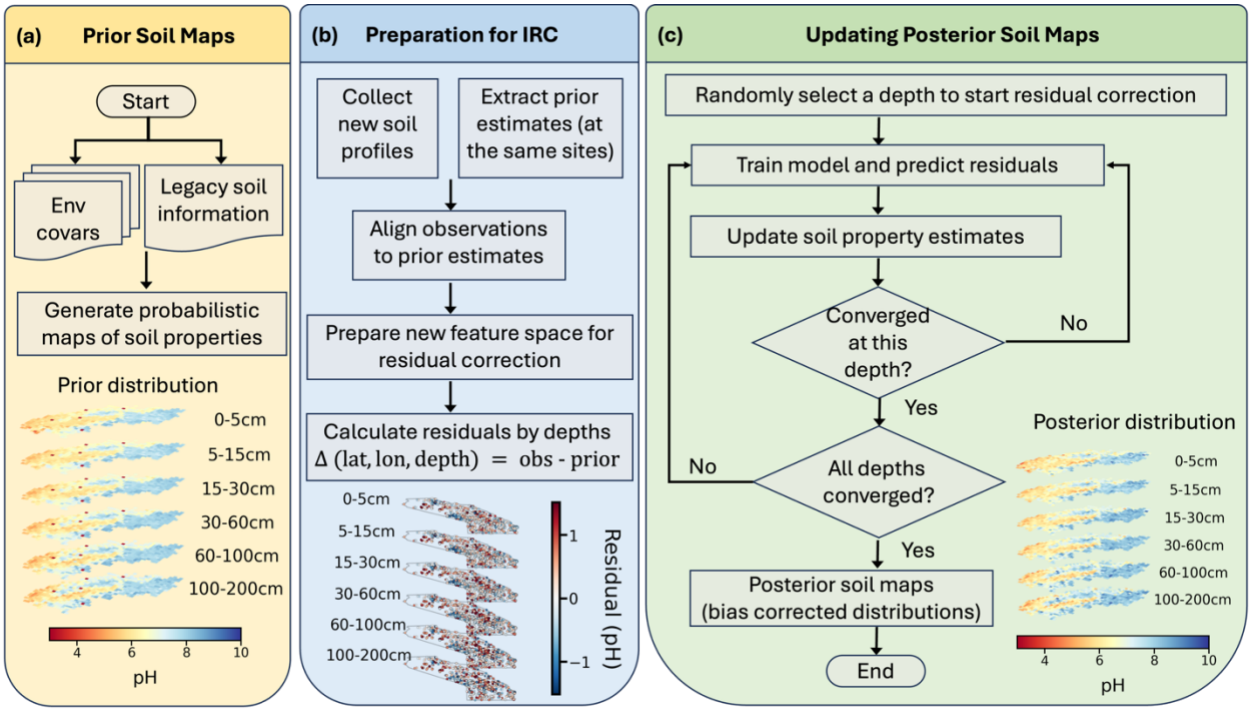


Figure 1: Workflow for updating posterior soil property maps. The process begins with panel (a), the preparation of environmental covariates (env covars) to generate probabilistic maps of soil properties (prior soil maps). As illustrated in panel (b), the preparation for residual correction involves adding additional soil profiles, spatially and vertically aligning prior soil map values with new profile observations, calculating residuals depth by depth, and preparing environmental covariates and soil covariates (new feature space) for residual correction. Finally, as shown in panel (c), the iterative residual correction step applies bias corrections across different depths, focusing on layers where residuals have not yet stabilized. During each iteration, the model predicts residuals for one depth at a time, randomly selecting a layer. Once residuals for a given depth converge, that layer is excluded from further updates, allowing the model to concentrate on remaining depths until all achieve stability. After verifying convergence across all depths,

the algorithm updates the posterior distribution of soil properties and produces the final soil maps (posterior soil property maps).

In this IRC framework, "prior probabilistic soil property maps" refer to spatially continuous soil property maps that provide an initial (prior) estimate of soil properties with associated uncertainty across the study area. These prior maps provide, for each pixel and depth interval, a distribution of possible soil property values with associated probabilities or weights. The IRC method does not require prior and new soil observations to be co-located at the same pixels. Instead, the method requires that a prior estimate exists at locations where new soil observations are available. By learning the relationship between residuals (differences between new observations and prior estimates) and environmental and soil covariates at sampled locations, the trained model can interpolate residual corrections across the study area.

2.1.1 Worked Example

The iterative residual correction method is further illustrated in Figure 2 using an example with a randomly selected soil column. Figure 2a shows the location of the selected soil column, where additional soil profile observations are available. The right panel displays the top-3 probable pH values (from prior soil maps) at each depth intervals (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm), while the left panel shows the three weights (probabilities) associated with these pH values. In this simplified example, we use 3 bins to represent the soil property distribution; however, in actual implementation, more

bins are maintained (typically top-12 probable values) to better capture soil variability. For this demonstration, Depth 2 (D_2; 5–15 cm) is randomly selected as the modeling layer to initiate the iterative correction process. Only one layer is modeled and updated for a given iteration. Note that in real model execution, model generally processes over 3,000 soil columns simultaneously in California, though only one column is shown here for clarity.

In Figure 2b, the table details features used to train the Random Forest regressor for residual prediction. The feature space consists of environmental covariates that remain fixed across iterations and soil covariates that are updated iteratively:

(1) Environmental covariates (21 dimensions): These capture spatial variations in soil-forming factors and remain unchanged throughout all iterations. The covariates include remote sensing data (Sentinel-1, Sentinel-2, GOES land surface temperature) and terrain attributes, identical to those used in the prior mapping method (Xu et al., 2025).

(2) Depth information (1 dimension): The centroid (median value) of the soil depth interval for the modeling layer (e.g., 10 cm for the 5–15 cm layer), describing the vertical position in the soil profile.

(3) Representative soil property values (1 dimension): The expected value (weighted mean) of the soil property at each pixel in the modeling layer, representing the current best estimate. This is computed as the weighted sum of top-probable values.

(4) Top-probable soil property values (1 dimension): The current predictions at each pixel (residuals plus previous prediction of soil property values), reflecting both intra-pixel and inter-pixel soil heterogeneity.

(5) Inter-layer differences (5 dimensions): Differences in top-probable predicted soil property values between the modeling layer and the other five depth layers. For instance, if modeling Depth 2, the inter-layer differences would be (D_2-D_1), (D_2-D_3), (D_2-D_4), (D_2-D_5), and (D_2-D_6). These features capture vertical correlations in the soil profile and aid in estimating spatial patterns.

(6) Weights (1 dimension): Probabilities associated with each top-probable soil property value. These weights remain fixed throughout iterations.

In summary, environmental covariates and weights remain static, while depth information, representative values, top-probable values, and inter-layer differences are updated across iterations based on the most recent soil property estimates.

A Random Forest regressor is then trained using the feature space to predict residuals for the modeling layer (D_2 in this example). The right panel in Figure 2c compares the distribution of pH values before and after residual adjustment in the current iteration. After applying the residual correction, convergence is checked for D_2 by comparing the median difference between the current and previous residuals. If D_2 has converged (difference below threshold), the algorithm proceeds to check whether all depth layers have converged. If all layers have converged, the iterative process terminates, and the final

posterior soil property maps are generated by adding the last predicted residuals to the prior values.

If either convergence check returns "No" (i.e., D_2 has not converged or other layers remain unconverged), the algorithm continues iterating. Here, the soil property values for D_2 are updated by adding the predicted residuals to the previous pH values. These updated values are then used to reconstruct the feature space following the same structure described above, updating the representative values, top-probable values, and inter-layer differences. By updating soil covariates layer by layer and iteratively refining the feature space, the next prediction retains prior knowledge while integrating new information about soil heterogeneity and vertical relationships for soil profiles (Wu et al., 2025). A new iteration begins by randomly selecting another unconverged layer, and the process repeats until convergence is achieved across all depth layers.

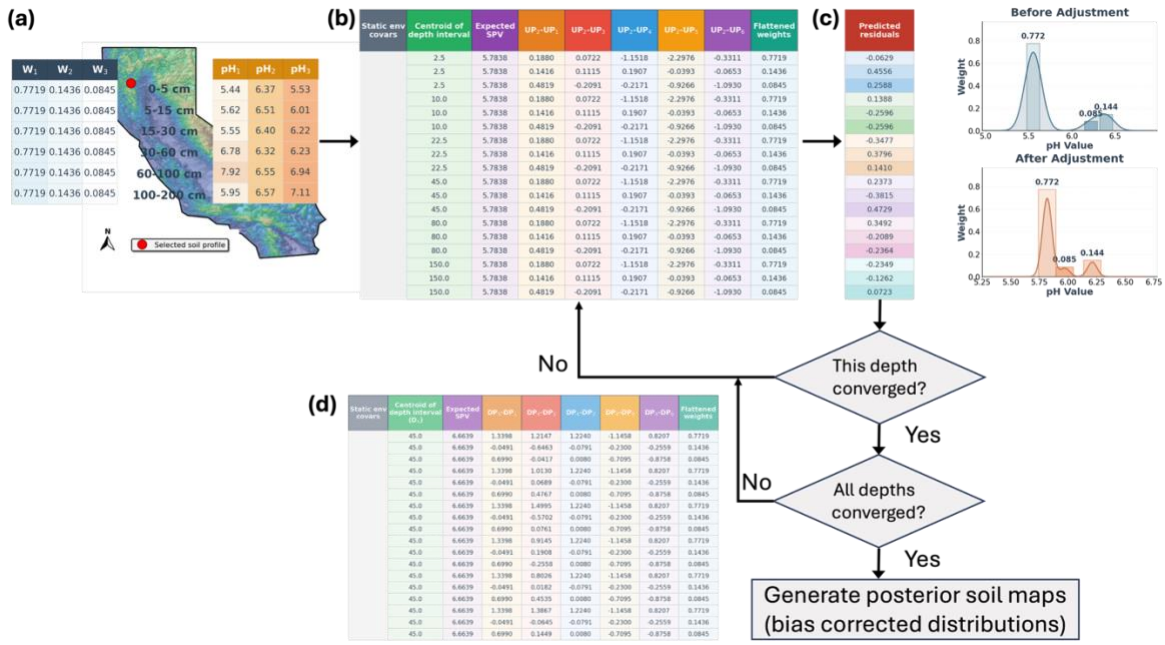


Figure 2: Schematic illustration of the iterative residual correction (IRC) method using a worked example at a randomly selected soil column. (a) Prior distributions and observation location: The map shows the location of the selected soil column within the study area. The right panel displays the top-3 probable pH values at each of the six depth intervals (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm), while the left panel shows the three weights (w_1, w_2, w_3) associated with these pH values. Depth 2 (D_2; 5–15 cm) is randomly selected for this iteration. (b) Feature space components: The table details the structure of the feature space used to train the Random Forest regressor for residual prediction. The feature space comprises both static and dynamic components. Static components include environmental covariates (satellite imagery, terrain attributes) that remain unchanged throughout iterations, and weights (w_1, w_2, w_3) associated with top-probable values. Dynamic soil covariates that are updated in each iteration include: the centroid of the depth interval (e.g., 10 cm for D_2), the expected (representative) soil

property value computed as the weighted mean, the top-probable soil property values reflecting intra-pixel heterogeneity, and inter-layer differences capturing vertical correlations (e.g., D_2-D_1, D_2-D_3). (c) Residual correction and convergence workflow: A Random Forest model trained on the feature space predicts residuals for the modeling layer D_2. The right panel compares the pH distribution before and after residual adjustment. The flowchart below describes the convergence logic: after predicting and applying residuals to D_2, the algorithm evaluates whether D_2 has converged. If D_2 has converged, the algorithm checks whether all depth layers have achieved convergence. If both checks pass, the final posterior soil property maps are generated by adding the last converged residuals to the prior values. (d) If either check fails, the algorithm updates the soil property values for D_2 by adding predicted residuals, reconstructs the feature space with the updated values, randomly selects another unconverged layer, and repeats the process. This iterative cycle continues until convergence is achieved across all six depth layers.

2.1.2 Convergence of Residual Correction

The residual correction process continues until the median difference between updated residuals and previous residuals falls below a predefined threshold. Convergence is achieved when the residuals stabilize across multiple iterations, indicating that further adjustments do not largely change the predictions. This stability ensures that the final posterior soil properties are reliable and consistent. The stopping criterion is a customizable parameter. In this work, it was set to the 5th percentile of the distribution of

value changes. To avoid over-correcting bias, only the last converged residuals are added to the prior prediction to generate the final posterior results.

2.1.3 Update with Constraints

During residual correction, a common issue arises where the addition of residuals to prior soil property values results in values that exceed physical bounds (such as sand content > 100%). To address this, a residual update process with constraints is implemented.

As illustrated in Figure 2c to 2d, after the Random Forest regressor predicts residuals for the layer (D_2), these residuals are added to the previous soil property values to generate updated predictions. Immediately after this addition step, the updated values are examined to check whether they fall within predefined physical bounds (e.g., 0% to 100% for particle size fractions, positive values for bulk density). This constraint check occurs before the convergence evaluation and before the updated values are used to reconstruct the feature space for the next iteration.

If any updated value exceeds the physical bounds, it is adjusted to the nearest valid bound (minimum or maximum). For example, if adding a residual of +15% to a prior sand content of 90% yields 105%, this value is capped at 100%. The "excess" residual (+5% in this case) is then redistributed proportionally (based on their weights) among the other top-probable values at the same pixel, ensuring that the total correction remains consistent with the model's prediction while maintaining physical plausibility. For particle size fractions (sand,

344 silt, clay), an additional compositional constraint ensures that the three fractions sum to
345 100% at each pixel after residual correction.
346
347 **2.2 California Case Study: Soil Data and Model Implementation**
348 **2.2.1 Soil Data**
349 To demonstrate the IRC method, we apply it to soil property mapping in California. We use
350 georeferenced soil profiles with laboratory measurements of soil properties. We compiled
351 soil profile data from three primary sources: the World Soil Information Service (WoSIS),
352 the National Soil Characterization Database (SCD), and field measurements conducted in
353 California (Batjes et al., 2024; National Cooperative Soil Survey, 2018; Scudiero et al.,
354 2024).
355
356 To ensure consistency across different data sources, we applied several quality control
357 steps. First, we checked the physical plausibility of all soil property values by defining a
358 valid range with specific minimum and maximum thresholds for each property. Any data
359 point falling outside these ranges was considered an error and removed. For soil texture,
360 we required the sum of sand, silt, and clay fractions to equal 100%. If a profile did not meet
361 this compositional constraint, it was excluded. After quality check, the datasets are
362 compatible because the WoSIS records for California are largely derived from the NCSS
363 database, and both the SCD and WoSIS datasets follow standardized laboratory protocols,
364 such as those from the Kellogg Soil Survey Laboratory (Soil, 1996; Soil Survey Staff, 2014).
365 For our own field measurements, we used the Integral Suspension Pressure (ISP+) method

366 to maintain precision for particle size analysis (Corwin and Scudiero, 2020; Scudiero et al.,
367 2024).
368
369 During preprocessing, we harmonized all soil data, which was originally reported at
370 different soil horizons, into six standard depth intervals: 0–5 cm, 5–15 cm, 15–30 cm, 30–
371 60 cm, 60–100 cm, and 100–200 cm (Arrouays et al., 2014). The harmonization was
372 performed using equal-area spline functions to interpolate soil property values from the
373 original horizon depths to these standard intervals (Hartemink et al., 2010, p.201). The
374 spline function fits a smooth curve through observed values at their measured depths,
375 then calculates the area under this curve within each standardized depth interval and
376 divides by the interval width to obtain the value. Location of soil profiles and their
377 distribution of soil property values are presented in Figure 3. Six soil properties are studied:
378 sand content, silt content, clay content, pH, soil organic matter (log-scaled), and oven-dry
379 bulk density. These samples were not co-located with the training samples used to
380 generate the prior maps (samples at the same locations were already removed). The
381 number of observations varies by soil property: pH has the most samples, followed by
382 oven-dry bulk density and soil organic matter. The sample sizes across properties can also
383 be inferred from the frequency histograms shown in the lower-left corner of each panel in
384 Figure 3. Across all depths combined, each soil property has more than 11000
385 observations in California. The number of observations generally decreases with depth,
386 with depths below 1 m having notably fewer samples compared to shallower layers.
387

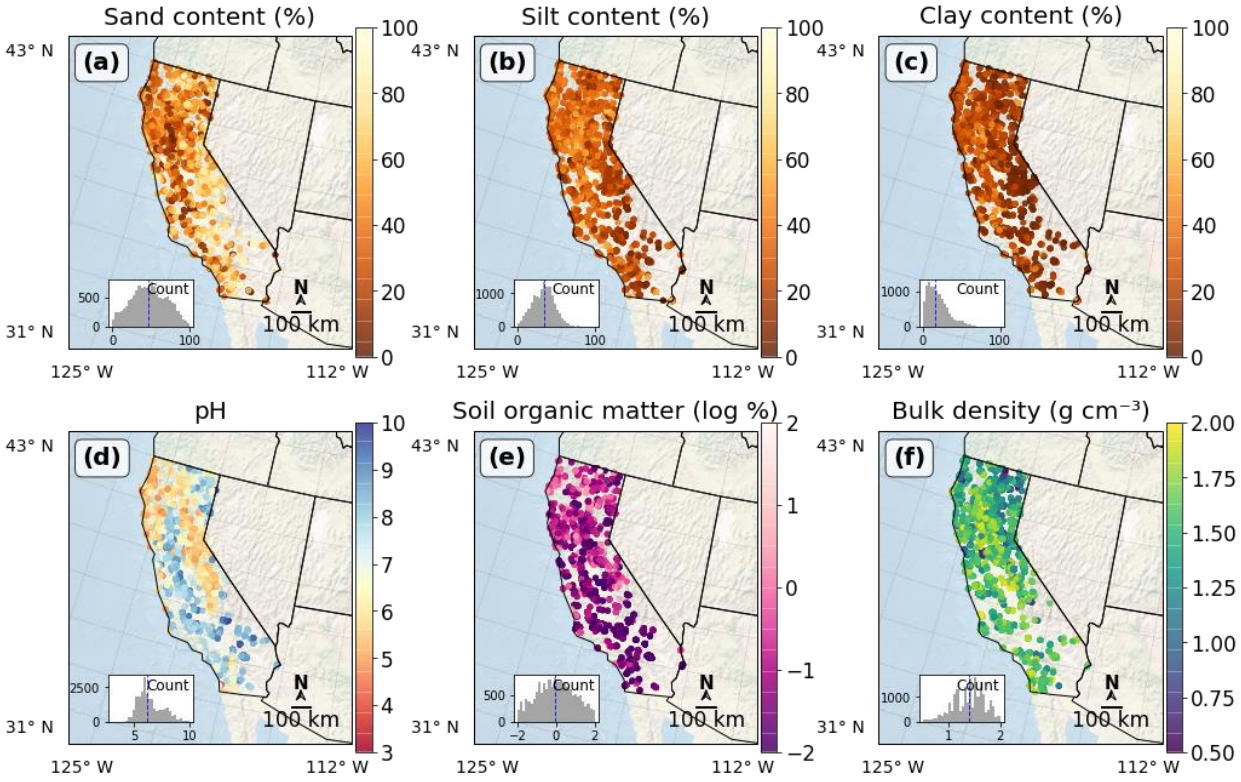


Figure 3: Spatial distribution and statistical characteristics of soil properties observations across California. The figure presents six soil parameters mapped using an Albers Equal Area projection: (a) sand content (mass %), (b) silt content (mass %), (c) clay content (mass %), (d) pH, (e) soil organic matter (log-scaled mass %), and (f) bulk density (g/cm^3). Each subplot displays sample locations as colored points, with field-collected samples shown as triangles to distinguish them from WoSIS (circles) and SCD (squares) samples. Distribution histograms in the lower left corner of each subplot show the frequency distribution of values, with blue dashed lines indicating median values. Distance scale bar and compass rose are provided in the right corner. Note that the total number of soil measurements varies by property and generally decreases with depth beyond the surface layer, with the surface layers and depths below 1 m generally having fewer observations.

2.2.1.1 World Soil Information Service (WoSIS)

The World Soil Information Service (WoSIS), managed by the International Soil Reference and Information Centre (ISRIC), aggregates global soil data from diverse sources, including national soil institutes, research organizations, and collaborative initiatives like the Global Soil Partnership (GSP) and the International Network of Soil Information Institutions (INSII). The database provides soil properties for different soil horizons, georeferenced in decimal degrees, and undergoes quality controls (Batjes et al., 2024). In California, WoSIS typically offers 2,000 to over 5,000 soil observations for the modeling soil property. Samples below 1-m depth are fewer than those from shallower layers.

2.2.1.2 Soil Characterization Database (SCD)

The Soil Characterization Database (SCD) is a subset of the National Cooperative Soil Survey (NCSS) database (National Cooperative Soil Survey, 2018). It records soil properties for each soil horizon within a soil profile (pedon), including soil texture, bulk density, and water retention. In California, SCD provides between 500 and over 1,000 soil samples per layer for the studied soil property. Each soil profile is georeferenced and includes metadata such as site location, land use, and sampling methods.

2.2.1.3 Ground Truth Soil Sampling and Measurements

Additional soil sampling was conducted to complement georeferenced soil profiles in California for model training and evaluation. These data are reported in (Scudiero et al., 2024) and are briefly discussed here. Multiple fields located between Salinas and Soledad

in California's Salinas Valley were selected to collect soil particle size fraction data (Figure 4). These fields, presented as red dots in Figure 4, were chosen because they were accessible, unfarmed during the sampling period, and spread across different parts of the valley.

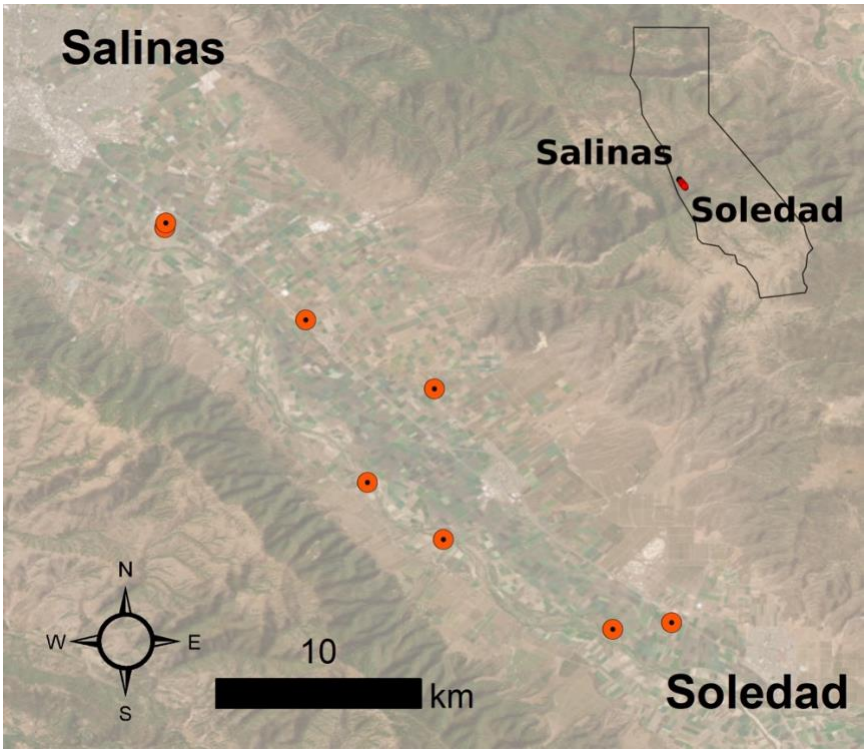


Figure 4: Map of sampling fields in the Salinas Valley in California. Each red dot represents a sampling field between Salinas and Soledad. An inset map (top right) shows the location of the sampling area within California. Scale bar and direction indicator are provided in the left corner. *Basemap: Esri World Imagery. Source: Esri, Maxar, Earthstar Geographics, and the GIS User Community.*

Soil apparent electrical conductivity (ECa) was measured across fields using an electromagnetic induction (EMI) sensor connected to a GPS receiver. Following the ECa-directed soil sampling protocols of Corwin and Scudiero (Corwin and Scudiero, 2020), the most representative soil samples were identified with ESAP software package and the Response Surface Sampling Design algorithm (Lesch et al., 2000; Lesch, 2005). 0-0.8 and 0-1.6 m soil profiles were further analyzed and followed with the expectation that ECa was a regional proxy for the field-scale variability of particle size fraction.

To measure particle size fraction, soil samples were then collected from multiple depths (0–0.1, 0.1–0.4, and 0.4–1.2 m) across fields. After collection, the samples were air-dried, ground, and sieved to remove particles larger than 2 mm; and then measured using the Integral Suspension Pressure method (The improved integral suspension pressure method (ISP+) for precise particle size analysis of soil and sedimentary materials; Wolfgang Durner, Sascha C. Iden) using PARIO™ system (METER Group AG, Munich, Germany).

2.2.2 Model Implementation for the California Case Study

For the California case study, prior soil property maps were generated using the pruned hierarchical Random Forest (pHRF) method (Xu et al., 2025). The pHRF-derivef soil maps were developed with soil pedons from the National Soil Information System (NASIS) and part of SCD (the remaining data not used in IRC method). After gaining prior estimate of soil properties, the IRC method was then applied using the additional soil observations from WoSIS, SCD, and field measurements, which were not used in generating the prior maps.

The convergence threshold for each soil property was set to the 5th percentile of the distribution of value changes between iterations.

Model training and evaluation were performed using out-of-bag (OOB) sampling, with OOB samples (samples withheld from the training process and not used to fit the models) that shared the same geolocation as training samples removed to prevent data leakage and reduce spatial autocorrelation effects. In each iteration, a new Random Forest model is trained to update residuals for one specific depth interval, and the same set of OOB samples remains excluded throughout to ensure independent validation.

3 Results

The iterative residual correction (IRC) method is applied to adjust pHRF-derived prior soil properties, including particle size fractions (sand, silt, clay), pH, oven-dry bulk density (BD), and soil organic matter (SOM) over California. This correction addresses biases in the prior soil property maps and updates the posterior distributions of these properties. These soil properties are important for land management and serve as essential inputs for pedotransfer functions. The residual correction is performed across California, covering six depth intervals: 0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm, and 100-200 cm.

3.1 Performance Evaluation of Posterior Soil Properties

Table 1 presents the performance metrics for the posterior predictions of six key soil properties: sand, silt, clay, pH, oven-dry bulk density (BD), and soil organic matter (SOM).

The metrics include the root mean square error (RMSE), coefficient of determination (R^2), and correlation coefficient (ρ). For example, sand prediction shows an RMSE of 9.322, an R^2 of 0.841, and a correlation coefficient of 0.918. pH prediction shows an RMSE of 0.270, an R^2 of 0.945, and a correlation coefficient of 0.972. These metrics are computed using out-of-bag (OOB) samples from random forest regressors. OOB samples are data points not included in the bootstrap samples used to train each tree in the random forest. Additionally, these metrics are evaluated by comparing the expected values of posterior predictions with co-located soil properties values; not computed on residuals.

Table 1 also shows variations in performance across different soil properties. SOM and bulk density show slightly worse metrics compared to particle size fractions and pH. For instance, SOM predictions have an RMSE of 1.961, an R^2 of 0.608, and a correlation coefficient of 0.801, and bulk density predictions have an RMSE of 0.164, an R^2 of 0.704, and a correlation coefficient of 0.843. Two main reasons can result in their lower performance. First, these properties are more dynamic in nature compared to particle size fractions and pH. SOM and bulk density can change over time due to factors such as land use practices. The prior predictions are trained using soil survey data that are older, while the posterior soil profiles used for evaluation may come from a different period. Second, SOM and bulk density are more challenging to model accurately. SOM is influenced by complex biological and soil-forming processes, such as decomposition rates and organic matter inputs. Similarly, bulk density is affected by soil compaction, organic matter content, and soil structure. All of them can vary spatially and temporally. Depth-wise

analysis of model performance is provided in the Supplementary Information (Table S1 and S2).

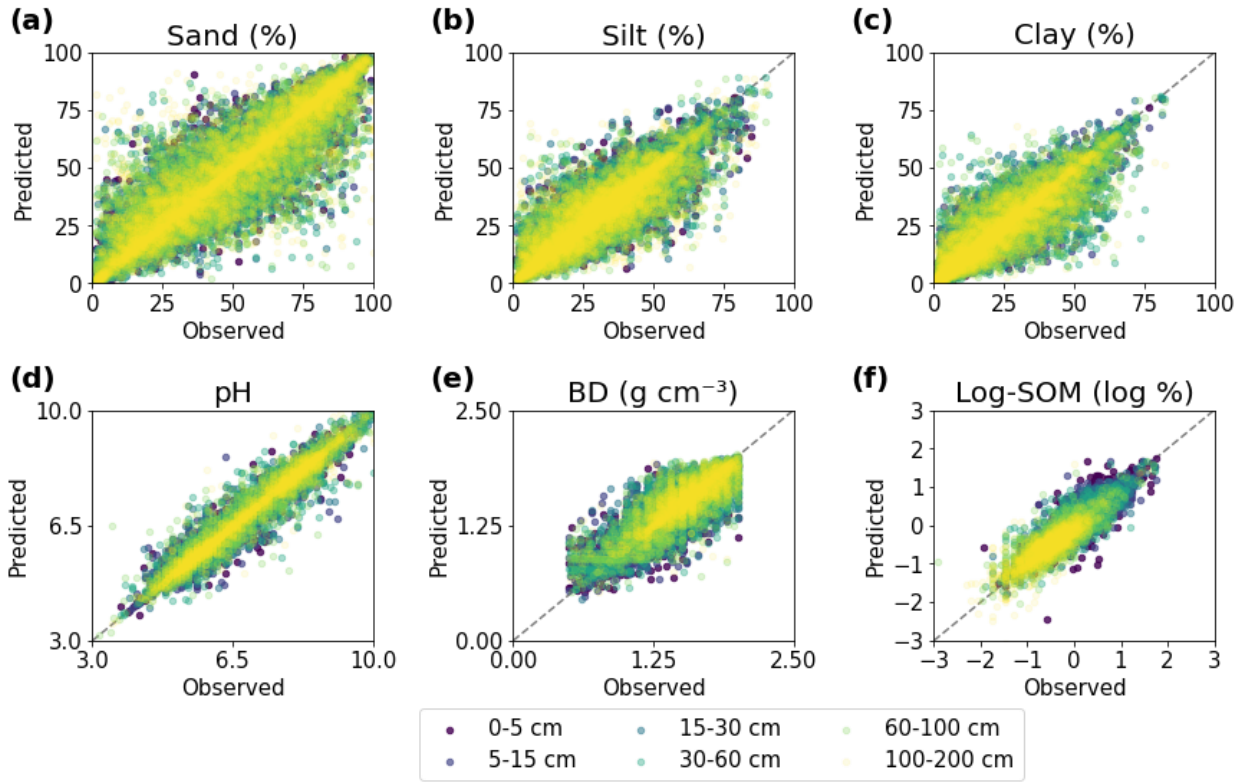
Table 1: Performance metrics (RMSE, R^2, and correlation coefficient ρ) for posterior predictions of soil properties, including sand, silt, clay, pH, oven-dry bulk density (BD), and soil organic matter (SOM). The table summarizes the range (minimum and maximum values) and accuracy metrics for each property averaged across all depth intervals.

Property	Unit	Min	Max	RMSE	R^2	φ
Sand	% mass	0.0	100.0	9.322	0.841	0.918
Silt	% mass	0.0	100.0	6.556	0.788	0.889
Clay	% mass	0.0	100.0	5.891	0.841	0.918
pH	log10([H^+])	3.0	10.0	0.270	0.945	0.972
BD (oven-dry)	g/cm^3	0.5	2.0	0.164	0.704	0.843
SOM	% mass	0.0	100.0	1.961	0.608	0.801

The posterior predictions of soil properties all align with the co-located observations and can capture the general trend of observations (Figure 5). Predictions of pH show the most concentrated clustering to the dashed line, indicating good agreement with observations across all depths. SOM and bulk density show relatively weaker performance compared to

other predicted soil properties. And this pattern of reduced accuracy persists throughout all depths.

As Figure 5 shows, the performance of the model tends to decline with increasing soil depth, except for SOM. This decline is primarily due to several reasons. First, the availability of soil data is often greater for shallower layers compared to deeper layers (such as > 1m), which limits the model's ability to learn patterns in deep layers. Second, remote sensing-derived soil covariates can only observe surface properties. Predictions for deeper layers rely on soil horizon information, soil profiles, geology, and parent material-related features. The certainty and quantity of them are less than easily measurable surface covariates. However, SOM shows better performance in deeper layers compared to surface layers. This is likely because surface SOM is highly variable due to factors like residue, land use, and management practices, while deeper SOM tends to be more stable.



528

529 **Figure 5: Evaluating posterior predictions with observations for six soil properties: (a)**
530 **sand, (b) silt, (c) clay, (d) pH, (e) bulk density (BD), and (f) log-scaled soil organic**
531 **matter (SOM). The left side shows scatter plots of posterior predictions versus**
532 **observations across six depth intervals, with each depth represented by a distinct**
533 **color. The dashed black line represents perfect prediction.**

534

535 **3.2 Comparison of Prior and Posterior Soil Predictions**

536 Prior and posterior predictions of soil properties are compared against co-located
537 observations to assess the added value of residual correction. The radar plots in Figure 6
538 illustrate the improvements achieved through the residual correction method using three
539 normalized metrics: 1-normalized absolute bias (1-|Bias|), coefficient of determination
540 (R^2), and 1-normalized RMSE by ranges of soil variability (1-nRMSE). These metrics are

computed with values of soil properties, instead of on their residuals. Values in Figure 6 closer to the outer edge of each plot indicate better model performance. Overall, all soil properties maintain reasonable normalized bias and nRMSE (with nRMSE values consistently less than 0.02 for both prior and posterior predictions). However, the prior predictions tend to underestimate the variability of soil properties. As a result, the normalized metrics for prior and posterior predictions are similar, while the R^2 values show some differences.

For all soil properties, posterior predictions consistently outperform prior predictions across all metrics. For particle size fractions, R^2 values show the largest improvements: sand increases from 0.35 to 0.84, silt from 0.19 to 0.79, and clay from 0.25 to 0.84. The nRMSE metric also shows improvements. Sand decreases from 0.19 to 0.09, silt from 0.14 to 0.07, and clay from 0.16 to 0.07, showing reductions in prediction errors using the residual correction.

Aggregating data from all depths, Figure 6 shows the degree of improvement across different soil properties. Prior pH predictions already demonstrate reasonable accuracy, with an R^2 of 0.54 and nRMSE of 0.11. After the residual correction, these metrics improve to 0.94 for R^2 and 0.04 for nRMSE. Bulk density and SOM show the biggest gains. For bulk density, the R^2 increasing from 0.16 to 0.70 and nRMSE reducing from 0.18 to 0.11. Prior SOM are underfitted with a low R^2 value. With the residual correction, the posterior SOM show a positive R^2 of 0.61. The nRMSE for SOM also improves from 0.07 to 0.04.

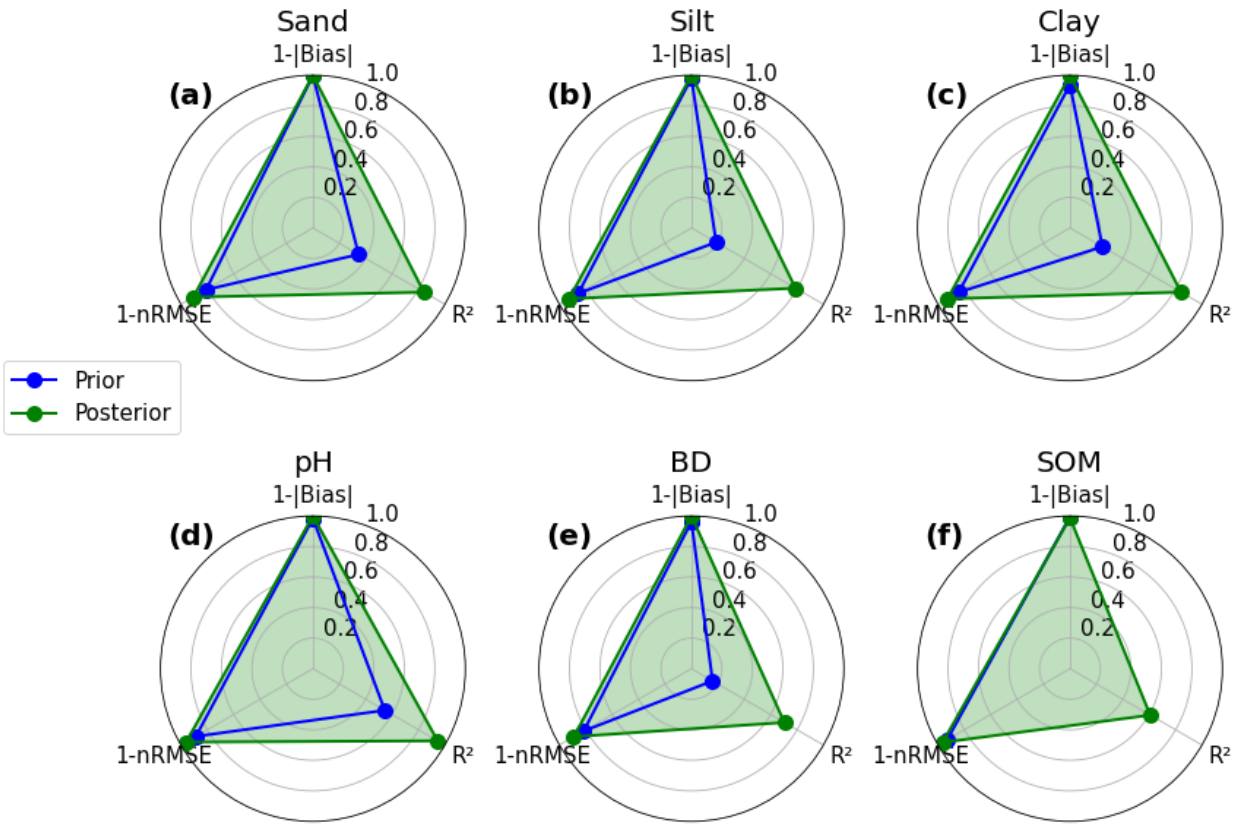


Figure 6: Radar plots comparing the performance metrics of prior and posterior predictions for six soil properties: (a) sand, (b) silt, (c) clay, (d) pH, (e) oven-dry bulk density (BD), and (f) soil organic matter (SOM). Each plot presents three metrics: 1-normalized absolute bias (1-|Bias|), coefficient of determination (R^2), and 1-normalized RMSE by ranges of soil variability (1-nRMSE). Prior predictions are shown in blue, and posterior predictions in green. All metrics are scaled from 0 to 1, where values closer to the outer edge of the plot indicate better model performance. The green shaded area highlights the improvement achieved by the posterior predictions over prior estimates.

574 Horizontal spatial patterns of the six soil properties are presented in Figure 7. In the
575 Central Valley California, soils are mostly medium textured with about 30% silt and lower
576 sand content compared to surrounding areas. In the Mojave and Colorado Deserts, high
577 sand contents (> 60%) with low clay contents are observed. SOM contents are also low in
578 these areas. The histograms show how residual correction adjusts the distribution of soil
579 properties.
580
581 For SOM and bulk density, the prior predictions often underestimate the observed
582 variation. Figure 7 shows that the residual correction processes add noticeable spatial
583 variations between prior and posterior soil maps. Prior bulk density values are often
584 clustered around 1.5 g/cm^3, whereas the posterior histogram presents a broader range,
585 spanning from 1.25 g/cm^3 to 1.6 g/cm^3, capturing more heterogeneity of bulk density.
586 Similarly, the residual correction adds soil heterogeneity to SOM. The posterior SOM can
587 delineate water bodies, where SOM content is abruptly lower than the surrounding areas.
588 Additionally, the posterior SOM maps present hill features in the desert areas.

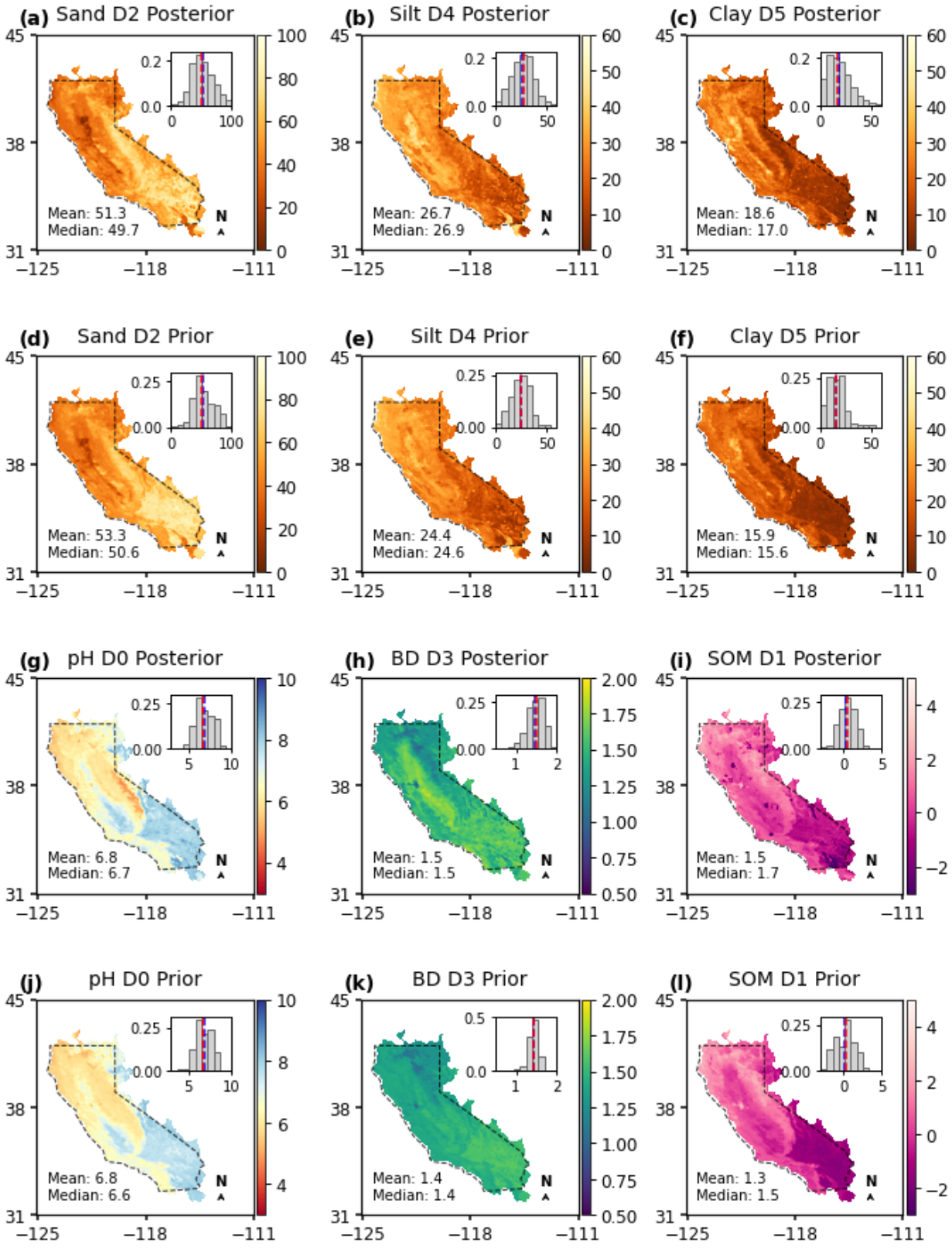


Figure 7: Spatial distribution of six soil properties (sand, silt, clay content, pH, bulk

density, and soil organic matter) across California. Maps of prior and posterior soil properties are compared. The corresponding frequency distributions of these soil properties are displayed in the right corner. Dashed polygons represent the continental part of California. In the histograms, the blue and red dashed lines represent the mean and median values, respectively. The maps labeled D0 to D5 correspond to the first vertical layer down to the deepest layer. Note the map and distribution of soil organic matter (SOM) is log-scaled. Mean and median values are computed from the original SOM data.

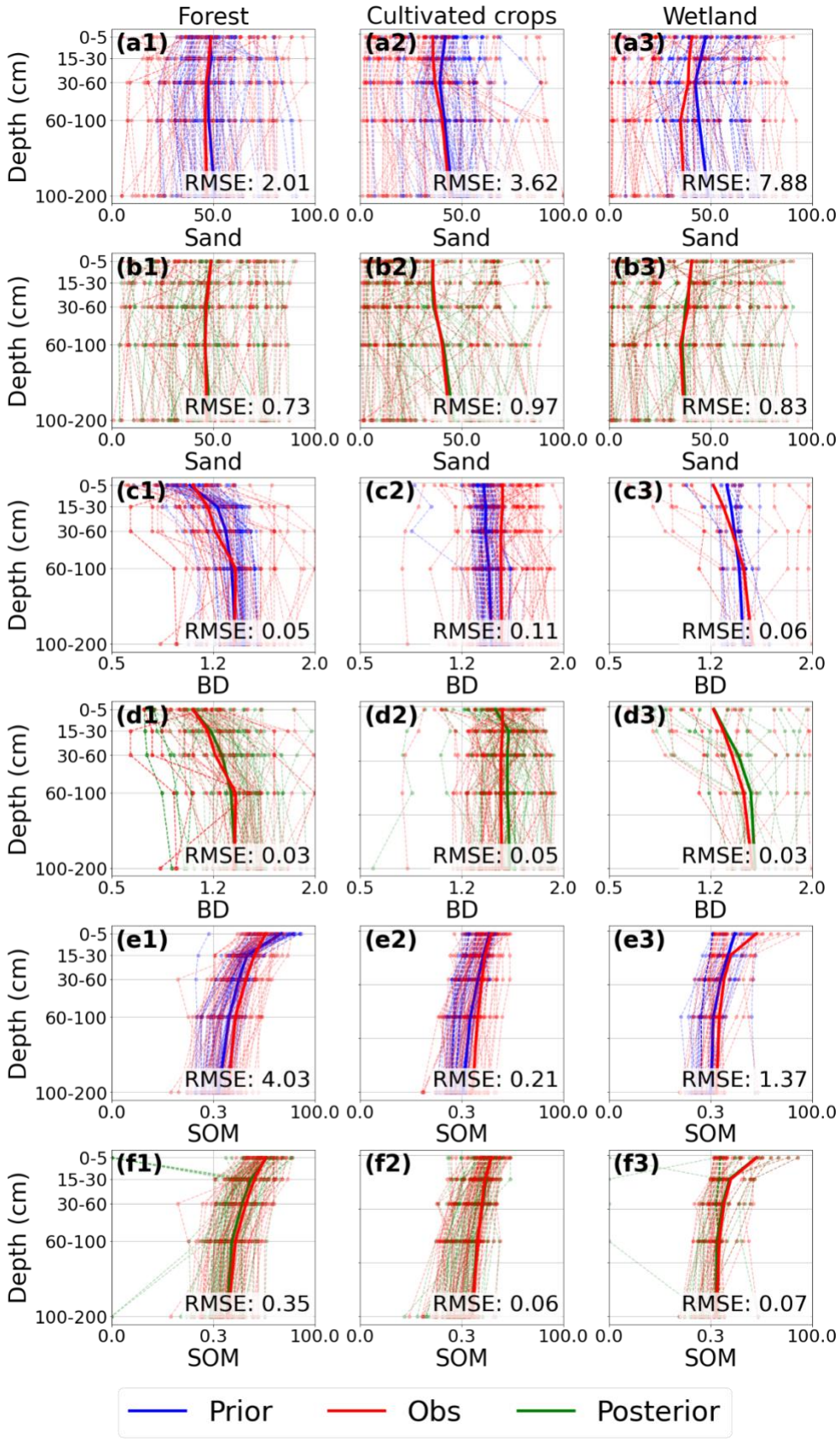
Soil profiles used for evaluating residual correction are grouped according to their corresponding pixel's land use classification from the National Land Cover Database (NLCD). Figure 8 presents selected vertical soil profiles of sand content, oven-dry bulk density, and SOM across three land use categories: forest, cultivated crops, and wetland. The number of samples varies by land use, with forests having the most, cultivated crops approximately half as many, and wetlands the fewest across California. To ensure a balanced visualization, a similar number of profiles are selected from each category. Sand content is chosen due to its broader range of variation (0-100%) compared to silt and clay (< 60% range). SOM and bulk density, which show relatively lower performance metrics, are included to assess the model's 'lower-bound performance'. These vertical profiles were not used during model training.

In Figure 8, solid lines represent the mean soil profiles for sand content, oven-dry bulk density, and SOM across forest, cultivated crops, and wetland land use categories. Blue lines, red lines, and green lines indicate prior, observation, and posterior predictions. Comparing the solid lines, the posterior predictions align more closely with the observed data compared to the prior estimates. However, the degree of alignment varies by soil property. For sand content and SOM, the posterior predictions show better agreement with observations, while bulk density predictions exhibit greater discrepancies, particularly in cultivated areas.

For sand content, the residual correction process improves estimates, especially in wetlands, with RMSE decreasing from 7.68 to 0.77 (%). Bulk density predictions perform better in forested and wetland areas. In cultivated crops, the posterior predictions show larger discrepancies. This suggests that bulk density is more challenging to predict in agricultural lands, particularly in shallow layers, likely due to agricultural activities. For SOM, the residual correction effectively improves estimates, especially in the surface layers of wetlands.

Dashed lines in Figure 8 represent individual soil profiles. Prior predictions often underestimated the variability in soil properties, struggling to capture extreme values. After the residual correction, the posterior predictions are better able to approximate these extremes. However, the correction process sometimes introduces additional noise. For example, some low SOM values (such as 0.001 g/cm^3) were generated during residual

correction, even though such values are not presented in the observed data. It is likely due to that we used the van Bemmelen factor (1.724) to convert the prior soil organic matter to soil organic carbon.


Forest
Cultivated crops
Wetland
Depth (cm)
0-5
15-30
30-60
60-100
100-200
(a1)
RMSE: 2.01
(a2)
RMSE: 3.62
(a3)
RMSE: 7.88
Sand
(b1)
RMSE: 0.73
(b2)
RMSE: 0.97
(b3)
RMSE: 0.83
(c1)
RMSE: 0.05
(c2)
RMSE: 0.11
(c3)
RMSE: 0.06
BD
(d1)
RMSE: 0.03
(d2)
RMSE: 0.05
(d3)
RMSE: 0.03
(e1)
RMSE: 4.03
(e2)
RMSE: 0.21
(e3)
RMSE: 1.37
SOM
(f1)
RMSE: 0.35
(f2)
RMSE: 0.06
(f3)
RMSE: 0.07
Prior
Obs
Posterior

637

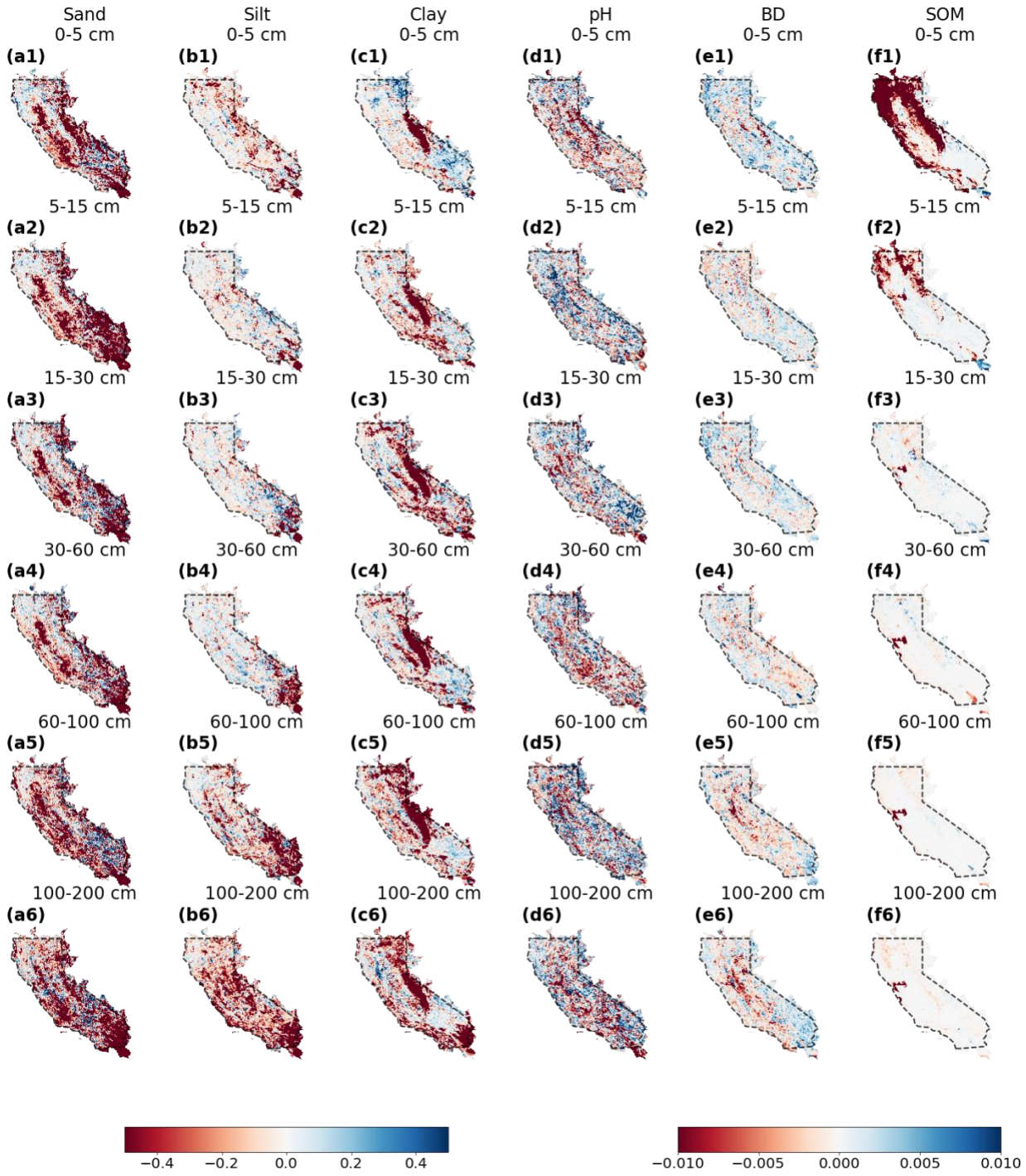
Figure 8: Vertical distribution of soil properties (sand content, oven-dry bulk density, and soil organic matter SOM) across three land use categories: forest, cultivated crops, and wetland. Prior estimates (blue), posterior estimates (green), and observations (red) are shown as depth profiles. Dashed lines represent individual measurements, and solid lines show mean values. RMSE is computed elementwise to evaluate model performance across all depths. X-axis and Y-axis represent value ranges of a soil property and vertical depth intervals, respectively.

3.3 Uncertainty Analysis

Figure 9 shows the differences between 5% — 95% posterior and prior prediction interval widths (PIWs) for six soil properties—sand, silt, clay, pH, bulk density, and SOM—from surface to 2-m deep. The differences are calculated by subtracting the prior PIWs from the posteriors. Red areas present a reduction in posterior PIW, indicating the residual correction has reduced uncertainties of soil properties predictions. Blue pixels suggest the opposite. White areas represent regions where the prior and posterior uncertainties are similar.

In Figure 9, most pixels show reduced uncertainty for sand content after residual correction, particularly in agricultural and desert regions. This improvement is attributed to the inclusion of additional soil profile data from these areas. For clay content, the posterior predictions consistently show reduced uncertainty across the Sierra Nevada Mountain ranges. For SOM, the posterior PIWs improved in shallower layers (0-15 cm) over both the

660 Coastal Ranges and the Sierra Nevada Mountains, with the coastal line showing notably
661 narrower PIWs. For pH, the results present a mixed pattern of PIWs after residual
662 correction, with some areas showing reduced uncertainty and others showing the
663 opposite. Similarly, bulk density exhibits a mixed pattern, though deeper layers (60 cm to 2
664 m) generally show reduced uncertainty in the Central Valley, California.



665

666 **Figure 9: Differences of 5% — 95% posterior and prior prediction interval widths (PIWs)**

667 **for soil properties across different depths. Each column represents a specific soil**

668 **property and rows show different depths. Black polygons represent the continental**

669 **part of California. Differences between posterior and prior PIWs are in a red-to-blue**

color scale. Red pixels indicate a decrease in posterior PIW, indicating residual correction reduces uncertainties. Vice versa for blue pixels. White areas indicate similar extent of uncertainties. The left colorbar corresponds to sand, silt, clay with wider ranges of PIW differences. The right colorbar represents other properties with smaller PIW changes.

4 Discussion

4.1 Limitations in Soil Profile Data

The effectiveness of residual correction depends on the spatial and vertical distribution of soil profiles used to calculate residuals. In regions with sparse sampling, such as California's desert areas (Figure 1), the limited number of profiles leads to interpolating the entire area using limited observations. If soil heterogeneity is not captured by these limited samples, the residual correction would overlook it. For soil texture, most data collected by staff working on multiple projects under the National Institute of Food and Agriculture (NIFA) and the Sustainable Agricultural Systems (SAS) programs range from the surface to 1.1 meters deep (additional field measurements used in this work). We use spline interpolation to predict soil texture data beyond 1.1-m depths. It assumes vertical continuity in soil properties, which may not reflect abrupt changes in subsurface layers.

Uncertainty also arises from converting some soil organic carbon (SOC) data to soil organic matter (SOM). We used the van Bemmelen factor (1.724) to convert SOC to SOM profiles. This factor does not hold true in scenarios such as organic-rich soils. Adding data

quality controls—such as filtering profiles based on metadata (such as soil type, land use)—could filter out samples that are not suitable for this conversion. However, this conversion still has uncertainties, since even for mineral soils, this factor still has a certain extent of variation depending on the organic matter composition (lower for soils with more decomposed organic matter), soil types (forest soils or wetland soils with anaerobic decomposition), and environmental influences (such as microbial activity).

4.2 Computational Challenges

The iterative residual correction process on distributions requires computational resources, particularly when applied to large-extent or high-resolution datasets. This process involves adjusting multiple values for each pixel, as each pixel represents a distribution of soil properties. This process can be approached in two ways. The first method involves correcting the residual values for each pixel, adding these residuals to update the posterior values of soil properties, and then converting these updated values to generate a posterior distribution of soil properties. The second method first converts all pixel values into the same histogram bins and then corrects the shape of these histogram bins for each pixel. Thus, the number of values retained per pixel affects computational expense. Based on our experience, using method two, especially for soil texture, requires 100-bin histograms. Using method one with 20 most probable prior property values for residual correction can achieve comparable results while reducing memory usage.

The iterative process of updating features and correcting residuals also plays a role. In our simulations, we observed that subsequent residual corrections generally align with previous ones. To ensure consistency, we require the corrections to converge more than three times across different depths. For example, residual correction for a 1-km soil property map over California takes approximately two hours after preprocessing the input data. However, processing higher-resolution datasets, such as those at a 10-meter scale, can demand significantly more computational resources. This highlights the trade-off between resolution and computational efficiency in DSM projects.

4.3 Temporal and Spatial Constraints

The current method does not account for temporal changes in soil properties, limiting its applicability to dynamic properties like soil organic matter or bulk density. Incorporating temporal covariates (such as seasonal land surface temperature, recent land-use changes) or stratifying soil profiles by collection date could address this. However, such improvements rely on the availability of temporally resolved soil data, which are often limited in quantities and sampling frequency.

Spatial clustering of soil samples poses another challenge. While duplicate profiles were removed during data preprocessing, nearby samples may still share a certain level of similarity due to spatial autocorrelation. This could lead to overly optimistic evaluation of residual correction performance. Two methods can help address this issue:

(1) Cross-validation with spatial considerations: Implement a cross-validation method for splitting training and validation sets with attention to sample locations. Ensure a minimum distance between training samples and evaluation data.

(2) Independent dataset evaluation: Use independent datasets to evaluate the model. CONUS-wide instrumental network, such as the U.S. Climate Reference Network and the National Ecological Observatory Network, provide independent soil data. However, these datasets have limitations as they were collected with clustering to certain landscapes, potentially introducing bias in the evaluation.

4.4 Similar Studies

Several continental-scale DSM products (or methods) are compared, including the Soil Survey Geographic Database (SSURGO), the Gridded National Soil Survey Geographic Database (gNATSGO), the Probabilistic Layers for the Assessment of Soils (POLARIS), Soil-Landscape Unified Synthesis (SOLUS), and the pruned Hierarchical Random Forest with iterative bias correction (pHRF with IRC) soil properties. SSURGO is a traditional, polygon-based product derived from expert field surveys and remains widely used in agricultural applications (Soil Survey Staff et al., 2023). gNATSGO mainly builds on SSURGO by rasterizing its map units to improve spatial coverage. And its estimation of soil properties still rely on utilizing metadata of legacy soil data (Soil survey staff, 2023). These two still inherit legacy data's limitations, such as scale inconsistency between soil map units and derived soil maps, inconsistencies with field observations, and report distribution of soil

properties with only three values (low end value, representative value, and high end value) (Rossiter et al., 2022; Soil Survey Staff, 2025; Xu et al., 2025).

Development of the following DSM products incorporates quantitative models in their methodology. POLARIS produces probabilistic soil property maps using machine learning and the DSMART algorithm (Chaney et al., 2016, 2019; Odgers et al., 2015), while the uncertainties in the DSMART algorithm can propagate into POLARIS. SOLUS integrates legacy soil data with georeferenced field observations and employs linear adjusted Random Forest to predict soil properties (Nauman et al., 2024). SOLUS hierarchizes soil data with different qualities into its training dataset, giving more attention to georeferenced observations. However, since it also uses resampled soil data derived from polygon-based soil map units, this process may introduce additional uncertainties into the final product. The pHRF with IRC follows a different approach. Unlike most DSM methods that directly predict soil properties from input data, this approach works in two steps: first, it generates a prior estimate of soil taxa and property values, then iteratively adjusts these estimates to improve model performance. In future work, the pHRF with IRC method will be applied on large scale and assessed with more soil properties to evaluate its generalizability.

5 Conclusion

The study introduces an iterative residual correction method for post processing used in a Digital Soil Mapping (DSM) framework. The method integrates additional soil profile data and iteratively optimizes the feature space to refine the distribution of soil properties until

778 the residual correction model converges. Convergence is achieved when the median
779 difference between updated and previous predictions falls below a predefined threshold,
780 ensuring consistent predictions. The proposed DSM method operates through two primary
781 steps: (1) generating prior soil property maps using the pruned hierarchical Random Forest
782 (pHRF) approach, and (2) performing iterative residual correction on the priors. Residuals
783 (differences between observed values and prior predictions) are calculated and added to
784 the prior values of soil property to adjust the statistical shape of the probability distribution
785 pixel-by-pixel. The feature space, which includes soil covariates, depth information, and
786 vertical correlations, is iteratively optimized to capture incremental adjustments to
787 subsequent predictions.
788
789 Using this method, we updated posterior distribution of soil properties for sand, silt, clay
790 content, soil pH, oven-dry bulk density, and soil organic matter over California. The results
791 show improvements in the accuracy of soil properties predictions, as shown by multiple
792 metrics including RMSE, R^2, and correlation coefficients. Furthermore, the iterative
793 residual correction model reduced prediction uncertainties, presenting narrower
794 prediction intervals compared to the priors.
795
796 Several innovations contribute to the method's improvements. First, the integration of
797 additional soil profiles allows the model to further learn from georeferenced soil
798 information, complementing prior soil property estimates derived from traditional
799 surveys. Second, the iterative update of feature space captures both spatial and vertical

soil heterogeneity through a carefully selected combination of soil covariates and vertical correlations among soil profile observations. Third, the convergence-based approach to residual correction ensures stable output of posterior predictions while avoiding overfitting since only converged residuals are added to the priors. Fourth, the implementation of physical constraints and compositional data handling maintains the realism of predicted soil properties. Future research could explore the application of this framework to other soil properties and environmental contexts, such as soil hydraulic properties and CONUS-wide simulation, to test the framework's generalization, supporting informed decision-making in soil-related applications.

Data Availability

Data will be made available on request. Code is available on https://github.com/emmaxu43/IRC_CA/tree/main.

Author Contributions

Chengcheng Xu and Nathaniel Chaney designed the study and developed the methodology. Chengcheng Xu wrote the original draft and wrote the codes to produce the methodology and analyses. Nathaniel Chaney supervised the work, provided resources and funding, and helped guide the research direction. Elia Scudiero provided funding, project management, co-supervision. Elia Scudiero and Ray Anderson provided soil property samples from California that were used as part of the input dataset. Chengcheng

Xu, Nathaniel Chaney, Elia Scudiero, and Ray Anderson discussed the results and contributed to revising and editing the manuscript.

Competing Interests

The authors declare that they have no conflict of interest.

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References

Arrouays, D., McKenzie, N., Hempel, J., Forges, A. R. de, and McBratney, A. B.: GlobalSoilMap: Basis of the global spatial soil information system, CRC Press, 496 pp., 2014.

Batjes, N. H., Calisto, L., and de Sousa, L. M.: Providing quality-assessed and standardised soil data to support global mapping and modelling (WoSIS snapshot 2023), Earth System Science Data, 16, 4735–4765, https://doi.org/10.5194/essd-16-4735-2024, 2024.

Chaney, N. W., Wood, E. F., McBratney, A. B., Hempel, J. W., Nauman, T. W., Brungard, C. W., and Odgers, N. P.: POLARIS: A 30-meter probabilistic soil series map of the contiguous United States, Geoderma, https://doi.org/10.1016/j.geoderma.2016.03.025, 2016.

Chaney, N. W., Minasny, B., Herman, J. D., Nauman, T. W., Brungard, C. W., Morgan, C. L. S., McBratney, A. B., Wood, E. F., and Yimam, Y.: POLARIS Soil Properties: 30-m Probabilistic Maps of Soil Properties Over the Contiguous United States, Water Resources Research, https://doi.org/10.1029/2018WR022797, 2019.

Chen, C., Liaw, A., and Breiman, L.: Using random forest to learn imbalanced data, University of California, Berkeley, 110, 24, 2004.

Chilès, J.-P. and Delfiner, P.: Geostatistics: modeling spatial uncertainty, in: Geostatistics: modeling spatial uncertainty, John Wiley & Sons, Ltd, 147–237, https://doi.org/10.1002/9781118136188.ch3, 2012.

Corwin, D. L. and Scudiero, E.: Field-scale apparent soil electrical conductivity, Soil Science Society of America Journal, 84, 1405–1441, https://doi.org/10.1002/saj2.20153, 2020.

871 Grunwald, S., Thompson, J. A., and Boettinger, J. L.: Digital Soil Mapping and Modeling at
872 Continental Scales: Finding Solutions for Global Issues, Soil Science Society of America
873 Journal, 75, 1201–1213, https://doi.org/10.2136/SSSAJ2011.0025, 2011.

874 Haghverdi, A., Najarchi, M., öztürk, H. S., and Durner, W.: Studying unimodal, bimodal, PDI
875 and bimodal-PDI variants of multiple soil water retention models: I. Direct model fit using
876 the extended evaporation and dewpoint methods, Water (Switzerland), 12,
877 https://doi.org/10.3390/w12030900, 2020.

878 Hartemink, A. E., Hempel, J., Lagacherie, P., McBratney, A., McKenzie, N., MacMillan, R. A.,
879 Minasny, B., Montanarella, L., de Mendonça Santos, M. L., Sanchez, P., Walsh, M., and
880 Zhang, G.-L.: GlobalSoilMap.net – A New Digital Soil Map of the World, in: Digital Soil
881 Mapping: Bridging Research, Environmental Application, and Operation, edited by:
882 Boettinger, J. L., Howell, D. W., Moore, A. C., Hartemink, A. E., and Kienast-Brown, S.,
883 Springer Netherlands, Dordrecht, 423–428, https://doi.org/10.1007/978-90-481-8863-
884 5_33, 2010.

885 Hengl, T., Heuvelink, G. B., and Stein, A.: A generic framework for spatial prediction of soil
886 variables based on regression-kriging, Geoderma, 120, 75–93, 2004.

887 Hengl, T., De Jesus, J. M., Heuvelink, G. B. M., Gonzalez, M. R., Kilibarda, M., Blagotić, A.,
888 Shangguan, W., Wright, M. N., Geng, X., Bauer-Marschallinger, B., Guevara, M. A., Vargas,
889 R., MacMillan, R. A., Batjes, N. H., Leenaars, J. G. B., Ribeiro, E., Wheeler, I., Mantel, S.,
890 and Kempen, B.: SoilGrids250m: Global gridded soil information based on machine
891 learning, PLoS ONE, https://doi.org/10.1371/journal.pone.0169748, 2017.

892 Jiang, Q., Fu, Q., and Wang, Z.: Delineating site-specific irrigation management zones,
893 Irrigation and Drainage, 60, 464–472, https://doi.org/10.1002/ird.588, 2011.

894 Lesch, S., Rhoades, J., and Corwin, D.: ESAP-95 version 2.01 R: User manual and tutorial
895 guide, Research Rpt, 146, 17, 2000.

896 Lesch, S. M.: Sensor-directed response surface sampling designs for characterizing spatial
897 variation in soil properties, Computers and Electronics in Agriculture, 46, 153–179,
898 https://doi.org/10.1016/j.compag.2004.11.004, 2005.

899 Li, N., Zhao, X., Wang, J., Sefton, M., and Triantafilis, J.: Digital soil mapping based site-
900 specific nutrient management in a sugarcane field in Burdekin, Geoderma, 340, 38–48,
901 https://doi.org/10.1016/j.geoderma.2018.12.033, 2019.

902 McBratney, A. B., Mendonça Santos, M. L., and Minasny, B.: On digital soil mapping,
903 Geoderma, 117, 3–52, https://doi.org/10.1016/S0016-7061(03)00223-4, 2003.

904 Minasny, B. and McBratney, A. B.: A conditioned Latin hypercube method for sampling in
905 the presence of ancillary information, Computers & geosciences, 32, 1378–1388, 2006.

Mueller, T. G., Pierce, F. J., Schabenberger, O., and Warncke, D. D.: Map Quality for Site-Specific Fertility Management, Soil Science Society of America Journal, 65, 1547–1558, https://doi.org/10.2136/sssaj2001.6551547x, 2001.

National Cooperative Soil Survey: NCSS Soil Characterization Database (Lab Data Mart), 2018.

Nauman, T. W., Kienast-Brown, S., Roecker, S. M., Brungard, C., White, D., Philippe, J., and Thompson, J. A.: Soil landscapes of the United States (SOLUS): Developing predictive soil property maps of the conterminous United States using hybrid training sets, Soil Science Society of America Journal, 88, 2046–2065, https://doi.org/10.1002/saj2.20769, 2024.

Nussbaum, M., Zimmermann, S., Walthert, L., and Baltensweiler, A.: Benefits of hierarchical predictions for digital soil mapping—An approach to map bimodal soil pH, Geoderma, 437, 116579, https://doi.org/10.1016/j.geoderma.2023.116579, 2023.

Odgers, N. P., McBratney, A. B., and Minasny, B.: Digital soil property mapping and uncertainty estimation using soil class probability rasters, Geoderma, 237, https://doi.org/10.1016/j.geoderma.2014.09.009, 2015.

Oliver, M. A. and Webster, R.: A tutorial guide to geostatistics: Computing and modelling variograms and kriging, CATENA, 113, 56–69, https://doi.org/10.1016/j.catena.2013.09.006, 2014.

Ortuani, B., Chiaradia, E. A., Priori, S., L'Abate, G., Canone, D., Comunian, A., Giudici, M., Mele, M., and Facchi, A.: Mapping Soil Water Capacity Through EMI Survey to Delineate Site-Specific Management Units Within an Irrigated Field, Soil Science, 181, 252, https://doi.org/10.1097/SS.0000000000000159, 2016.

Poggio, L., De Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D.: SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240, https://doi.org/10.5194/SOIL-7-217-2021, 2021.

Powers, J. S., Corre, M. D., Twine, T. E., and Veldkamp, E.: Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation, Proceedings of the National Academy of Sciences, 108, 6318–6322, https://doi.org/10.1073/pnas.1016774108, 2011.

Ramcharan, A., Hengl, T., Nauman, T., Brungard, C., Waltman, S., Wills, S., and Thompson, J.: Soil Property and Class Maps of the Conterminous United States at 100-Meter Spatial Resolution, Soil Science Society of America Journal, 82, 186–201, https://doi.org/10.2136/sssaj2017.04.0122, 2018.

Rossiter, D. G., Poggio, L., Beaudette, D., and Libohova, Z.: How well does digital soil mapping represent soil geography? An investigation from the USA, SOIL, 8, 559–586, https://doi.org/10.5194/soil-8-559-2022, 2022.

Schmidinger, J. and Heuvelink, G. B. M.: Validation of uncertainty predictions in digital soil mapping, Geoderma, 437, 116585, https://doi.org/10.1016/j.geoderma.2023.116585, 2023.

Scudiero, E., Corwin, D. L., Markley, P. T., Pourreza, A., Rounsaville, T., Bughici, T., and Skaggs, T. H.: A system for concurrent on-the-go soil apparent electrical conductivity and gamma-ray sensing in micro-irrigated orchards, Soil and Tillage Research, 235, 105899, 2024.

Sharififar, A., Sarmadian, F., Malone, B. P., and Minasny, B.: Addressing the issue of digital mapping of soil classes with imbalanced class observations, Geoderma, 350, 84–92, https://doi.org/10.1016/j.geoderma.2019.05.016, 2019.

Shi, G., Sun, W., Shangguan, W., Wei, Z., Yuan, H., Zhang, Y., Liang, H., Li, L., Sun, X., Li, D., Huang, F., Li, Q., and Dai, Y.: A China dataset of soil properties for land surface modeling (version 2), https://doi.org/10.5194/essd-2024-299, 29 August 2024.

Soil, K.: Survey laboratory methods manual, Soil Survey Investigations Report, 1996.

Soil Survey Staff: Kellogg Soil Survey Laboratory methods manual, U.S. Department of Agriculture, Natural Resources Conservation Service, Lincoln, Nebraska, 2014.

Soil survey staff: Gridded National Soil Survey Geographic (gNATSGO) Database for the Conterminous United States, 2023. Natural Resources Conservation Service, United States Department of Agriculture.

Soil Survey Staff: Gridded Soil Survey Geographic (gSSURGO) Database for the Conterminous United States, 2025. Natural Resources Conservation Service, United States Department of Agriculture.

Soil Survey Staff, Natural Resources Conservation Service, and United States Department of Agriculture: Soil Survey Geographic (SSURGO) Database for the CONUS, 2023. Natural Resources Conservation Service, United States Department of Agriculture.

Sylvain, J.-D., Anctil, F., and Thiffault, É.: Using bias correction and ensemble modelling for predictive mapping and related uncertainty: A case study in digital soil mapping, Geoderma, 403, 115153, https://doi.org/10.1016/j.geoderma.2021.115153, 2021.

Takoutsing, B., Heuvelink, G. B. M., Stoorvogel, J. J., Shepherd, K. D., and Aynekulu, E.: Accounting for analytical and proximal soil sensing errors in digital soil mapping, European Journal of Soil Science, 73, e13226, https://doi.org/10.1111/ejss.13226, 2022.

Vereecken, H., Schnepf, A., Hopmans, J. W., Javaux, M., Or, D., Roose, T., Vanderborght, J., Young, M. H., Amelung, W., Aitkenhead, M., Allison, S. D., Assouline, S., Baveye, P., Berli, M., Brüggemann, N., Finke, P., Flury, M., Gaiser, T., Govers, G., Ghezzehei, T., Hallett, P., Hendricks Franssen, H. J., Heppell, J., Horn, R., Huisman, J. A., Jacques, D., Jonard, F.,

977 Kollet, S., Lafolie, F., Lamorski, K., Leitner, D., McBratney, A., Minasny, B., Montzka, C.,
978 Nowak, W., Pachepsky, Y., Padarian, J., Romano, N., Roth, K., Rothfuss, Y., Rowe, E. C.,
979 Schwen, A., Šimůnek, J., Tiktak, A., Van Dam, J., van der Zee, S. E. A. T. M., Vogel, H. J.,
980 Vrugt, J. A., Wöhling, T., and Young, I. M.: Modeling Soil Processes: Review, Key
981 Challenges, and New Perspectives, Vadose Zone Journal, 15, vzj2015.09.0131,
982 https://doi.org/10.2136/vzj2015.09.0131, 2016.

983 Vereecken, H., Amelung, W., Bauke, S. L., Bogena, H., Brüggemann, N., Montzka, C.,
984 Vanderborght, J., Bechtold, M., Blöschl, G., Carminati, A., Javaux, M., Konings, A. G.,
985 Kusche, J., Neuweiler, I., Or, D., Steele-Dunne, S., Verhoef, A., Young, M., and Zhang, Y.:
986 Soil hydrology in the Earth system, Nat Rev Earth Environ, 3, 573–587,
987 https://doi.org/10.1038/s43017-022-00324-6, 2022.

988 Wu, Y., Huang, Y., Chen, Z., Yao, Z., Fu, Y., Liu, K., Luo, X., and Wang, D.: Iterative Feature
989 Space Optimization through Incremental Adaptive Evaluation,
990 https://doi.org/10.48550/arXiv.2501.14889, 24 January 2025.

991 Xu, C., Huang, J., Hartemink, A. E., and Chaney, N. W.: Pruned hierarchical Random Forest
992 framework for digital soil mapping: Evaluation using NEON soil properties, Geoderma, 459,
993 117392, https://doi.org/10.1016/j.geoderma.2025.117392, 2025.

994 Zhang, G. and Lu, Y.: Bias-corrected random forests in regression, Journal of Applied
995 Statistics, 39, 151–160, https://doi.org/10.1080/02664763.2011.578621, 2012.

996