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Mapping and modeling soil organic carbon in the Eastern Allegheny Plateau and Mountains using legacy data

Katey M. Yoast

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MAPPING AND MODELING SOIL ORGANIC CARBON IN THE EASTERN ALLEGHENY PLATEAU AND MOUNTAINS USING LEGACY DATA

Katey M. Yoast

Thesis submitted to the College of Agriculture, Natural Resources, and Design at
West Virginia University in partial fulfillment for the requirements for the degree
of Masters of Science in Soil Science

Committee:

James A. Thompson, Ph.D., Chair
Louis M. McDonald, Ph.D.
Brenden E. McNeil, Ph.D.
Michael P. Strager, Ph.D.

Division of Plant and Soil Sciences

Morgantown, West Virginia

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MLRA 127

Abstract

Mapping and Modeling Soil Organic Carbon in the Eastern Allegheny Plateau and Mountains Using Legacy Data

Katey M. Yoast

The deeply dissected topography and diverse climate of the Eastern Allegheny Plateau and Mountains (Major Land Resource Area (MLRA) 127) create challenges for dynamicpedoecological modeling needed for ecosystem management adaptation to a changing climate. The spatial distribution of soil organic carbon (SOC), one of the most dynamic soil properties, has been previously estimated and mapped using the State Soil Geographical Database (STATSGO2) and the more detailed Soil Survey Geographic Database (SSURGO) for MLRA 127, estimating mean SOC to a depth of 1 m to be 2.60 and 4.40 kg m⁻², respectively. Previous studies have shown that these approximations underestimate true carbon stock due to unpopulated organic horizons and inconsistencies within the databases. Between 1960 and 2009, the USDA-NRCS Kellogg Soil Survey Lab (KSSL) sampled and characterized 254 pedons within MLRA 127 based on soil survey needs. Each pedon had a site description and associated chemical and physical lab analyses to support its taxonomic classification. Data mining revealed that 13% of these 254 pedons lacked soil organic carbon data for one or more horizons and 50% lack bulk density (BD) values. Random forest (RF) and median and mean techniques were assessed, validated, and then used to populate missing BD and SOC data. Geographically weighted regression (GWR) and GWR kriging (GWRK) techniques were then used to model SOC stock in MLRA 127 using prepared and fully populated KSSL pedons and environmental covariates. The resulting SOC predictions were independently validated with measured Rapid Carbon Assessment (RaCA) samples and uncertainty was assessed using the fuzzy k-means with extragrades algorithm. Comparisons between GWR and GWRK models created in this study to the RaCA prediction model developed by NRCS showed that nonparametric spatial modeling techniques such as GWRK and RF are able to effectively predict SOC stock within a MLRA. The error rates calculated from the GWR, GWRK, and RaCA models were much lower than previous studies, indicating that SOC prediction by MLRA might be the most suitable way for

NRCS to predict SOC stock and that GWRK should be the recommended approach for DSM of SOC. Total biosphere carbon calculated using the Forest Inventory Analysis (FIA) model and substituting GWRK soil for soil carbon and forest litter revealed that soils contain 79% of the total carbon in the terrestrial biosphere of MLRA 127. The methodology presented in this thesis, beginning with preparing KSSL data and ending with an interpolated GWRK model with 95% prediction intervals depicting the SOC stock of the upper 1 m of soil in MLRA 127, is recommended to the NRCS as a guideline for future DSM approaches. Creating, validating, and assessing uncertainty of a SOC model created from measured data and environmental covariates will enhance the understanding of terrestrial biosphere carbon and support national climate change initiatives such as the U.S. Carbon Cycle Science Program.

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Chapter 1: Modeling Soil Organic Carbon Stock from Legacy Data and Environmental Covariates

Introduction

Soil organic carbon (SOC), a dynamic soil property and the largest pool of terrestrial organic carbon in the biosphere (Jobbágy and Jackson, 2000; Minasny et al., 2013; Stockmann et al., 2013), plays a critical role in supplying nutrients to plants, improving soil structure and aggregate stability, contributing to cation exchange capacity, and developing sustainable land management practices (Schulte, 1988; Droogers and Bouma, 1997; Jobbágy and Jackson, 2000; Stolt et al., 2010; Batlle-Auguilar et al., 2011). Numerous studies have attempted to understand the importance of SOC, estimate carbon stock, and model SOC stock and change on regional, national, and global scales (Jobbágy and Jackson, 2000; Guo and Gifford, 2002; Batlle-Auguilar et al., 2011; Grunwald, 2011; Minasny et al., 2013). Although global estimates of SOC stocks have been made, the dynamic nature and vertical distribution of SOC remains poorly understood (Jobbágy and Jackson, 2000; Heimann and Reichstein, 2008). Given this time of changing climate and increased demand for soil productivity, it is imperative that SOC models are used to help manage soil carbon sequestration and carbon greenhouse gas fluxes in and out of ecosystems. In order to understand the dynamic nature of SOC and its relation to greenhouse gas fluxes, it is important to first recognize what SOC is and its role in pedogenesis, identify the interrelated variables that influence SOC, and then examine previous studies that will aid in the development of quantifying SOC for a desired geographical area.

Literature Review

Properties of Soil Organic Carbon

In the terrestrial food web, organic matter is deposited by plants and animals and is then utilized by primary consumers such as algae, bacteria, or fungi to produce humus. Soil organic matter (SOM), containing approximately 58% SOC, is defined as all materials of biological origin found in soils regardless of state of decomposition, including plant and animal residues on the surface or in soils, living roots, biological organisms, decomposing or decomposed litter, and burnt material of varying sizes (PIRSA, 2010). According to Stolt et al. (2010), SOM is a major fuel source for microbial activity, provides macro- and micronutrients, serves as a sink for heavy metals, is a major contributor to soil exchange capacity, is the storehouse of all SOC, and is a

crucial component of soil aggregation, infiltration, and structure. SOC is comprised of four separate carbon fractions (Table 1) that vary in size, decomposition rate, and function: plant residues, particulate organic matter (POM), humus, and recalcitrant organic matter (PIRSA, 2010). Organisms (including microorganisms and vegetation) are one of the five soil forming factors of soil formation (Jenny, 1941). Organisms break down litter to produce nutrients that support plant growth. Over time the non-labile carbon that is produced through SOM decomposition accumulates and binds to soil particles, producing a carbon sink and contributing to soil structure. The rate of decomposition and extent of the carbon sink depends on the other soil forming factors: climate, parent material, relief, and time (Jenny, 1941).

Stockmann et al. (2013) published a summary of all of the knowns and unknowns regarding SOC and outlined the following knowns at a global scale: (i) soil contains about 2,344 Gt of SOC in upper three meters with 1,500 Gt occurring in the first meter and 615 Gt in the upper twenty centimeters of the soil profile, (ii) approximately 8.7 Gt of carbon are emitted to the atmosphere globally each year by anthropogenic sources, (iii) humus has a turnover rate of approximately 27 years, and (iv) decomposition of organic matter returns most of the carbon in litter to the atmosphere. Although the carbon cycle is well known, the processes that enable the carbon cycle remain poorly understood. According to Stockmann et al. (2013), the following interactions need further research: (i) the interaction between temperature and the labile and recalcitrant form of SOC; (ii) the long-term effects of priming soils with organic matter; (iii) the interactions of microbial communities during organic matter decomposition and stabilization; (iv) the long-term effect of land management and environmental factors on SOM; (v) the distribution of SOM in the soil matrix and the effects of biological, chemical, and physical processes overtime; (vi) the amount of respired versus transferred C during decomposition; and (vii) the overall composition of SOM. Given all of the unknown interactions and complexities of SOC, field and lab observations, legacy data, and digital soil mapping (DSM) should be utilized when available to better quantify the dynamic spatiotemporal nature of SOC (Droogers and Bouma, 1997; Stolt et al., 2010; Batlle-Aguilar et al., 2011; Minasny et al., 2013; Sulaeman et al., 2013).

Soil Legacy Data

The United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS) maintains soil surveys encompassing 9.7 million km² in the United States (U.S.)

and its territories as two vector and raster map products: the soil survey geographic (SSURGO) database and U.S. General Soil Map (STATSGO2), formerly the State Soil Geographic (STATSGO) database. SSURGO is made up of approximately 3,000 independent soil surveys (Thompson et al., 2012) that have different vintages and scales ranging from 1:12,000 to 1:125,000. STATSGO2 was created through the generalization of legacy independent soil surveys where available; spatial covariates such as geology, topography, vegetation, climate, and Land Remote Sensing Satellite (LANDSAT) images were used in combination with tacit knowledge to map areas that didn't have legacy soil surveys. STATSGO2 is mapped at 1:250,000 for all of the U.S. and its territories except for Alaska which is mapped at 1:1,000,000 (Grunwald et al., 2011). Soil Survey Offices are responsible for maintaining and updating STATSGO2 and SSURGO for their respective Major Land Resource Areas (MLRA) (Fig. 1.1). MLRA are geographically associated land resource units that are important delineations for interstate, regional and national planning (United States Department of Agriculture, 2006). Both SSURGO and STATSGO2 display soils as discrete map units that contain one or more soil components. STATSGO2 is made up of soil association units that contain up to 21 named components (soil series or higher taxa) while SSURGO map units only contain one to three named components (Causarano et al., 2008). Although a STATSGO2 or SSURGO map unit may contain more than one soil component in its tabular data stored in the National Soil Information System (NASIS) database, soil components and their associated soil properties are not depicted spatially. Instead, map unit properties are spatially represented by the dominant soil component, area weighted average, or the most limiting soil component (Soil Survey Division Staff, 1993; Tesfa et al., 2009). This representative component falls within the range in characteristics (RIC) listed in the Official Soil Series Descriptions (OSD) and is supported by tacit knowledge of soil scientists and Kellogg Soil Survey Laboratory (KSSL) data from the National Cooperative Soil Survey (NCSS) soil characterization database.

Legacy data in the United States, consisting of STATSGO2, SSURGO, KSSL pedons, historic soil surveys, and field observations, are currently being used for land use and management planning (regional and field-scale) and as covariates for DSM. These legacy products, suitable for regional land use planning and management, are generalized and static, are not designed for field-scale interpretation or DSM, often contain discontinuities at survey area boundaries and methodological discrepancies, and lack uncertainty or error assessments (Moore

et al., 1993; Hartemink et al., 2008; Grunwald et al., 2011). Problems associated with legacy soil data are a result of the origin of soil surveys and sampled pedons, ranging from the lack of a statistical sampling design to age of completion to the decisions made by soil survey project leaders. To combat the simplest problem with legacy data—discontinuities and discrepancies at political boundaries—the NRCS is currently harmonizing existing soils data stored in the NASIS database through the Soil Data Join Recorrelation (SDJR) project. SDJR is designed to consolidate similar map units in soil survey areas across an MLRA, evaluate and document each map unit, eliminate as many tabular join issues as possible, and populate NASIS with future field and spatial editing projects (Anderson, 2012). Through SDJR, the KSSL pedons will be updated to current *Soil Taxonomy* (Soil Survey Staff, 2014) and correlated to the appropriate soil series. SDJR is the first step in creating a seamless soils dataset for the U.S. that will allow future disaggregation and rasterization of soil survey data (Golden, 2012). In order to utilize legacy soil data as an input for DSM, the data must first be prepared (Sulaeman et al., 2013). Preparing legacy soil data consists of addressing inconsistencies in the database and differences in methodologies, tabular harmonization such as SDJR, and removing erroneous data. Once prepared, legacy soil data can be used to train geospatial models in order to explore spatial and temporal soil patterns and properties (Grunwald et al., 2011; Sulaeman et al., 2013).

Lab characterization pedon data and site descriptions for soils sampled by NRCS are available to the public through the NCSS soil characterization database. Approximately 20,000 pedons were sampled by soil scientists in the United States over the last 40 years for university or federal research, establishment of a soil series, soil survey updates, or population of RIC in OSD (NCSS National Cooperative Soil Characterization Database, 2013). When considering SOC modeling, some KSSL pedons are missing bulk density (BD) and SOC data (especially for organic horizons), rock fragment content, land use information, sampling protocol information, and proper georeferencing (Jenkins, 2001; West et al., 2010; Minasny et al., 2013; Wills et al., 2013). Wills et al. (2013) examined the KSSL database and found that of the 176,000 horizons with C measurements, only 40% had BD values populated. Furthermore, all the BD values were determined using the saran coated clod method (3B1c) (Burt, 2004). Using the clod method on soil horizons with high root, organic matter, or rock fragment contents may result in an inaccurate BD determination (Jenkins, 2001). Of the 176,000 carbon measurements, 28% were analyzed by dry combustion (4H2a1-3) (Burt, 2004), 65% by wet combustion (6A1c) (Burt,

2004), and 7% with both. In dry combustion, all forms of soil C are converted into carbon dioxide (CO_2) and the evolved CO_2 is measured. SOC is then calculated by subtracting inorganic C (carbonates) from total C. Wet combustion, also known as the Walkley-Black modified acid-dichromate digestion, involves chemically oxidizing the most active forms of SOC to CO_2 with ferrous sulfate (FeSO_4) and then quantifying the FeSO_4 used in the chemical reaction (Soil Survey Staff, 2011). Due to its higher precision, accuracy, and lower chemical production, dry combustion has become the standard SOC method for the KSSL and most of the world (Tivet et al., 2012). SOC estimates by wet combustion, used by the KSSL prior to the 1990s, have been shown to underestimate true SOC content due to incomplete oxidation (Tivet et al., 2012; Michaelson et al., 2013), overestimate SOC in deeper horizons (Grossman et al., 2001), and be invalid if SOC is greater than 8% (Soil Survey Staff, 2011). In order to avoid methodological biases in datasets with both wet and dry combustion measurements, a C-equivalent correction regression factor must be applied to horizons analyzed by wet combustion (Tivet et al., 2012; Wills et al., 2013).

Estimating Missing Legacy Data

Because missing data is a common problem with soil legacy pedons, techniques such as parametric multiple linear regression (MLR), pedotransfer functions (PTF), and look-up tables are often used to infer missing data (Sequeira et al., 2014). According to Batjes (2003), the most desirable method for filling data gaps is collecting additional measured soil data, followed by using national expert estimates and common sense, and lastly using taxotransfer rules to derive soil property estimates. Missing BD values are predominately calculated from PTF that incorporate other soil properties within the same horizon, such as SOC or clay content, and/or site properties such as land cover (Brejda et al., 2001; Calhoun et al., 2001; Nave and Johnson, 2011; Michaelson et al., 2013). Calhoun et al. (2001) compared PTF developed from field, lab, and field + lab data and found that field + lab PTF predicted BD with the highest accuracy. Although PTF have been shown to be useful for populating missing legacy data, Tomasella et al. (2000) warn against applying regionally developed PTF to other regions and against using correlated variables in order to avoid multicollinearity. Wills et al. (2013) and West et al. (2010) used a nationally derived mean BD of 1.45 g cm^{-3} for mineral soils and 0.25 g cm^{-3} for organic horizons to replace missing BD in KSSL pedons. Similarly, Buell and Markewich (2004) calculated missing BD from median BD of soil texture class. Batjes et al. (2003) suggest using

the median instead of the mean to better estimate the center of the data. Parametric techniques, such as MLR, yield a continuous equation that is often a result of implausible normality assumptions (Minasny et al., 2008). Thus, non-parametric techniques such as random forests (RF), artificial neural networks (ANN), k-nearest neighbor (k-NN), and boosted regression trees (BRT) are best suited for estimating missing soil legacy data. These four techniques have been shown to perform similarly, although researchers have preferred one method over another in several studies (Nemes et al., 2006; Hudak et al., 2008; Myers et al., 2009; Strobl et al., 2009; Ghehi et al., 2011). Myers et al. (2009) compared the following modeling techniques to predict BD: RF, BRT, regression tree, general additive models (GAM), multivariate adaptive regression splines (MARS), and generalized linear models (GLM). They found all techniques to perform similarly, with MARS performing the best by only a slight margin. Sequeira et al. (2014) created PTF using the RF algorithm to predict BD from horizon designation, median depth of the horizon, thickness, and texture class. When BD values were available from horizons above or below the horizon with a missing BD value, BD of the available horizon was incorporated into the RF algorithm. The RF algorithm is unique in that it is recursive, allows continuous and categorical variables with up to 32 categories each, incorporates interactions among predictor variables, can handle unbalanced classes, produces variable importance, and requires little data manipulation. Montillo (2009) summarized the advantages and limitations of ANN, k-NN, BRT, support vector machines (SVM), and MARS (Table 2). He concluded that RF has about the same accuracy as SVM and ANN, but is conceptually more interpretable, faster to train, has fewer parameters, can handle missing data, readily handles larger numbers of predictors, and doesn't require cross-validation. BRT are often more accurate at predicting a continuous response, but perform about the same as RF for classification. Spatial autocorrelation is not directly accounted for in any of the aforementioned models unless position information was incorporated as covariates in the models. Mascaro et al. (2014) found that incorporating position information in their RF model enhanced the predictive ability of the model by accounting for spatial autocorrelation. According to Montillo (2009), RF is advantageous over BRT in that it grows trees independently of one another, is quicker, requires fewer parameters, and does not over-fit the data. Contradictorily, some studies have shown that RF can over-fit data, especially in small datasets. The *ntree* and *mtry* parameters should be tuned for every RF model to reduce the chance of over-fitting (Segal, 2004; Statnikov et al., 2008).

In order to utilize KSSL data, Sulaeman et al. (2013) suggest the following preparation steps: (i) identification, selection, database development and population; (ii) tabular and spatial harmonization; and (iii) dataset integration. Missing data are best predicted using a nonparametric statistical model like RF with uncorrelated field and lab data as input variables. Preparing legacy data for the DSM framework provides a benchmark for future DSM studies and additional data collections. Although DSM modeling is the future of soil survey, it can never be a complete substitute for detailed ongoing collection of field and lab data (Elith et al., 2006; Tsai et al., 2010; Sulaeman et al., 2013).

Digital Soil Mapping of Soil Organic Carbon

DSM is a quantitative spatial modeling technique established in the 1990s that combines environmental covariates, such as the soil forming factors established by Jenny (1941), with legacy data or current field and lab observations to infer pedogenic properties or patterns across various temporal and/or spatial scales (Brungard, 2009; Grunwald, 2010; Minasny et al., 2013). By expanding the work of Jenny (1941), McBratney et al. (2003) developed the *scorpan* spatial prediction function:

$$S = f(s, c, o, r, p, a, n) + \varepsilon \quad [\text{Eq. 1 – 1}]$$

where a soil property or class (S) is a function of soil observations (s), climate (c), organisms (o), relief (r), parent materials (p), age (a), and spatial position (n), and ε are the spatially correlated errors (residuals). The empirical quantitative function (f) can represent complex non-linear data-mining techniques such as regression trees and RF, simple linear models, or geostatistical models such as kriging (McBratney et al., 2003; Minasny et al., 2013).

The *scorpan* function assumes that soil observations used to calibrate the model represent the entire range of variation of the c, o, r, p, a, and n covariates and that the *scorpan* covariates correlate with soil properties (Minasny et al., 2008). Areas with limited or traditional legacy data do not represent the entire range of variation of the covariates, but are often the only source of SOC data due to budget and time constraints (Minasny et al., 2008, 2013). Bui et al. (2009) developed a linear decision tree model from sparse, non-statistical legacy point data and *scorpan* covariates to estimate SOC stock in Australia. They concluded that estimating SOC with sub-kilometer resolution is possible with limited and biased legacy point data if soil forming factors

are incorporated into the DSM model. Soil properties or classes have been predicted at unsampled locations using geospatial methodologies since the late 1960s. Geospatial techniques have greatly expanded since then due to the establishment of geographic information systems (GIS), remote sensing, and the availability of high resolution digital datasets (Kumar et al., 2012). Today soil properties can be predicted continuously across a geographical area using *scorpan* covariates and an empirical quantitative function (f). MLR, ordinary kriging (OK), regression trees, and regression kriging (RK) are the most common quantitative functions used for DSM of SOC (Kumar et al., 2012). RK is different from MLR, OK, and regression trees in that it incorporates kriged residuals with global regression to account for spatial autocorrelation and trend, capturing more of the variability in the dataset. Kumar et al. (2012) refers to MLR, OK, regression trees, and RK models as stationary because they do not vary with absolute location across space. Geographically weighted regression (GWR) is a simple regression function that allows varying coefficient weights for the environmental covariates across space. Although GWR uses spatially varying covariate coefficients, it does not directly consider spatial autocorrelation in model development (Kumar et al., 2012). Geographically weighted regression kriging (GWRK) combines the frameworks of GWR and RK models to account for spatial non-stationarity and spatial autocorrelation of the residuals. Kumar et al. (2012) compared RK and GWRK and found that GWRK more precisely estimated SOC stock in Pennsylvania.

Minasny et al. (2013) reviewed previous studies of DSM of SOC and composed an outline of future considerations. The considerations of Minasny et al. (2013) for advancing the art and science of mapping SOC include: (i) obtaining representative and statistically-based soil samples, (ii) obtaining the best possible covariate data with the least amount of artifacts and error, (iii) further investigating the spatial decomposition of covariate datasets, (iv) estimating change in SOC through change in covariate data, (v) incorporating mechanistic simulation models for spatial prediction, (vi) developing a global soil map of SOC at a fine resolution, and (vii) developing new techniques to better predict SOC change. As finer resolution covariate data and statistically-designed soil samples become more available, it is expected that uncertainty in SOC models will be reduced and more variance will be explained by the model.

Environmental Covariates

Environmental covariates used in DSM differ depending on the study area, available data, and the correlation between the desired soil property or class and its environmental influences.

Soil observations, consisting of soil legacy data or recent field or lab measurements, are either fully incorporated into the model or are split into model training and validation sets (Kumar et al., 2012). The other *scorpan* covariates are used to train the model and create a continuous predictive surface.

Climate data exist in the form of measurements at meteorological stations and can be combined with a digital elevation model (DEM) data and derivatives to produce a continuous climate raster (Brungard, 2009). In the U.S., the Parameter-elevation Regressions on Independent Slopes Model (PRISM) provides gridded 30-year normals at a resolution of 800 m for the following climatic properties: precipitation, average maximum temperature, average temperature, and average minimum temperature. Meteorological station data in the U.S. are available through the National Oceanic and Atmospheric Administration (NOAA) and through NRCS in the form of Soil Climate Analysis Network (SCAN) and SNOTEL data.

Vegetation is often chosen to represent organisms given the impracticality of quantifying fauna (Brungard, 2009). Normalized Difference Vegetation Index (NDVI) is commonly used in DSM to capture vegetative cover from red and near infrared (NIR) reflectance. The red band captures the absorption of chlorophyll while the NIR band captures leaf cellular structure and plant health. The Global Land Cover Facility (GLCF) created a national NDVI data set for the U.S. from 16-day snapshots collected onboard the Moderate-resolution Imaging Spectroradiometer (MODIS) satellite from 2001 to 2006 (Carroll et al., 2004). Previous studies have either chosen one representative 16-day coverage for NDVI or used weighted regression techniques to compile multiple 16-day snapshots. Mishra et al. (2010) used the MODIS NDVI values of June 26 to July 11 2001 to estimate SOC stock in several Midwestern states while Gray and Song (2012) used a composite MODIS NDVI created from weighted nonlinear least squares regression to produce a temporal model of leaf area index. Landsat 7 Enhanced Thematic Mapper (ETM+) bands 2 (green visible), 4 (NIR), and 7 (mid-infrared (MIR)) along with NDVI have been used to represent the vegetation *scorpan* component (Boettinger et al., 2008). Landsat Geocover, designed by the Global Landcover Facility (GLCF), simplified Landsat 7 ETM+ downloads for DSM by allowing users to download 2-4-7 and 2-3-4 band combinations without having to download all Landsat bands and scenes (GLCF, 2005). Remotely sensed Landsat multi-spectral data should be considered to help represent vegetation, parent material, and soil *scorpan* covariates in DSM (Boettinger et al., 2008).

Relief is the most widely used *scorpan* covariate in DSM (Minasny et al., 2013). Terrain attributes of relief exist as primary or secondary DEM derivatives. Primary derivatives, such as slope gradient, slope aspect, slope curvatures, and flow direction are calculated directly from elevation. Secondary derivatives such as the compound topographic index (CTI) are combinations of primary derivatives that describe spatially dependent processes (Brungard, 2009). Brungard (2009) found that 52-88% of the variation in SOC, depth of the A horizon, and soil depth was explained by slope gradient and CTI at a spatial resolution of 30 m in a 275 km² study area in southwest Utah. Minasny et al. (2013) suggest that terrain attributes should be used in DSM at resolutions less than 100 m while landscape position should be used with resolutions greater than 100 m. Jasiewicz and Stepinski (2012) developed a pattern recognition landform classifier technique that identifies geomorphological phenotypes (geomorphons) from a DEM. Every cell in a DEM is assigned an appropriate geomorphon and a pattern recognition algorithm determines the appropriate spatial scale at each location. The ten most common landform elements derived from geomorphons are: flat, peak, ridge, shoulder, spur, slope, pit, valley, footslope, and hollow (Jasiewicz and Stepinski, 2012). These elements help differentiate soils based on landscape position, similar to traditional soil survey, but in a raster format. Other landform delineation techniques (Schmidt and Hewitt, 2004; Iwahashi and Pike, 2007) have also been used to represent relief. Schmidt and Hewitt (2004) developed a fuzzy land element classification algorithm that assigns fuzzy membership in 15 land elements to each raster cell. Iwahashi and Pike (2007) used an automated nested-means classification algorithm to assign landform classes based on the mean of slope gradient, local convexity, and surface texture in nested two-fold partitions.

Parent material, often represented by lithology, determines the chemical composition and grain size of minerals that are exposed to chemical weathering at the beginning of pedogenesis (Brungard, 2009). Bedrock geology is mapped in the U.S. by the United States Geological Survey (USGS) at a scale of 1:250,000. Gamma radiometrics have been shown to correlate with soil moisture, clay content, and SOC and have been used in DSM models to help represent parent material (Minasny et al., 2013). A gamma radiometric survey measures the spatial distribution of potassium (K), thorium (Th), and uranium (U) within the upper 30-45 cm of the soil profile. The resulting RBG image shows K as a percentage and Th and U as parts per million (ppm) (DEPI,

2013). Gamma radiometrics, along with other remotely sensed imagery such as Landsat, give continuity to USGS lithology polygons to better represent parent materials.

The age of soil is an important covariate to consider when using DSM due to its influence on chemical, biological, and physical soil reactions. Since age determination techniques such as optical luminescence are labor and cost intensive, soil age has not previously been characterized in DSM models (Brungard, 2009). The spatial position of soil is inherently built into DSM. Minasny et al. (2013) composed a summary table of covariates used in previous SOC studies (Table 3). Environmental covariates provide the geospatial link that enables soil scientists to model aspects of pedogenesis.

Uncertainty and Validation

Minasny et al. (2013) reviewed previous DSM of SOC studies and found that most studies involved compiling a soils database and covariate datasets for an area of interest, training a prediction function with soil observations, interpolating or extrapolating a prediction function over the area of interest, and validating the prediction function with existing or independent datasets. Out of the 40 studies they reviewed, half were not validated and the other half were validated using cross-validation or internal validation. Uncertainty was not addressed in most of the studies. Both validation and uncertainty estimations are needed to assess the overall accuracy of a model and for interpretation and risk assessment management (Nemes et al., 2009).

Uncertainty is a measure of confidence for a prediction from model structure, inputs, and parameters (Malone et al., 2011; Minasny et al., 2013). In their review of DSM of SOC, Minasny et al. (2013) found that SOC content and rock fragment content were the main sources of uncertainty when modeling SOC stock. Most data mining studies of SOC did not address uncertainty, while most geostatistical studies did. Previous geostatistical studies have quantified uncertainty through Monte Carlo simulation, Taylor analysis, bootstrapping, Bayesian approaches, or an empirical fuzzy k-means with extragrades algorithm (Minasny et al., 2013). Minasny et al. (2013) suggest using the fuzzy k-means with extragrades algorithm to quantify uncertainty for large geographical areas or when combining data mining tools with RK due to its high computational power and ability to quantify model parameter uncertainty. The fuzzy k-means with extragrades algorithm partitions covariates into several classes, where each class is represented by a prediction interval derived from the empirical distribution as a weighted average of membership values. This approach identifies and penalizes observations outside of

the domain of the calibration data and allows a new observation to be assigned to an established class based on class centroids (Minasny et al., 2013). Malone et al. (2011) developed the fuzzy k-means with extragrades approach and found that it performed well with SOC and available water holding capacity (AWC). Malone et al. (2011) suggest that future work be done to further test the approach with different calibration sample sized and soil attributes. Methods for improving uncertainty estimations are continually being tested and updated in order to better capture the extent to which errors are propagated through a model.

Validation of modeled SOC is performed through cross-validation, internal validation, or independent sampling. Cross-validation techniques, such as leave-one-out and n-fold, recursively split observations within a database by leaving one out or splitting into n-folds to assess the accuracy of the calibrated model. Internal validation is performed by splitting or randomly holding back observations using a pre-determined percentage of the database to train a model and is then tested with the observations that were held back. Ancillary data are used to validate a model using the independent sampling technique (Minasny et al., 2013). Of the 40 studies that Minasny et al. (2013) reviewed, only half were validated. The random holdback internal validation method was used for all of the validated SOC studies. Both the cross-validation and internal validation techniques may produce biased estimates due to biased data inputs or spatially correlated prediction errors. Although unbiased independent sampling is the recommended validation approach, time and affordability often limit the applicability of independent validation. When uncertainty and validation assessments are both included in a study, the end user is able to better understand the nature and distribution of the input data, model error, and the overall accuracy and applicability of the model. Uncertainty and validation allow for a better understanding of the dynamic nature of SOC in relation to its correlated covariates across space and are thus needed for all SOC prediction studies (Minasny et al., 2013).

Research Rationale

Because soil contains three to four times more carbon than the atmosphere (Batlle-Aguilar et al., 2011), small changes in SOC content can have great impacts on the global carbon budget (Bui et al., 2009). In order to understand, predict, and manage these impacts, an initial assessment of SOC stock and its dynamic nature is needed within the realm of soil survey (Stolt et al., 2010). Due to its unique and diverse vegetative, climatic, geologic, and pedogenic properties, MLRA 127 (Eastern Alleghany Plateau and Mountains) was chosen as the study area

for this research. SOC estimates for MLRA 127 have historically incorporated soil databases or soil characterization data gathered for soil survey purposes, not on actual SOC studies designed for MLRA 127 (Jenkins, 2001). SSURGO and STATSGO2 databases have often underestimated true SOC stock due to lack of organic horizon population and conservative representative values (Zhong and Xu, 2011; Nauman et al., 2012). SOC estimates for MLRA 127 range from 2.2 kg m⁻² (Bliss et al., 1995) to 32.0 kg m⁻² (Kern, 1994) (Table 4). This wide range of SOC stock estimates coupled with lack of uncertainty assessments and validation indicates a need to better understand and capture SOC variability across MLRA 127.

Study Area

MLRA 127 includes parts of five states (Maryland, New York, Pennsylvania, Virginia, and West Virginia) and encompasses 50,370 km² (19,440 mi²) (Fig. 1.2). The physiography of this area consists of the Kanawha and Allegheny Mountain Sections of the Appalachian Plateaus Province of the Appalachian Highlands, and is located just west of the Allegheny Front (United States Department of Agriculture, 2006). The high escarpment of the Allegheny Front separates the deeply dissected Appalachian Plateaus Province (MLRA 127) to the west from the folded and faulted Valley and Ridge Province (MLRA 147) to the east (United States Department of Agriculture, 2006). Elevation ranges from 300 to 800 m (980 to 2,625 ft) in the plateau portion of MLRA 127 to 1,100 to 1,400 m (3,600 to 4,600 ft) in the mountainous portion located in southeastern West Virginia. The geology of MLRA 127 consists of alternating beds of sandstone, limestone, coal, and shale of the Permian, Mississippian, Pennsylvanian, and Cambrian ages. River valleys in this region are composed of stratified, unconsolidated alluvial deposits of sand, silt, clay, and gravel, with some outwash and glaciofluvial deposits in the northwest corner of Pennsylvania (United States Department of Agriculture, 2006). The footslopes and mid to lower backslopes of hills consists of colluvium from residual bedrock. MLRA 127 has all four climatic seasons, with an average annual temperature of 6 to 12°C (43 to 54°F). Most of the precipitation occurs as intense, convective thunderstorms occurring in the spring and summer. Average annual precipitation ranges from 840 to 1,725 mm (33 to 68 in), increasing in a southern direction and with elevation. Average annual snowfall ranges from 890 mm (35 in) in southern MLRA 127 to 2,285 mm (90 in) in the northern part (United States Department of Agriculture, 2006). The frost-free period ranges from 115 days in high elevations or in the north to 205 days in the lower elevations of southern MLRA 127. Ultisols and Inceptisols are the dominant soil

orders of MLRA 127, with Entisols, Alfisols, and Spodosols occurring to a lesser extent. The soils in this area are dominantly in the udic or aquic moisture regimes and mesic temperature regime, with the high-elevation and northern soils occurring in the perudic moisture regime and frigid temperature regime (United States Department of Agriculture, 2006). These soils have mixed or siliceous mineralogy and are generally moderately deep to very deep with excessively well to somewhat poor drainage classes. MLRA 127 supports high-quality hardwoods, such as oak, black cherry, yellow-poplar, and maple, at the lower elevations and intermixed deciduous and coniferous species at higher elevation, including red spruce, hemlock, birch, maple, black cherry, and beech (United States Department of Agriculture, 2006). Due to the geographical makeup of MLRA 127, most of the area is forested (76%). The remaining areas have been cleared to support crops (7%), pasture (7%), urban development (6%), other land uses (3%), and water (1%) (United States Department of Agriculture, 2006).

Objectives

This research was aimed at developing a framework for the NRCS to model SOC as a continuous function using legacy KSSL data and environmental covariates. The objectives of this research were to:

- a) Populate missing KSSL data using RF, median by horizonation and texture class, and mean by horizonation and texture class to provide a better input for the DSM of SOC.*
- b) Model SOC through GWRK as a function of harmonized legacy KSSL data and environmental covariates and assess the validity and uncertainty of the GWRK model.*
- c) Assess ecosystem carbon using the Forest Inventory Analysis model and GWRK SOC model to determine the role that SOC has in relation to terrestrial biosphere carbon.*

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Figures and Tables

Figure 1.1 Structure and hierarchy of USDA-NRCS Major Land Resource Area Offices (MOs) and soil survey products from most general and smallest scale MOs to most specific x,y sites and pedons, edited from (http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053637).

Figure 1.2 The Eastern Allegheny Plateau and Mountains (MLRA 127) encompassing parts of Maryland, New York, Pennsylvania, Virginia, and West Virginia.

Table 1.1 The four soil SOC fractions and their size, stability, turnover time, and key functions adapted from PIRSA (2010).

Organic Carbon Pool	Size	Stability	Turnover Time	Key Functions
Crop Residues (shoot and root residues on and in the soil)	>2mm	Labile	Days	Crop residues are readily broken down by microorganisms to provide energy and nutrients to the biological community in the soil.
Particulate Organic Matter (smaller plant debris)	0.05 - 2mm			Particulate organic matter (POM) is broken down relatively quickly in suitable conditions, but more slowly than crop residues. POM is important for soil structure and provision of energy for biological processes and nutrients.
Humus (decomposed material dominated by molecules stuck to soil minerals)	< 0.05mm			Humus plays a role in all key soil functions, but is particularly important in the retention and provision of nutrients.
Recalcitrant Organic Matter (biologically stable, dominated by pieces of charcoal)	Variable	Very stable/relatively inert	Hundreds of years	Recalcitrant organic matter decomposes very slowly and if present in large enough quantities, can contribute to cation exchange capacity as well as mediating soil temperature.

Table 1.2. A comparison of machine learning techniques adapted from Montillo (2009).

Characteristic	Neural Networks	SVM	Trees	MARS	k-NN, Kernals
Natural handling of "mixed" data	●	●	●	●	●
Handling of missing data	●	●	●	●	●
Robustness to outliers in input space	●	●	●	●	●
Insensitive to monotone transformations of inputs	●	●	●	●	●
Computational scalability (large N)	●	●	●	●	●
Ability to deal with irrelevent inputs	●	●	●	●	●
Ability to extract linear combinations of features	●	●	●	●	●
Interpretability	●	●	●	●	●
Predictive power	●	●	●	●	●

Key: ● = good, ● = fair, and ● = poor.

Table 1.3. A review of environmental covariates used in digital soil mapping of carbon. Adapted from Minasny et al. (2013).

Covariates	References
Aerial Image	Chen et al., 2000; Muñoz and Kravchenko, 2011
Apparent Electrical Conductivity (ECa)	Simbahan et al., 2006; Miklos et al., 2010
Climate	McKenzie and Ryan, 1999; Henderson et al., 2005; Bui et al., 2009; Mishra et al., 2009; Stroorvogel et al., 2009; Mishra et al., 2010; Phachomphon et al., 2010; Martin et al., 2011; Zhang et al., 2011; Wheeler et al., in press
Compound Topographic Index	Moore et al., 1993; Gessler et al., 2000; Rawlins et al., 2009
Depth to Groundwater	Meersmans et al., 2008; Kempen et al., 2011
Elevation/Relief/Slope	McKenzie and Ryan, 1999; Henderson et al., 2005; Simbahan et al., 2006; Bui et al., 2009; Mishra et al., 2009; Rawlins et al., 2009; Phachomphon et al., 2010; Vasques et al., 2010; Razakamanarivo et al., 2011
Gamma Radiometrics	Malone et al., 2009; Rawlins et al., 2009; Miklos et al., 2010; Wheeler et al., in press
Hyperion Hyperspectral Data	Gomez et al., 2008
Hyperspectral image	Selige et al., 2006; Stevens et al., 2010 Grimm et al., 2008; Meersmans et al., 2008; Mora-Vallejo et al., 2008; Bui et al., 2009; Stroorvogel et al., 2009;
Land Cover/Use	Mendonca Santos et al., 2010; Mishra et al., 2010; Kempen et al., 2011; Martin et al., 2011; Wiesmeier et al., 2011; Zhang et al., 2011
Landsat	Henderson et al., 2005; Minasny et al., 2006; Huang et al., 2007; Bui et al., 2009; Malone et al., 2009; Marchetti et al., 2010; Mendonca Santos et al., 2010; Vasques et al., 2010
Legacy Lab Data	Henderson et al., 2005; Bui et al., 2009; Mishra et al., 2009; Mishra et al., 2010;
Lithology	McKenzie and Ryan, 1999; Henderson et al., 2005; Bui et al., 2009; Mendonca Santos et al., 2010; Mishra et al., 2010; Wiesmeier et al., 2011; Wheeler et al., in press
NDVI	Bou Kheir et al., 2010; Burnham and Sletten, 2010; Mishra et al., 2010; Zhao and Shi, 2010; Kunkel et al., 2011
Paleogeography	Kempen et al., 2011
Parent Material	Grimm et al., 2008; Bou Kheir et al., 2010
Potential Insolation	Kunkel et al., 2011
Remotely Sensed VIS-NIR-SWIR Imagery	Bartholomeus et al., 2011
Soil Classification	Henderson et al., 2005; Simbahan et al., 2006; Grimm et al., 2008; Meersmans et al., 2008; Bui et al., 2009; Rawlins et al., 2009; Bou Kheir et al., 2010; Phachomphon et al., 2010; Ungaro et al., 2010; Kempen et al., 2011; Martin et al., 2011; Wiesmeier et al., 2011; Zhang et al., 2011
Surface Reflectance from IKONOS	Simbahan et al., 2006
Terrain Attributes/Topography/Geomorphology	Mueller and Pierce et al., 2001; Henderson et al., 2005; Thompson and Kolka, 2005; Minasny et al., 2006; Grimm et al., 2008; Mora-Vallejo et al., 2008; Malone et al., 2009; Stroorvogel et al., 2009; Bou Kheir et al., 2010; Marchetti et al., 2010; Mendonca Santos et al., 2010; Miklos et al., 2010; Mishra et al., 2010; Muñoz and Kravchenko, 2011; Zhao and Shi, 2010; Kempen et al., 2011; Wiesmeier et al., 2011; Wheeler et al., in press
Vis-NIR Portable Spectrometer	Huang et al., 2007; Gomez et al., 2008; Muñoz and Kravchenko, 2011

Table 1.4. Average SOC Estimates for the upper 1m of soil in the Eastern Allegheny Plateau and Mountains adapted from Jenkins (2001).

Source	SOC (kg m ⁻²)
Kern (1994)	
Ecosystem Approach	28.1 - 32.0
Soil Taxonomy	13.6 - 15.0
Eswaran et al. (1993)	
World Soils Map	10.6 - 12.1
Bliss et al. (1995)	
Soil Interpretation Database	2.2
Jenkins (2001)	
Mesic Series	8.9 - 11.7
Frigid Hardwood Sites	12.9 - 18.8
Frigid Spruce Sites	11.3 - 13
Mishra et al. (2010)	10.3
STATSGO2 MLRA 127	2.6
gSSURGO MLRA 127	4.4
Rapid Carbon Assessment	9.0

Chapter 2: Populating Missing Soil Organic Carbon Legacy Data

Abstract

Soil organic carbon (SOC), a dynamic soil property and the largest pool of terrestrial organic carbon in the biosphere, plays a critical role in supplying nutrients to plants, improving soil structure and aggregate stability, contributing to cation exchange capacity, and developing sustainable land management practices. Due to cost of sampling and laboratory analyses, legacy soil data are often used to train and validate SOC models. Missing data and methodological inconsistencies are common limitations to legacy soil databases such as the Kellogg Soil Survey Laboratory (KSSL) database. Data preparation, including data assemblage, updating series correlation, methodological correction factors, normality testing, outlier assessment, and estimation and validation of missing data, is essential for the extrapolation of soil properties across space. MLRA 127 (Eastern Alleghany Plateau and Mountains) was chosen as the study area for this research due to its complex, high dissected topography and diverse climatic, vegetative, and pedogenic properties that present challenges to pedoecological mapping. KSSL pedons sampled by the Natural Resources Conservation Service (NRCS) within MLRA 127 were downloaded from the National Cooperative Soil Survey (NCSS) soil characterization database and classified using the most current version of U.S. *Soil Taxonomy*. Because SOC stock is calculated from rock fragments (volume %), SOC (%), soil thickness, and 33 kPa bulk density (g cm^{-3}), these specific data were prepared. SOC data that were determined by wet combustion were converted to dry combustion total carbon percentages using a nationally developed pedotransfer function (PTF) to avoid methodological biases. Missing SOC and bulk density (BD) data were predicted using random forest (RF) and mean and median values by horizon designation and texture class. Outliers were identified using box and whisker plots and were both incorporated and removed from analysis to determine their role in prediction. RF performed best at predicting BD ($R^2 = 0.69$, RMSE = 0.16). Mean by horizon designation and texture class with outliers included performed slightly better than RF for SOC ($R^2 = 0.93$, RMSE = 3.96 and $R^2 = 0.9$, RMSE = 4.7, respectively). RF is a better predictor model for mineral horizons while mean by horizon and texture class is better for predicting organic horizons. Given the stability of prediction and simplicity of training and validation, RF is the recommended method for populating missing soil legacy data.

Introduction

Lab characterization pedon data and site descriptions for soils sampled by the NRCS are available to the public through the NCSS soil characterization database. Approximately 20,000 pedons were sampled by soil scientists in the United States over the last 40 years for university or federal research, establishment of a soil series, soil survey updates, or population of the range in characteristics for a soil series (NCSS National Cooperative Soil Characterization Database, 2013). Some of these KSSL pedons are missing BD and SOC data (especially for organic horizons), rock fragment content, land use history, sampling protocols, and are not always georeferenced (Jenkins, 2001; West et al., 2010; Minasny et al., 2013; Wills et al., 2013). Wills et al. (2013) examined the KSSL national database and found that of the 176,000 horizons with SOC measurements, only 40% had BD values populated. All of the BD were measured using saran coated clods (3B1c) (Burt, 2004). Using the clod method on soil horizons with high root content, organic matter, or rock fragment content may result in inaccurate BD (Jenkins, 2001). Of the 176,000 carbon measurements, 28% were characterized by dry combustion (4H2a1-3) (Burt, 2004), 65% by wet combustion (6A1c) (Burt, 2004), and 7% with both. In dry combustion, all forms of soil carbon are converted into carbon dioxide (CO_2) and the evolved CO_2 is measured. SOC is then calculated by subtracting inorganic carbon (carbonates) from total carbon. Wet combustion, performed as the Walkley-Black modified acid-dichromate digestion, involves chemically oxidizing the most active forms of SOC to CO_2 with ferrous sulfate (FeSO_4) and then quantifying the FeSO_4 used in the chemical reaction (Soil Survey Staff, 2011). Due to its high precision, accuracy, and low chemical wastes, dry combustion has become the standard SOC method for the NRCS and most of the world (Tivet et al., 2012). SOC estimates by wet combustion, used by the KSSL prior to the 1990s, have been shown to underestimate total SOC due to incomplete oxidation (Tivet et al., 2012; Michaelson et al., 2013), overestimate SOC in deeper horizons (Grossman et al., 2001), and be invalid if SOC is greater than 8% (Soil Survey Staff, 2011). In order to avoid methodological biases in datasets with both wet and dry combustion measurements, a carbon-equivalent correction regression factor must be applied to horizons analyzed by wet combustion (Tivet et al., 2012 and Wills et al., 2013).

Populating missing soil legacy data has been historically achieved through pedotransfer functions (PTF). For calculating SOC, these functions are usually only applicable to the study area for which they were developed, often contain correlated variables that lead to

multicollinearity, and make implausible normality assumptions (Tomasella et al., 2000; Minasny et al., 2008). Because most soil data are not normally distributed even with common transformations, nonparametric techniques such as boosted regression tree (BRT), random forest (RF), k-nearest neighbor (k-NN), and neural networks are recommended (Jobbágy and Jackson, 2000; Minasny et al., 2008; Keller et al., 2012; Pan et al., 2013; Razafimbelo et al., 2013). These four techniques have been shown to perform similarly, although researchers have preferred one method over another among different studies (Nemes et al., 2006; Hudak et al., 2008; Myers et al., 2009; Strobl et al., 2009; Ghehi et al., 2011). Myers et al. (2009) compared RF, BRT, regression tree, general additive models (GAM), multivariate adaptive regression splines (MARS), and generalized linear models (GLM) techniques to predict BD. They found all techniques to perform similarly, with MARS performing the best by only a slight margin. Montillo (2009) summarized the advantages and limitations of artificial neural networks (ANN), k-NN, BRT, SVM, and MARS (Table 2.1). He concluded that RF has about the same accuracy as SVM and ANN, but is more interpretable, faster to train, has fewer parameters, can handle missing data, readily handles larger numbers of predictors, and doesn't require cross-validation. BRT are often more accurate at predicting a continuous response, but perform about the same as RF for classification. According to Montillo (2009), RF is advantageous over BRT because RF grows trees independently of one another, is quicker to run, requires less parameters, and does not over-fit the data.

There are two main sources of model prediction error that lead to over- or under-fitting a dataset: bias and variance (Fig. 2.1). Error due to bias is the difference between the average modeled predictions and the actual values. Error due to variance is a measure of the variability within the modeled predictions for a given point over several model iterations. Through RF, many decision trees are generated based on a random sampling of covariates and points within the training dataset. These decision trees are then averaged together to yield a “full” RF model. The bias error of a full RF model is equal to the bias error of a single decision tree, but variance error in the full model will be lower than that of a single decision tree (Breiman, 2001; Fortmann-Roe, 2012). Given the complexity of RF models, variance error is the most common cause of over-fitting.

According to Batjes (2003), the most desirable method for filling data gaps is collecting additional measured soil data, followed by using national expert estimates and tacit knowledge,

and lastly using taxotransfer rules to derive soil property estimates. Wills et al. (2013) and West et al. (2010) used a nationally derived mean BD of 1.45 g cm^{-3} for mineral soils and 0.25 g cm^{-3} for organic horizons to replace missing BD in KSSL pedons. Similarly, Buell and Markewich (2004) calculated missing BD from median BD of soil texture class. Sequeira et al. (2014) used RF to predict missing KSSL BD from the following soil properties: horizon designation, textural class, median soil horizon depth, and horizon thickness. The measured BD of horizons above, below, adjacent, or not adjacent to horizons missing BD measurements were also incorporated in the RF model when applicable. The objective of this study was to incorporate the methodology used by Sequeira et al. (2014) and develop a standard methodology for populating missing KSSL data for use in digital soil mapping and modeling. Missing SOC and BD were predicted and cross-validated from prepared KSSL data using RF and mean and median values by horizon designation and texture.

Material and Methods

Obtaining and Preparing KSSL data

KSSL site and pedon data within MLRA 127 were downloaded from the NCSS soil characterization database and were then prepared for missing KSSL data population. Preparation included evaluating site and pedon data, updating the pedon taxonomic classification to current U.S. *Soil Taxonomy* (Soil Survey Staff, 2014), and assembling site and pedon data into one database (Sulaeman et al., 2013). Only sites that were georeferenced or contained detailed site location descriptions were used in this study. Mine soils and pedons that could not be fully classified in U.S. *Soil Taxonomy* were also excluded from this study. As a result, 254 pedons within MLRA 127 were evaluated, updated to current U.S. *Soil Taxonomy* (Soil Survey Staff, 2014), and correlated to an established soil series (Appendices A and B). During the evaluation, it was found that 135 of the 254 sites were not correlated to any soil series and two of the 254 sites were not sampled or correlated as any soil series. When updated to current *Soil Taxonomy*, 169 of the 254 pedons had properties outside of the Range in Characteristics (RIC) of the correlated series and were therefore identified as series taxadjuncts. The most common properties outside of the RIC were horizon color or texture and depth to fragipan, argillic horizon, or bedrock. Forty of the 128 pedons in the KSSL database were correlated to the incorrect soil series based on the current version of *Soil Taxonomy*.

KSSL data can be queried from the NCSS characterization database and downloaded by layer data tiers that contain pedon ID, soil horizons and depths, soil property analyses, and corresponding KSSL methods (Burt, 2004). Site data containing geographic location and pedon data containing taxonomic classifications can also be downloaded. For this study, the following horizon data were downloaded from the NCSS soil characterization database: field and lab texture class, sand, silt, clay, total nitrogen, C:N, pH in water, SOC, total carbon, carbonates, 33 kPa BD, oven-dried BD, sodium, base saturation, extractable acidity, aluminum, aluminum plus half iron oxalate, cation exchange capacity (CEC), optical density, and rock fragments > 2mm. Horizon Munsell value, Munsell chroma, estimated rock fragment volume, geographic coordinates, series sampled as, series correlated as, taxonomy, new series correlated as, depth class, epipedon, and land cover were manually recorded for each site or horizon from site and pedon descriptions. Sites were then projected in ArcGIS and intersected with geology (Dicken et al., 2005; Nicholson et al., 2005), temperature regime (Waltman et al., 2006), and moisture regime (Winzeler et al., 2013). These three properties were added to the MLRA 127 KSSL database due to their importance in soil series and taxonomic classification. For the KSSL horizons in MLRA 127, it was found that 50% were missing BD and 13% were missing SOC.

Carbon-equivalent Correction Factor

Total carbon by dry combustion was first used in 1993 for the KSSL pedons in MLRA 127. All pedons sampled before 1993 quantified SOC by wet combustion. Only the eighteen pedons sampled in 1995 measured carbon by both wet and dry combustion. In order to avoid methodological biases in this study, a carbon-equivalent correction regression factor was used to adjust SOC in pedons sampled prior to 1993 (Tivet et al., 2012; Wills et al., 2013). Tivet et al. (2012) recommend using carbon-equivalent correction factors derived from data within the area of interest instead of using regionally or nationally derived correction factors. Since the eighteen pedons that contained both wet and dry combustion measurements only represented three counties in MLRA 127, a nationally developed carbon-equivalent correction regression factor developed by Wills et al. (2013) was used to transform SOC values sampled before 1993:

$$(\text{OC (dry combustion)} = 0.25 + 0.86 (\text{wet combustion})) \quad [\text{Eq. 2-1}]$$

Since zero or trace amounts of carbonates were reported for all pedons in MLRA 127, total carbon from dry combustion was assumed to be SOC.

Outliers

KSSL pedon data, like most environmental data, contain outliers due to errors associated with sampling, field description, lab analyses, data entry, or uncharacteristic environmental variability. In this study, methods for populating missing lab data were compared with and without outliers. Outliers were detected visually and quantitatively for horizon and texture class combinations of SOC content and BD using box-and-whisker plots. Outliers were identified as samples that extended above or below the whiskers. The whiskers represented 1.5 times the interquartile range (IQR) for the given horizon designation and corresponding texture classes (Sequeira et al., 2014) (Fig. 2.2).

Normality

Normality was assessed visually by histograms and statistically by the D'Agostino's test in R with and without outliers (Appendix C). The D'Agostino's test was chosen to assess normality because sample sizes of SOC and BD were greater than 50 (U.S. EPA, 2002). The D'Agostino skewness, kurtosis, and chi-squared statistics for both SOC and BD with and without outliers by horizon and texture were calculated in R. Skewness is a measure of asymmetry and is calculated in Appendix C as:

$$\sqrt{b_1} = m_3/m_2^{3/2} \quad [\text{Eq. 2-2}]$$

where

$$m_k = \sum (x_i - \bar{x})^k / n \quad [\text{Eq. 2-3}]$$

and $\bar{x}$ is the sample mean.

$$\bar{x} = \sum x_i / n. \quad [\text{Eq. 2-4}]$$

Kurtosis is a measure of curvature and is calculated as:

$$b_2 = m_4/m_2^2 \quad [\text{Eq. 2-5}]$$

The D'Agostino chi-squared statistic is an omnibus test in that it can detect deviations from normality caused by skewness or kurtosis (D'Agostino et al., 1990). It is calculated as:

$$K^2 = Z^2(\sqrt{b_1}) + Z^2(b_2) \quad [\text{Eq. 2-6}]$$

where $Z^2(\sqrt{b_1})$ and $Z^2(b_2)$ are normal approximations of skewness and kurtosis and K^2 has approximately a chi-squared distribution with two degrees of freedom when normally distributed. The skewness, kurtosis, and D'Agostino statistics revealed that the data were not normally distributed (Table 2.2). Logarithmic and square root transformations were also explored, but failed to exhibit normality. Because the data were not normally distributed, nonparametric techniques such as RF, median, and mean were used in this study on the untransformed dataset.

Random Forest

RF is a nonparametric, recursive partitioning machine learning technique that trains regression trees with a random subset of covariates and a random sample from the training set. In standard classification and regression trees (CART), each node is determined based on the best split among all variables. In RF, each node is split using the best among a subset of predictors (*mtry*) randomly sampled at each node (Liaw and Wiener, 2002). Samples that were not randomly selected for the construction of a given decision tree are used for out-of-bag error (ERR_{OOB}) calculations. ERR_{OOB} is an internal cross-validation technique built into RF models that can be used to prevent over-fitting and determine the optimal number of trees (*ntree*) and *mtry* values to minimize model error (Vincenzi et al., 2011). According to Breiman (2001), RF is robust against over-fitting. Contradictorily, some studies have shown that RF can over-fit data, especially in small datasets. The *ntree* and *mtry* parameters should be tuned for every RF model to reduce the chance of over-fitting (Segal, 2004; Statnikov et al., 2008).

Prepared KSSL SOC and BD data were randomly split into 70% training and 30% testing datasets (Appendix D). Because the *randomForest* package in R can only handle 32 categories within a given variable, horizon designations were grouped into 13 final horizon designations (Table 2.3) (Sequeira et al., 2014). The following variables were included in the RF model: median horizon depth, horizon designation, texture class, sand, silt, clay, Munsell value, Munsell

chroma, epipedon, pedon depth, land cover, soil order, geologic age, dominant geologic rock type, second dominant geologic rock type, geologic group, temperature regime, pH, moisture regime, soil climate zone derived from the tacit knowledge of MLRA 127 soil scientists, soil taxonomic mineralogy class, clay activity class, subgroup, great group, and particle-size class. The *ntree* and *mtry* parameters in the RF model were determined by the lowest ERR_{OOB} in each model (Table 2.4) (Vincenzi et al., 2011). Once the model was created from the training set, it was applied to the test set. Because outliers did not affect the performance of RF, only RF with outliers is reported in this study.

Mean and Median by Horizon Designation and Texture Class

The same training and test sets used in the RF model were used to calculate the mean and median of each horizon designation and texture class combination in the training set (Appendix E). These means and medians were then applied to the test set. If a horizon designation texture class combination (e.g., A/silty clay) had only one observation or was not in the training or test set, it was assigned the mean or median value of the closest texture class (e.g., A/silty clay loam). The texture class nearest on the texture triangle was determined to be the closest texture class.

Model Validation and Comparison

Linear regression was used to determine the relationship between observed and predicted values for the RF model and mean and median techniques:

$$y_i = \beta_0 + \beta_1 x_i + u_i \quad [\text{Eq. 2-7}]$$

where y_i is the predicted value for sample i , x_i is the observed value for sample i , β_1 is the slope of the best fit line, β_0 is the intercept, and u_i is the error term for observation i . The coefficient of determination (R^2) (Eq. 8) and root mean square error (RMSE) (Eq. 9) statistical tests were used for model validation and comparison:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad [\text{Eq. 2-8}]$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad [\text{Eq. 2-9}]$$

where n is the number of observations, i is the sample, y_i is the dependent variable, $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the mean of the y_i values (UCLA Statistical Consulting Group, 2011).

Variable importance quantified by the RF model was used to assess the dataset and compare the different RF models. The variable importance measurement in a RF model estimates the relative importance of a variable by quantifying prediction error when OOB data for a given variable are permuted while all others are left unchanged. Prediction error is first calculated on the OOB portion of the data and then for each variable using a random permutation of the values for a given variable. Lastly, the differences in prediction errors for each variable are averaged over all trees. In RF regression trees, variable importance is quantified using the following parameters: percentage increase in mean squared errors (%IncMSE) and increase in node purity (IncNodePurity). The %IncMSE is the difference between the prediction errors averaged over all trees, normalized by the standard deviation of the differences. The IncNodePurity is measured by residual sum of squares as the total decrease in node impurities as a result of splitting on a given variable, averaged over all trees. Higher values in both of the %IncMSE and IncNodePurity parameters indicate more important variables in the RF model (Liaw and Wiener, 2002).

Results and Discussion

Outliers did not limit the predictability of the models (Tables 2.5 through 2.8). Mean by horizon designation and texture with outliers performed slightly better than RF for predicting SOC ($R^2 = 0.93$, RMSE = 3.96 and $R^2 = 0.9$, RMSE = 4.7, respectively) (Figs. 2.3 through 2.6; Tables 2.5 and 2.6), while RF performed best for predicting BD ($R^2 = 0.69$, RMSE = 0.16) (Figs. 2.7 through 2.10; Tables 2.7 and 2.8). The RF model performed best for mineral horizons while mean by horizon and texture performed best for predicting organic horizons. The small sample size and high variability in the organic horizons limited the predictability of the RF model, making the mean and median techniques more desirable for predicting organic horizons. When all horizons were being modeled, however, the RF model outperformed the mean and median models in stability of prediction for both BD and SOC.

Horizon designation and soil taxonomic great group were found to be important variables for predicting BD and SOC (Figs. 2.11 and 2.14). For SOC, horizon designation, color (Munsell chroma and value), and depth were more important for predicting organic horizon while horizon texture and soil taxonomic great group were more important for predicting mineral horizons (Figs. 2.12 and 2.13). For BD, horizon designation, depth, and soil taxonomic great group were

more important for predicting organic horizons while Munsell chroma, soil taxonomic group, and dominant geologic rock type were more important for predicting mineral horizons (Figs. 2.15 and 2.16). Epipedon and land cover were the least important variables for predicting BD and SOC.

The BD RF models of Sequeira et al. (2014) had similar R^2 and RMSE values as those in this study. The R^2 and RMSE statistics for the SOC models were higher than BD, indicating that the covariates were explaining more of the variance in the model, but the standard deviation of the unexplained variance was higher. SOC values in the full model ranged from 0.01 to 73.7% while BD values ranged from 0.04 to 2.01 g cm⁻³. Given the high variability in SOC, it is logical that SOC has a higher standard deviation of unexplained variance than BD. The high variance in the SOC data coupled with the complexity of the RF model might have led to over-fitting (Fortmann-Roe, 2012). Future research is needed to detect and account for over-fitting in RF models (Segal, 2004; Statnikov et al., 2008; Fortmann-Roe, 2012).

Conclusions

Data preparation, updating soil series correlation, methodological correction factors, normality testing, outlier assessment, and estimation and validation of missing data is essential for data extrapolation (Sulaeman et al., 2013). In this study, KSSL data were downloaded and assembled for MLRA 127, taxonomic classification and series correlation were updated to current Soil Taxonomy, wet combustion SOC values were converted to dry combustion through a PTF, normality was tested by D'Agostino's statistic, outliers were identified through box and whisker plots, and known BD and SOC data were split into training and testing sets for analysis. Given the stability of prediction and simplicity of training and validation, RF is the recommended method for populating missing soil legacy data (Sequeira et al., 2014). RF, having similar predictive power as all other nonparametric machine learning techniques, provides a quick, interpretable estimation of any soil property that can be improved with more data and variables (Nemes et al., 2006; Hudak et al., 2008; Myers et al., 2009; Strobl et al., 2009; Ghehi et al., 2011). Although RF is the recommended method for populating missing soil legacy data, research is still needed to detect and account for over-fitting in RF models (Segal, 2004; Statnikov et al., 2008; Fortmann-Roe, 2012). Tuning of the *ntree* and *mtry* have been shown to reduce over-fitting in RF models, but techniques have not been developed to measure the amount of over-fitting that occurs in RF models (Segal, 2004; Statnikov et al., 2008).

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Figures and Tables

Figure 2.1 The relationship between model complexity and error adapted from Fortmann-Roe (2012).

Figure 2.2 Two examples of the box and whisker plots used to determine outliers in horizon designation and texture class combinations.

Figure 2.3 Scatter plot of predicted and observed SOC percentages using the mean by horizon and texture method with outliers included.

Figure 2.4 Scatter plot of predicted and observed SOC percentages using the RF method.

Figure 2.5 Scatter plot of predicted and observed organic horizon SOC percentages using the RF method.

Figure 2.6 Scatter plot of predicted and observed mineral horizon SOC percentages using the RF method.

Figure 2.7 Scatter plot of predicted and observed BD values using the median by horizon and texture method with outliers included.

Figure 2.8 Scatter plot of predicted and observed BD values using the RF method.

Figure 2.9 Scatter plot of predicted and observed organic horizon BD values using the RF method.

Figure 2.10 Scatter plot of predicted and observed mineral horizon BD values using the RF method.

Figure 2.11 Variable importance plot for SOC percentages predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Figure 2.12 Variable importance plot for organic horizon SOC percentages predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Figure 2.13 Variable importance plot for mineral horizon SOC percentages predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Figure 2.14 Variable importance plot for BD values predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Figure 2.15 Variable importance plot for organic horizon BD values predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Figure 2.16 Variable importance plot for mineral horizon BD values predicted by RF. The higher the percent increase of mean square error and node purity, the greater the importance of the given variable.

Table 2.1 A comparison of machine learning techniques adapted from Montillo (2009).

Characteristic	Neural Networks	SVM	Trees	MARS	k-NN, Kernels
Natural handling of "mixed" data	●	●	●	●	●
Handling of missing data	●	●	●	●	●
Robustness to outliers in input space	●	●	●	●	●
Insensitive to monotone transformations of inputs	●	●	●	●	●
Computational scalability (large N)	●	●	●	●	●
Ability to deal with irrelevant inputs	●	●	●	●	●
Ability to extract linear combinations of features	●	●	●	●	●
Interpretability	●	●	●	●	●
Predictive power	●	●	●	●	●

Key: ● = good, ● = fair, and ● = poor.

Table 2.2 The D'Agostino chi-square, skewness, and kurtosis statistics for both SOC and BD with and without outliers by horizon and texture.

	Horizon	Texture	Horizon	Texture	Horizon	Texture
Method	χ^2		df		p-value	
SOC with Outliers	1,223	729	12	19	<0.001	<0.001
SOC without Outliers	1,287	759	12	19	<0.001	<0.001
BD with Outliers	318	115	11	15	<0.001	<0.001
BD without Outliers	394	134	11	15	<0.001	<0.001

Table 2.3 Observation and outlier sample sizes by final horizon designation as suggested by Sequeira et al. (2014).

Horizon Designation	Soil Organic Carbon		Bulk Density	
	N^a	N^b	N^a	N^b
A	208	16	72	30
Ap	31	7	21	6
B	247	30	203	43
BA	78	9	50	18
Bhs	94	9	59	10
Bt	352	45	291	58
Bx	177	20	172	17
BC	108	8	77	10
C	134	12	71	12
E	84	1	45	9
Oi	162	9	14	0
Oe	86	0	15	3
Oa	75	0	9	0
Total	1,836	166	1,099	216

^a Observation size, ^b Outlier size

Table 2.4 Random Forest parameters and their resulting mean square errors and variances explained for SOC and BD.

	ntree	mtry	Mean Square Error	% Variance Explained
Organic Carbon	1000	6	21.7	90.6
Organic Carbon: Organic Horizons	1250	2	95.9	29.6
Organic Carbon: Mineral Horizons	1000	5	6.11	65.71
Bulk Density	900	4	0.03	65.5
Bulk Density: Organic Horizons	1500	2	0.06	7.85
Bulk Density: Mineral Horizons	1500	6	0.03	54.2

Table 2.5 Coefficient of determination values for SOC predictions of mineral (min), organic (org), and both mineral and organic (min+org) horizons using RF, mean, and median methods.

	Random Forest	Mean with Outliers	Mean without Outliers	Median with Outliers	Median without Outliers
SOC (min+org)	0.90	0.93	0.91	0.93	0.91
SOC (min)	0.72	0.62	0.42	0.54	0.42
SOC (org)	0.26	0.49	0.28	0.47	0.28

Table 2.6 Root mean square errors for SOC predictions of mineral (min), organic (org), and both mineral and organic (min+org) horizons using RF, mean, and median methods.

	Random Forest	Mean with Outliers	Mean without Outliers	Median with Outliers	Median without Outliers
SOC (min+org)	4.70	3.96	4.84	4.03	4.85
SOC (min)	1.55	1.69	2.43	1.86	2.43
SOC (org)	8.94	8.40	10.25	8.51	10.24

Table 2.7 Coefficient of determination values for BD predictions of mineral (min), organic (org), and both mineral and organic (min+org) horizons using RF, mean, and median methods.

	Random Forest	Mean with Outliers	Mean without Outliers	Median with Outliers	Median without Outliers
BD (min+org)	0.69	0.51	0.40	0.50	0.40
BD (min)	0.57	0.43	0.36	0.41	0.34
BD (org)	0.00	0.54	0.79	0.55	0.79

Table 2.8 Root mean square errors for BD predictions of mineral (min), organic (org), and both mineral and organic (min+org) horizons using RF, mean, and median methods.

	Random Forest	Mean with Outliers	Mean without Outliers	Median with Outliers	Median without Outliers
BD (min+org)	0.16	0.18	0.20	0.18	0.20
BD (min)	0.17	0.18	0.20	0.18	0.20
BD (org)	0.21	0.17	0.10	0.17	0.10

Chapter 3: Modeling Soil Organic Carbon through Geographically Weighted Regression Kriging

Abstract

Because soil contains three to four times more carbon than the atmosphere, small changes in soil organic carbon (SOC) content can have profound impacts on the global carbon budget. In order to understand, predict, and manage these impacts, an initial assessment of SOC stock and its dynamic nature is needed within the realm of soil survey. MLRA 127 (Eastern Alleghany Plateau and Mountains) was chosen as the study area for this research due to its complex, highly dissected topography and diverse pedoecologic properties. Previous 1 m SOC stock estimates for MLRA 127 range from 2.20 kg m⁻² to 32.00 kg m⁻². This wide range of SOC stock estimates coupled with lack of uncertainty assessments and validation addresses a need to better understand and capture SOC variability across MLRA 127. In this study, SOC stock was modeled using environmental covariates and prepared Kellogg Soil Survey Laboratory (KSSL) pedons through geographically weighted regression (GWR) and geographically weighted regression kriging (GWRK). The resulting GWR and GWRK models were validated through ancillary data collected from the Rapid Carbon Assessment (RaCA) project and previous graduate research projects. Uncertainty was assessed using the fuzzy k-means with extragrades algorithm to create prediction intervals and a confusion index (CI). It was found that the RaCA model had the lowest error (RMSE = 0.22) followed by the GWRK prediction model (RMSE = 0.31) and the GWR model (RMSE = 0.41). The CI produced in the uncertainty assessment revealed that class membership was highest in areas with relatively low SOC (0 to 20 kg m⁻²) and lowest in areas with relatively high SOC (40 to 50 kg m⁻²). Total biosphere carbon, calculated using the Forest Inventory Analysis (FIA) model and substituting GWRK soil for soil carbon and forest litter, revealed that soils in MLRA 127 contain 69% of the total carbon in the biosphere. This finding has significant implications on land management and land use in MLRA 127 given that 76% of the MLRA is forested. Future research is needed to better understand carbon sequestration and land use conversion effects on terrestrial biosphere carbon.

Introduction

Digital soil mapping (DSM) is a quantitative spatial modeling technique established in the 1990s that combines environmental covariates, such as the soil forming factors established by

Jenny (1941), with legacy data or current field and lab observations to infer pedogenic properties or patterns across various temporal and/or spatial scales (Brungard, 2009; Grunwald, 2010; Minasny et al., 2013). By expanding the work of Jenny (1941), McBratney et al. (2003) developed the *scorpan* spatial prediction function:

$$S = f(s, c, o, r, p, a, n) + \varepsilon \quad [\text{Eq. 3 – 1}]$$

where a soil property or class (S) is a function of soil observations (s), climate (c), organisms (o), relief (r), parent materials (p), age (a), and spatial position (n), and ε are the spatially correlated errors (residuals). The empirical quantitative function (f) can represent complex non-linear data-mining techniques such as regression trees and random forests (RF), simple linear models, or geostatistical models such as kriging (McBratney et al., 2003; Minasny et al., 2013).

Environmental covariates used in DSM differ depending on the study area, available data, and the correlation between the desired soil property or class and its environmental influences. Soil observations, consisting of soil legacy data or recent field or lab measurements, are either fully incorporated into the model or are split into model training and validation sets (Kumar et al., 2012). The other *scorpan* covariates are used to train the model and create a continuous predictive surface. Climate data used in DSM exist in the form of measurements at meteorological stations and can be combined with a digital elevation model (DEM) data and derivatives to produce a continuous climate raster. Vegetation from remotely sensed imagery is often chosen to represent organisms given the impracticality of quantifying fauna (Brungard, 2009). Relief, represented by a digital elevation model (DEM) and its derivatives, is the most widely used *scorpan* covariate in DSM (Minasny et al., 2013). Parent material, often represented by lithology, determines the chemical composition and grain size of minerals that are exposed to chemical weathering at the beginning of pedogenesis (Brungard, 2009). The age of soil is an important covariate to consider when using DSM due to its influence on chemical, biological, and physical soil reactions. Because age determination techniques such as optical luminescence are labor and cost intensive, soil age has not previously been characterized in DSM models (Brungard, 2009). The spatial position of soil is inherently built into DSM. Environmental covariates provide the geospatial link that enables soil scientists to model aspects of pedogenesis.

Soil properties and classes have been predicted at unsampled locations using geographic or spatial methodologies since the late 1960s. Geospatial techniques have greatly expanded since then due to the establishment of geographic information systems (GIS), remote sensing, and the availability of high resolution digital datasets (Kumar et al., 2012). Today soil properties can be predicted continuously across a geographical area using *scorpan* covariates and an empirical quantitative function (f). MLR, ordinary kriging (OK), regression trees, and regression kriging (RK) are the most common quantitative functions used for DSM of SOC (Kumar et al., 2012). RK is different than MLR, OK, and regression trees in that it incorporates kriged residuals with global regression to account for spatial autocorrelation, and thus can more accurately estimate SOC. Kumar et al. (2012) refers to MLR, OK, regression trees, and RK models as stationary because they do not vary with absolute location across space. Geographically weighted regression (GWR) is a simple regression function that allows varying coefficient weights for the environmental covariates across space. Although GWR uses spatially varying covariate coefficients, it does not directly consider spatial autocorrelation in model development (Kumar et al., 2012). Geographically weighted regression kriging (GWRK) combines the frameworks of GWR and RK models to account for spatial non-stationarity and spatial autocorrelation of the residuals. Kumar et al. (2012) compared RK and GWRK and found that GWRK more precisely estimated SOC stock in Pennsylvania.

Minasny et al. (2013) reviewed 40 previous DSM of SOC studies and found that uncertainty was rarely reported and that if validation was performed, internal validation was used. Minasny et al. (2013) suggest using the fuzzy k-means with extragrades algorithm to quantify uncertainty for large geographical areas or when combining data mining tools with RK due to its high computational power and ability to quantify model parameter uncertainty. The fuzzy k-means with extragrades algorithm partitions covariates into several classes. Each class is represented by a prediction interval derived from the empirical distribution as a weighted average of membership values. This approach identifies and penalizes observations outside of the domain of the calibration data and allows a new observation to be assigned to an established class based on class centroids (Minasny et al., 2013). Validation of modeled SOC is performed through cross-validation, internal validation, or independent sampling. Both the cross-validation and internal validation techniques may produce biased estimates due to biased data inputs or spatially correlated prediction errors. Although unbiased independent sampling is the

recommended validation approach, time and affordability often limit the applicability of independent validation. When uncertainty and validation assessments are both included in a study, the end user is able to better understand the nature and distribution of the input data, model error, and the overall accuracy and applicability of the model (Nemes, 2009). Uncertainty and validation allow for a better understanding of the dynamic nature of SOC in relation to its correlated covariates across space and are thus needed for all SOC prediction studies (Minasny et al., 2013).

The objective of this study was to predict SOC stock in MLRA 127 through GWR and GWRK models using KSSL pedons and available *scorpan* covariates (Table 3.1). Previous 1 m SOC stock estimates for MLRA 127 range from 2.20 kg m⁻² (Bliss et al., 1995) to 32.00 kg m⁻² (Kern, 1994) (Table 3.2). The Soil Survey Geographic (SSURGO) and the State Geographic (STATSGO2) databases often underestimate true SOC stock due to lack of organic horizon population and conservative representative values (Zhong and Xu, 2011; Nauman et al., 2012). This wide range of SOC stock estimates coupled with lack of uncertainty assessments and validation addresses signifies a need to better understand and capture SOC variability across MLRA 127. In this study, validation was assessed using an independent dataset developed from Rapid Carbon Assessment (RaCA) pedons and Sponaugle (2005). Once validated, the models were compared to the predicted RaCA model (Soil Survey Staff, 2013) and uncertainty was assessed using the fuzzy k-means with extragrades algorithm (Minasny et al., 2013).

Materials and Methods

Study Area

MLRA 127 was chosen as the study area for this research due to its complex, highly dissected topography and diverse pedoecologic properties. MLRA127 stretches from southwestern New York to Virginia, encompassing 50,370 km² (19,440 mi²) through Maryland, New York, Pennsylvania, Virginia, and West Virginia. Elevation ranges from 300 m to 800 m (980 ft to 2,625 ft) in the plateau portion of MLRA 127 to 1,100 m to 1,400 m (3,600 ft to 4,600ft) in the mountainous portion located in southeastern West Virginia (Fig. 3.1). The geology of MLRA 127 consists of alternating beds of sandstone, limestone, coal, and shale of the Permian, Mississippian, Pennsylvanian, and Cambrian ages. River valleys in this region are composed of stratified, unconsolidated alluvial deposits of sand, silt, clay, and gravel, with some outwash and glaciofluvial deposits in the northwest corner of Pennsylvania (United States

Department of Agriculture, 2006). The footslopes and mid to lower backslopes of hills consists of colluvium from residual bedrock. MLRA 127 has all four climatic seasons, with an average annual temperature of 6 to 12°C (43 °F to 54°F). Most of the precipitation occurs as intense, convective thunderstorms occurring in the spring and summer. Average annual precipitation ranges from 840 mm to 1,725 mm (33 in to 68 in), increasing in a southern direction and with elevation. Average annual snowfall ranges from 890 mm (35 in) in southern MLRA 127 to 2,285 mm (90 in) in the northern part (United States Department of Agriculture, 2006). The frost-free period ranges from 115 days in high elevations or in the north to 205 days in the lower elevations of southern MLRA 127. Ultisols and Inceptisols are the dominant soil orders of MLRA 127, with Entisols, Alfisols, and Spodosols occurring to a lesser extent. The soils in this area are dominantly in the udic moisture regime and mesic temperature regime, with the high-elevation and northern soils occurring in the frigid temperature regime (United States Department of Agriculture, 2006). These soils have mixed or siliceous mineralogy and are generally moderately deep to very deep with excessively well to somewhat poor drainage classes. MLRA 127 supports high-quality hardwoods, such as oak, black cherry, yellow-poplar, and maple, at the lower elevations and intermixed deciduous and coniferous species at higher elevation, including red spruce, hemlock, birch, maple, black cherry, and beech (United States Department of Agriculture, 2006). Due to the geographical makeup of MLRA 127, most of the area is forested (76%). The remaining areas have been cleared to support crops (7%), pasture (7%), urban development (6%), other land uses (3%), and water (1%) (United States Department of Agriculture, 2006).

Environmental Covariates

The prepared KSSL data from Chapter 2 were used to calculate SOC stock in the upper meter of soil for the 254 KSSL pedons in MLRA 127. These pedons along with *scorpan* environmental covariates were used to train the GWR and GWRK models. The *scorpan* covariates used in this study were numerical and chosen based on availability of national coverage and correlation to SOC. Although some software permit binary or dummy coded categorical data in GWR models, the combined use of categorical and numerical data is not recommended for GWR due to a high risk of local multicollinearity.

Climate was represented by the 1981-2010 30-year normals derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). The PRISM algorithm uses a 30-

arcsec National Elevation Dataset (NED) DEM and available meteorological station data to calculate a climate-elevation regression that is interpolated to produce continuous precipitation and temperature rasters (PRISM, 2004). Vegetation was represented by 16-day Enhanced Vegetation Index (EVI) imagery obtained through the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite and Landsat GeoCover standardized and orthorectified green, near-infrared (NIR) and mid-infrared (MIR) bands and band ratios (GLCF, 2005; Boettinger et al., 2008). The EVI, generated from the Normalized Difference Vegetation Index (NDVI) imagery, is more receptive to canopy structural variations and less sensitive to chlorophyll than the NDVI (Huete et al., 2002). In this study, mean, median, minimum, and maximum EVI values were calculated for 2000-2009 and for each climatic season (Tedrow and Weber, 2011). Relief, the most widely used *scorpan* covariate in the DSM of SOC (Minasny et al., 2013), was represented by the hydrologically corrected Elevation Derivatives for National Applications (EDNA) derived from the 30m NED. The following DEM attributes and derivatives were calculated using SAGA and ArcMap: slope gradient, normalized slope height, convergence index, southwestness, northeastness, eastness, northness, SAGA topographic wetness index, LS factor, total curvature, plan curvature, profile curvature, valley depth, stream power index, terrain ruggedness index, terrain surface convexity, terrain surface texture, flow path length, relative position, multiresolution valley bottom flatness, multiresolution ridge top flatness, and mid-slope position. Parent material was represented by seven gamma radiometric covariates: potassium (K), thorium (Th), uranium (U), total exposure, K/Th, K/U, and Th/U.

A total of 64 *scorpan* covariates were assessed for multicollinearity and the ability to predict SOC through Pearson's r , Kendall's τ , Spearman's ρ , and RF. Covariates that showed the highest correlation to SOC that were not calculated from another covariate with a higher correlation to SOC were selected to train the GWR model. The following 14 covariates were selected to calculate SOC: gamma radiometric total exposure, available water storage (0-100 cm), elevation, precipitation, maximum annual temperature, Landsat GeoCover MIR band, Landsat GeoCover green/NIR band ratio, convergence index, terrain roughness index, northeastness, valley depth, minimum fall EVI from 2000 to 2009, mean winter EVI from 2000 to 2009, and median spring EVI from 2000 to 2009 (Table 3.1).

Calculation of Soil Organic Carbon Stock

The SOC stock for each site was calculated by summing the SOC concentrations in each horizon from the surface to 1 m depth as follows:

$$C_{stock} = \sum_{i=1}^n \frac{C_i \times \rho_b \times D_i \times \left(\frac{100 - RFV_i}{100}\right)}{10} \quad [\text{Eq. 3-2}]$$

where C_{stock} is the SOC stock (kg m^{-2}) up to 1 m depth, i is the horizon, C_i is the SOC concentration (g g^{-1}) in the i th horizon, ρ_b is the bulk density (g cm^{-2}), D_i is the thickness of the i th horizon (cm), and RFV_i is the rock fragment volume content of the i th horizon (dimensionless). Random forest (RF) was used to prepare KSSL data for SOC stock calculation in Chapter 2 of this thesis.

Geographically Weighted Regression Kriging

Geographically weighted regression (GWR) is a simple regression function that allows varying coefficient weights for the environmental covariates across space. Although GWR uses spatially varying covariate coefficients, it does not directly consider spatial autocorrelation in model development (Kumar et al., 2012). The equation for GWR used in GWR 4.0 software is:

$$\hat{C}_{gwr(s_0)} = \sum_{k=0}^p \hat{\beta}_k(s_0) \times X_k(s_0) \quad [\text{Eq. 3 - 3}]$$

where $\hat{C}_{gwr(s_0)}$ is the predicted SOC stock at location s_0 , p is the total number of environmental covariates, $\hat{\beta}_k$ are the unknown regression coefficients that are spatially variant, and $X_k(s_0)$ are the k th environmental covariates with the value X_k at location s_0 (Kumar et al., 2012). The GWRK approach takes the residuals produced by the GWR model and kriges them to the study area using isotropic variogram parameters. The kriged residuals are added to the GWR model to produce a GWRK model:

$$\hat{C}_{gwrk(s_0)} = \hat{C}_{gwr(s_0)} + \hat{\varepsilon}_{ok}(s_0) \quad [\text{Eq. 3 - 4}]$$

where $\hat{C}_{gwrk}(s_0)$ is the predicted SOC stock at location (s_0), $\hat{C}_{gwr}(s_0)$ is the GWR model calculated in Eq. (3 – 3), and $\hat{\varepsilon}_{ok}(s_0)$ are the residual values interpolated by ordinary kriging (OK) (Kumar et al., 2012).

In this study, the 254 prepared KSSL sites in MLRA 127 were used to train the GWR model. Due to limited computing power, 250 m, 800 m, and 2,000 m spatial resolutions were explored to determine an appropriate spatial resolution to model SOC at a Major Land Resource Area (MLRA) scale. Environmental covariate values were extracted to the point grids using ArcMap software and the GWR model trained by the 254 KSSL sites was applied to the points at varying spatial resolutions using GWR 4.0 software with the following settings: adaptive Gaussian kernel, all covariates treated as local (non-stationary), and bandwidth size determined by biased-corrected Akaike Information Criterion (AICc). Next, SOC stock was calculated for the varying spatial resolution point grids by multiplying the environmental covariate coefficients by the environmental covariate values and then adding the y-intercept for each point location. The calculated SOC stock for each point was then interpolated using OK in ArcMap across the study area. The normality and spatial autocorrelation of the GWR KSSL residuals were assessed in ArcMap using the Moran's I statistic, semivariogram analysis, and spatial observations. Ten out of the 254 KSSL sites were removed due to being outliers on the quantile-quantile plot or being highly clustered or dispersed. The remaining 244 GWR KSSL residuals were kriged through OK in ArcMap using the parameter optimization option was used for OK to determine best fit of the semiovariogram through minimisation of the mean square error. The kriged residuals were added to the GWR interpolation to produce the GWRK model. The GWRK models were then validated using 175 independent observations from RaCA and Sponaugle (2005) to determine the appropriate spatial resolution.

Validation and Uncertainty

Before validation and uncertainty were assessed for the GWR and GWRK models at the appropriate spatial resolution, a visual comparison between the GWR, GWRK, and RaCA models was performed. The RaCA prediction model was derived through a statistical modeling effort from NRCS and university partners. In 2010, 32,084 soil profiles in the upper 1 m of soil were described and sampled across the United States based on land use and soil type. RF was used to model and interpolate soil carbon as a function of visible near-infrared scans (Soil Survey Staff, 2013).

The GWR and GWRK models were validated using 175 independent observations from the RaCA and Sponaugle (2005) (Appendices F and G). The RaCA prediction model was validated with the 254 prepared KSSL pedons within MLRA 127 (Appendices A and B). Once validated, mean estimation error (MEE), mean absolute estimation error (MAEE), and root mean square error (RMSE) were calculated for the GWR, GWRK, and RaCA models as described in Eqs. (3-5) – (3-7) (Kumar et al., 2012).

$$\text{MEE} = \frac{\sum_{i=1}^n [\hat{C}(s_i) - C(s_i)]}{n} \quad [\text{Eq. 3 – 5}]$$

$$\text{MAEE} = \frac{\sum_{i=1}^n |\hat{C}(s_i) - C(s_i)|}{n} \quad [\text{Eq. 3 – 6}]$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n [\hat{C}(s_i) - C(s_i)]^2}{n}} \quad [\text{Eq. 3 – 7}]$$

where $\hat{C}(s_i)$ is the predicted value at s_i location, $C(s_i)$ is the observed value at location s_i , and n is the total number of sample observations. Standard data transformations were explored for the GWR and GWRK models, including lognormal, square root, squaring, Box-Cox, etc., but normality was not achieved, making the normality assumptions for r^2 invalid. This is true in almost all environmental modeling (Keller et al., 2012; Razafimbelo et al., 2013). A recent study by Mishra et al. (2010) did not report r^2 values for their SOC stock predictions. RMSE, MEE, and MAEE do not assume normality and were therefore used to statistically compare the GWR, GWRK, and RaCA models.

Once validated, overall uncertainty of the GWRK model was determined by the fuzzy k-means with extragrades algorithm using FUZME software (Minasny and McBratney, 2002; Malone et al., 2011; Minasny et al., 2013). The fuzzy k-means with extragrades algorithm minimizes the following function:

$$J_{e(c,M)} = \alpha \sum_{i=1}^n \sum_{j=1}^c m_{ij}^{\varphi} d_{ij}^2 + (1 - \alpha) \sum_{i=1}^n m_{i*}^{\varphi} \sum_{j=1}^c d_{ij}^{-2} \quad [\text{Eq. 3 – 8}]$$

where C is the $c \times p$ matrix of class centroids (where c is the cluster and p is the number of variables), M is the $n \times c$ matrix of partial memberships (where n is the number of observations), $m_{ij} \in [0,1]$ is the partial membership of the i th observation to the j th cluster, $\varphi \geq 1$ is the fuzziness exponent, d_{ij}^2 is the square distance between the i th observation and j th cluster center, and m_{i*} represents membership to the extragrade class. The *alpha* (α) parameter in this function is used to determine the degree of importance attributed to the extragrade class.

The fuzzy k-means with extragrades algorithm partitions covariates into several classes, where each class is represented by a prediction interval derived from the empirical distribution as a weighted average of membership values. First, the fuzzy k-means with extragrades algorithm arranged the observations (N) and the environmental covariates (M) in a matrix (175 x 20). Iteratively, the algorithm was run using cluster sizes of two through 10, Mahalanobis as the distance metric, and fuzzy exponent value (ω) of 1.3 (Verheyen et al., 2001; Malone et al., 2011). Observations that did not lie between the main clusters were determined by the algorithm to be extragrades (outliers) and were assigned to an extragrade class. The optimal number of classes, where the fuzzy performance index (FPI) and the modified partition entropy (MPE) were minimized, was found to be 3 (Fig. 3.2). FPI measures the degree of separation between classes and the MPE defines the degree of fuzziness created by a specified number of classes for a defined ω value (Malone et al., 2011). The highest membership value to a cluster was used to determine which cluster each observation was assigned to. A confusion index (CI) was also generated from the FUZME software and was interpolated in ArcMap. This index measures the degree of class overlap in attribute space, depicting how well an observation was classified. The closer to zero the CI is, the more likely the observation belongs to the dominant class. The closer to one the CI is, the difference between the dominant and subdominant classes are negligible and there is confusion with the classification of the observation (Gorsevski et al., 2003). The upper 95% and lower 5% cluster prediction intervals (PIC) were calculated by summing the PIC and cluster centroids for every observation:

$$PIC_i^L = \sum_{j=1}^c m_{ij} PIC_j^L \quad [Eq. 3 - 9]$$

$$PIC_i^U = \sum_{j=1}^c m_{ij} PIC_j^U \quad [Eq. 3 - 10]$$

where PIC^L_i and PIC^U_i represent the weighted lower and upper prediction intervals (PI) for the i th observation, PIC^L_j and PIC^U_j are the lower and upper PI for each cluster j , and m_{ij} is the membership grade of the i th observation to the cluster j . The extragrade cluster error distributions were accounted for using Eqs. (3-11) – (3-12) (Malone et al., 2011):

$$PIC^L_{ej} = 2 \times q_{2.5} \quad [\text{Eq. 3 – 11}]$$

$$PIC^U_{ej} = 2 \times q_{2.5} \quad [\text{Eq. 3 – 12}]$$

where PIC^L_{ej} and PIC^U_{ej} represent the lower and upper PI of the extragrade class and q is the quantile value of the extragrade cluster error distribution. This method penalizes extragrade regions where there is very low prediction confidence. Once the weighted PI were calculated, the lower and upper prediction limits (PL^L_i and PL^U_i) were calculated for each observation by summing the GWRK model value to PL^L_i and PL^U_i (Malone et al., 2011). The lower and upper prediction limits were then interpolated in ArcMap.

Results and Discussion

Descriptive Statistics

The statistical distribution of the SOC stock in the KSSL pedons used to train the GWR model was highly positively skewed, had more peaked values than a normal distribution, and was more spatially clustered than spatially random processes (Table 3.1). Standard data transformations were explored for the KSSL pedons, including lognormal, square root, squaring, Box-Cox, etc., but normality was not achieved. Untransformed KSSL SOC data were used to train the GWR model. The residuals of the GWR model mirrored the statistical distribution of the KSSL SOC data with positive skewness (1.14) and kurtosis (4.93) and a positive Moran's I statistic (0.09). The kriged residuals showed that the GWR model tended to overestimate SOC in the northeastern and southwestern part of MLRA 127, indicating an anisotropic trend in the GWR model (Fig. 3.3).

GWR and GWRK Models

Due to limited computing power, 250 m, 800 m, and 2,000 m spatial resolutions of the covariate data were explored to determine an appropriate spatial resolution to model SOC at a MLRA scale (Fig. 3.4). The root mean square error (RMSE) was lowest at 250 m (0.28),

followed by 2,000 m (0.31), and 800 m (0.48) while the mean absolute error (MAEE) was equivalent for the 250 m and 2,000 m spatial resolutions (0.02) and higher for 800 m (0.04) (Table 3.3). Statistical validation showed that the GWRK model performed similarly at 250 m, 800 m, and 2,000 m spatial resolutions. Pixel noise was apparent at the 250 m and 800 m spatial scales (Fig. 3.4). Given the similarity in statistical performance and decreased pixel noise, the 2,000 m spatial resolution was chosen for modeling SOC in MLRA 127 (Figs. 3.3 and 3.4). At a 2,000 m spatial resolution, the GWR and GWRK models reported SOC values ranging from 0 to 41 kg m⁻², with means of 15 kg m⁻² in the GWR model and 16 kg m⁻² in the GWRK model. Both of these models showed highest SOC in the Monongahela National Forest and the lowest in Pennsylvania and New York (Figs. 3.5 and 3.6). The RaCA model predicted SOC values ranging from 0 kg m⁻² to 258 kg m⁻², with a mean of 9 kg m⁻² (Fig. 3.7). When compared to the RaCA model, the GWR and GWRK models produced much smaller ranges and higher mean values. These statistical differences were due to the methodological errors and limited sampling in the higher carbon areas in the Monongahela National Forest. The RaCA model did show high SOC values in the Monongahela National Forest, but also showed equally as high values in New York. All three of the models depicted significantly more SOC than estimates derived from STATSGO2 (Fig. 3.8; Table 3.3) and SSURGO (Fig. 3.9; Table 3.3).

The mean SOC values of the GWR and GWRK models were similar to those predicted by Kern et al., (1994) using the taxonomy approach (Table 3.2). The taxonomy approach used KSSL and Soil Interpretation Record data to calculate SOC by taxonomic units created using National Resource Inventory data. Kern et al. (1994) found that the taxonomic approach tended to give more reliable results for Histosols, shallow soils, and soils with high rock fragment content when compared to the ecosystem approach. The GWR and GWRK models may have predicted similarly to the taxonomic approach since they all utilized measured data. The taxonomic approach was modeled at a 1:7,500,000 spatial resolution while the GWR and GWRK approaches were modeled at a finer resolution of 2,000 m x 2,000 m, showing more spatial variability in SOC stock. Mean SOC stock in the upper meter of soil in MLRA 127 has been predicted to be greater than 10 kg m⁻² in most studies, including this one (Eswaren et al., 1993; Kern, 1994; Jenkins, 2001; Mishra et al., 2010; Soil Survey Staff, 2013) (Table 3.2).

Validation

The GWR and GWRK models were validated using 175 independent observations from RaCA and Sponaugle (2005) (Appendices F and G). Additionally, the RaCA model was validated in this study with the 254 prepared KSSL pedons within MLRA 127 (Appendices A and B). The RaCA model reported the lowest RMSE and MAEE at 0.22 kg m^{-2} and 0.02 kg m^{-2} , respectively (Table 3.4). The RaCA model had a lower SOC stock mean (9 kg m^{-2}) than the GWRK (16 kg m^{-2}) and GWR (19 kg m^{-2}) models and showed less variation across MLRA 127. The GWRK model performed the second best with a RMSE of 0.31 kg m^{-2} and MAEE of 0.02 kg m^{-2} (Table 3.4).

The GWRK approach used to predict SOC in Pennsylvania by Kumar et al. (2012) yielded a RMSE of 2.61 kg m^{-2} and MAEE of 2.34 kg m^{-2} . Mishra et al. (2010) used GWR, regression kriging (RK), and multiple linear regression (MLR) to predict SOC stock in the upper 0.5 m for Midwestern MLRA, including MLRA 127. Their results showed that GWR performed the best with a RMSE of 6.40 kg m^{-2} and MAEE of 3.38 kg m^{-2} . The error rates reported in this study are much lower than previous studies, indicating that: (i) SOC prediction by MLRA might be the most suitable way for NRCS to predict SOC stock, (ii) GWRK should be the recommended approach for the DSM of SOC, and (iii) Future research is needed to statistically validate spatial, nonparametric models.

Uncertainty

Uncertainty of the GWRK model was assessed using the fuzzy k-means with extragrade algorithm in the FUZME software (Minasny and McBratney, 2002). The CI revealed that class membership was highest in areas with relatively low SOC (10 to 20 kg m^{-2}) and lowest in areas with moderate to moderately high SOC (30 to 50 kg m^{-2}) (Fig. 3.10). Strong variability in the training data, areas with limited training data, and strong variability in the environmental covariate data resulted in high a CI in most of the study area outside of the training sites. The spatial variability of SOC stock is due to extrinsic and intrinsic factors. The methodology presented in this study was able to explain some of the extrinsic variability through use of environmental covariates and spatial relationships. Intrinsic variability from factors like pedoturbation, microtopography, and biological influences has been shown to be more important than extrinsic factors in determining overall pedodiversity (Phillips, 2001). Intrinsic variability

was not addressed in this study due to the coarse spatial resolution and time constraints. Future research is needed to capture the intrinsic variability of SOC in MLRA 127.

95% prediction intervals were calculated from adding the sum of the cluster centroids multiplied by the cluster prediction intervals to the modeled GWRK values. The lower GWRK prediction interval ranged from 0 to 40 kg m⁻², with a mean of 13 kg m⁻² (Fig. 3.11) while the high GWRK prediction interval ranged from 9 to 69 kg m⁻², with a mean of 23 kg m⁻² (Fig. 3.12). Because the GWR and GWRK models were trained by KSSL pedons with forested, pastured, and cropped land uses, it is hypothesized that the lower prediction interval reflects SOC stock under cropped land use and the higher prediction interval reflects the SOC stock capacity of soils in MLRA 127 under forested land cover. A long-term land use conversion study would need to be conducted to prove this hypothesis in MLRA 127, but based on previous land use studies of Guo and Gifford (2002) and Zhou et al. (2008), this range in SOC stock due to land use is not unrealistic.

Total Carbon Stock

The USDA Forest Service (FS) has developed the Forest Inventory and Analysis (FIA) program to estimate total biosphere carbon. In a forested ecosystem, there are seven sources of carbon. Aboveground carbon is composed of live aboveground vegetation, downed dead vegetation, standing dead vegetation, and understory vegetation. Belowground carbon is composed of soil carbon, forest litter (including fresh leaves, fine woody debris, and humus), and live belowground vegetation. For soil carbon estimation in the FIA program, the FS developed models using geographical area, forest type, and in some cases, stand age (USDA-USFS, 2014; Woodall and Monleon, 2008).

In this thesis, we were able to better capture the variability of SOC stock in MLRA 127 as compared to current NRCS soil survey products. In order to enhance the FIA estimation of total biosphere carbon and to understand the quantitative role that SOC has in the biosphere within MLRA 127, SOC stock values modeled by GWRK were substituted for soil carbon and forest litter values estimated by the FIA model. Total carbon (in Pg) was then calculated as follows:

$$TC_s = \sum cc_s^2 \times C_s \times CF_s \quad [Eq. 3 - 13]$$

where TC_s is the total carbon for the given source, cc_s^2 is the raster cell area, C_s is the predicted carbon value, and CF_s is the conversion factor to ensure that TC_s is in petagrams (Pg). Total SOC stock was also calculated for the gridded SSURGO (gSSURGO), GWR, GWRK, RaCA, GWRK-low prediction interval, and GWRK-high prediction interval models (Table 3.5). Total SOC stock for the upper 1 m in MLRA 127 ranged from 0.23 Pg in gSSURGO to 1.28 Pg in the high prediction interval for the GWRK model. According to the FIA model, the total SOC stock is 0.29 Pg (Table 3.6) when litter is included and the total carbon in the biosphere is 0.67 Pg (Table 3.7), showing that SOC makes up 43% of the total biosphere carbon in MLRA 127 (Fig. 3.13). When SOC values from the low, representative, and high GWRK model were substituted for the SOC and litter values in the FIA model, total carbon in the biosphere in MLRA 127 ranged from 1.01 Pg to 1.50 Pg to 1.65 Pg, respectively. SOC was shown to represent 60%, 69%, and 71% of the total biosphere carbon in MLRA 127, respectively (Figs. 3.14 through 3.16; Tables 3.5 and 3.7).

Using the representative GWRK estimate for SOC, soil accounted for 69% of the total carbon in MLRA 127. SOC reported in the FIA model only represents the upper 20 cm of soil while SOC in the GWRK model encompasses the upper 1 m of soil. Given the methodological differences between the FIA SOC estimate and the GWRK estimate and the low error statistics reported for the GWRK model, it is expected that the GWRK estimate for SOC is more realistic for estimating total biosphere carbon. In MLRA 127, more carbon is stored in soils than in plant materials, supporting research from Jobbágy and Jackson (2000).

Conclusions

Soil organic carbon (SOC), a dynamic soil property and the largest pool of terrestrial organic carbon in the biosphere (Jobbágy and Jackson, 2000; Minasny et al., 2013; Stockmann et al., 2013), plays a critical role in supplying nutrients to plants, improving soil structure and aggregate stability, contributing to cation exchange capacity, and developing sustainable land management practices (Schulte, 1988; Droogers and Bouma, 1997; Jobbágy and Jackson, 2000; Stolt et al., 2010; Batlle-Auguilar et al., 2011). In order to understand, predict, and manage these impacts, an initial assessment of SOC stock and its dynamic nature is needed within the realm of soil survey (Stolt et al., 2010). In this study, it was shown that nonparametric spatial modeling techniques such as GWR and GWRK are able to effectively predict SOC stock within a MLRA. The error rates reported in this study are much lower than previous studies, indicating that: (i)

SOC prediction by MLRA might be the most suitable way for NRCS to predict SOC stock, (ii) GWRK should be the recommended approach for the DSM of SOC, and (iii) future research is needed to statistically validate spatial, nonparametric models. Spatial models can always be improved with more statistically-designed soil samples to train and validate the models and finer resolution covariate data that have limited artifacts and errors. The methodology presented in this thesis, beginning with preparing KSSL data and ending with an interpolated GWRK model with 95% prediction intervals depicting the SOC stock of the upper 1 m of soil in MLRA 127, is recommended to the NRCS as a guideline for future DSM research.

The biosphere carbon assessment using the FS FIA model presented in this chapter revealed that there is more carbon stored in soil than in the entire biosphere in MLRA 127. This finding has huge implications on land management and land use in MLRA 127 given that 76% of the MLRA is forested. Future research is needed to better capture the intrinsic variability of SOC and understand carbon sequestration in relation to land use conversion effects in the Eastern Allegheny Plateau and Mountains.

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Figures and Tables

Figure 3.1 The Eastern Allegheny Plateau and Mountains (MLRA 127) encompassing parts of Maryland, New York, Pennsylvania, Virginia, and West Virginia.

Figure 3.2 Cluster performance graph as a function of number of classes, fuzzy performance index (FPI), and the modified partition entropy (MPE) calculated using FUZME software.

Figure 3.3 Residuals from the GWR model interpolated using OK.

Figure 3.4 SOC stock in the upper meter of soil in MLRA 127 predicted by GWRK with the following resolution sizes: (a) 250 m, (b) 800 m, and (c) 2,000 m.

Figure 3.5 SOC stock in the upper meter of soil in MLRA 127 predicted through GWR.

Figure 3.6 SOC stock in the upper meter of soil in MLRA 127 predicted through GWRK with 2,000 m spatial resolution.

Figure 3.7 SOC stock in the upper meter of soil in MLRA 127 predicted by RaCA (Soil Survey Staff, 2013).

Figure 3.8 SOC stock in the upper meter of soil in MLRA 127 currently in STATSGO2.

Figure 3.9 SOC stock in the upper meter of soil in MLRA 127 currently in SSURGO.

Figure 3.10 Confusion index of SOC stock in the upper meter of soil in MLRA 127 calculated using fuzzy *k*-means with extragrade analysis. As the confusion index increases, the difference between the dominant and subdominant classes become negligible and there is confusion with the classification of the observation.

Figure 3.11 Lower 95% prediction limit for the upper meter of SOC stock across MLRA 127 calculated using fuzzy k-means with extragrade analysis.

Figure 3.12 Upper 95% prediction limit for the upper meter of SOC stock across MLRA 127 calculated using fuzzy k-means with extragrade analysis.

Figure 3.13 Total carbon stock, including above and below ground sources, in MLRA 127 as reported by the Forest Inventory and Analysis tool with 250 m resolution.

Figure 3.14 Total carbon stock, including above and below ground sources, in MLRA 127 as reported by the Forest Inventory and Analysis tool, substituting the geographically weighted regression kriging representative values for soil organic carbon with 2,000 m spatial resolution.

Figure 3.15 Total carbon stock, including above and below ground sources, in MLRA 127 as reported by the Forest Inventory and Analysis tool, substituting the lower 95% prediction limit geographically weighted regression kriging for soil organic carbon with 2,000 m spatial resolution.

Figure 3.16 Total carbon stock, including above and below ground sources, in MLRA 127 as reported by the Forest Inventory and Analysis tool, substituting the upper 95% prediction limit geographically weighted regression kriging for soil organic carbon with 2,000 m spatial resolution.

Table 3.1. Normality and spatial autocorrelation analysis of the covariates used to predict SOC.

	chi2	skewness	kurtosis	p-value: omnibus	p-value: skewness	p-value: kurtosis	moran's i	p-value: moran's i
Precipitation	1.22	-1.07	-0.3	0.54	0.29	0.78	0.98	0
Convergence index	24.81	3.01	3.97	<0.0001	2.00 x 10 ⁻³	<0.0001	0	0.81
Terrain ruggedness index	38.67	6	1.64	<0.0001	<0.0001	0.1	0.2	0
Valley depth	190.12	11.35	7.82	<0.0001	<0.0001	<0.0001	0.03	0.15
Fall EVI minimum	29.46	-5.18	1.61	<0.0001	<0.0001	0.11	0.16	0
Elevation	45.74	6.42	2.6	<0.0001	<0.0001	9.20 x 10 ⁻³	0.72	0
Spring EVI median	17.64	3.58	-2.2	<0.0001	<0.0001	0.03	0.53	0
Winter EVI mean	35.46	4.48	3.93	<0.0001	<0.0001	<0.0001	0.18	0
Northeastness	588.33	-20.85	12.4	<0.0001	<0.0001	<0.0001	-0.01	0.15
Green/Near- Infrared Landsat GeoCover	393.72	16.55	10.94	<0.0001	<0.0001	<0.0001	0.02	0.22
Mid-infrared Landsat GeoCover	32.37	5.23	2.23	<0.0001	<0.0001	0.02	0.11	0
1 m Available water storage	7.13	-1.9	1.87	0.03	0.06	0.06	0.39	0
Total Gama Radiation (U, K, and Th)	12.59	0.65	-3.49	1.84 x 10 ⁻³	0.52	4.84 x 10 ⁻⁴	0.29	0
Average Maximum Temperature	82.56	2.18	-8.82	<0.0001	0.03	<0.0001	0.87	0
1 m KSSL SOC Stock	53.57	6.67	3.01	<0.0001	<0.0001	2.60 x 10 ⁻³	0.10	0

Table 3.2 Average SOC Estimates for the upper 1m of soil in the Eastern Allegheny Plateau and Mountains adapted from Jenkins (2001).

Source	SOC (kg m ⁻²)
Kern (1994)	
Ecosystem Approach	28.1 - 32.0
Soil Taxonomy	13.6 - 15.0
Eswaran et al. (1993)	
World Soils Map	10.6 - 12.1
Bliss et al. (1995)	
Soil Interpretation Database	2.2
Jenkins (2001)	
Mesic Series	8.9 - 11.7
Frigid Hardwood Sites	12.9 - 18.8
Frigid Spruce Sites	11.3 - 13
Mishra et al. (2010)	10.3
STATSGO2 MLRA 127	2.6
gSSURGO MLRA 127	4.4
Rapid Carbon Assessment	9.0
GWR	18.6
GWRK	16.1

Table 3.3 Statistical summary of the GWRK model with the following resolution sizes: 250 m, 800 m, and 2,000 m.

	Spatial Resolution		
	----- m -----		
	250	800	2,000
RMSE	0.28	0.48	0.31
MEE	-0.04	0.05	0.04
MAEE	0.02	0.04	0.02

Table 3.4 Statistical summary of the GWR, GWRK, and RaCA SOC stock models in MLRA 127.

Method	RMSE	MEE	MAEE
	-----kg m ⁻² -----		
GWRK	0.31	0.04	0.02
GWR	0.41	0.05	0.09
RaCA	0.22	-0.02	0.02

Table 3.5 Estimations of the total SOC stock in the upper 1 m of soil in MLRA 127. LowGWRK represents the lower 95% prediction interval and highGWRK represents the higher 95% prediction interval.

Estimation Source	SOC Stock -----Pg-----
gSSURGO	0.23
RaCA	0.71
GWR	1.24
lowGWRK	0.64
GWRK	1.13
highGWRK	1.28

Table 3.6 Estimations of the sources of above and below ground carbon stock in MLRA 127 from the Forest Inventory and Analysis tool.

Carbon Source	Carbon -----Pg-----
Above Ground Carbon in Live Trees	0.29
Forest Standing Dead Carbon	3.00×10^{-3}
Forest Understory Carbon	4.00×10^{-3}
Below Ground Carbon in Live Trees	0.05
Forest Down Dead Carbon	0.03
Forest Litter Carbon	0.06
Soil Organic Carbon	0.23

Table 3.7 Estimations of the total carbon stock in MLRA 127 from the Forest Inventory and Analysis tool and the the Forestry Inventory and Analysis tool with SOC and Forest Litter Carbon replaced with GWRK SOC stock. LowGWRK represents the lower 95% prediction interval of the GWRK SOC, rvGWRK represents the modeled SOC, and highGWRK represents the upper 95% prediction interval of the GWRK SOC.

Estimation Source	Total Terrestrial Biosphere Carbon -----Pg-----
FIA	0.66
FIA with lowGWRK replacement	1.01
FIA with rvGWRK replacement	1.50
FIA with highGWRK replacement	1.65

Chapter 4: Conclusions and Recommendations for the Natural Resources Conservation Service

Review of Objectives

The purpose of this study was to develop standard methodology and recommendations for the Natural Resources Conservation Service (NRCS) to calculate soil organic carbon (SOC) stock across a Major Land Resource Area (MLRA) using legacy lab data, geospatial covariates, and legacy soil survey products. Due to its unique and diverse vegetative, climatic, geologic, and pedogenic properties, MLRA 127 (Eastern Alleghany Plateau and Mountains) was chosen as the study area. This research was aimed at developing a framework for the NRCS to model SOC as a continuous function using legacy Kellogg Soil Survey Laboratory (KSSL) data and environmental covariates. The objectives of this research were to:

- d) Populate missing KSSL data using Random Forest (RF), median by horizonation and texture class, and mean by horizonation and texture class to provide a better input for the digital soil mapping (DSM) of SOC.*
- e) Model SOC through geographically weighted regression kriging (GWRK) as a function of harmonized legacy KSSL data and environmental covariates and assess the validity and uncertainty of the GWRK model.*
- f) Assess ecosystem carbon using the Forest Inventory Analysis (FIA) model and GWRK SOC model to determine the role that SOC has in relation to terrestrial biosphere carbon.*

The statistical summary of the methodology used in Chapter 2 to predict missing KSSL data revealed that both RF and mean (by horizon and texture class) were valid approaches to populating missing KSSL data in MLRA 127, with RF being the preferred standard method for NRCS (Tables 2.4 – 2.7). Comparisons between the geographically weighted regression (GWR) and GWRK models created in this study to the rapid carbon assessment (RaCA) prediction model developed by NRCS (Soil Survey Staff, 2013) in Chapter 3 showed that nonparametric spatial modeling techniques such as GWRK and RF are able to effectively predict SOC stock within a MLRA. The error rates calculated from the GWR, GWRK, and RaCA models were much lower than previous studies, indicating that SOC prediction by MLRA might be the most

suitable way for NRCS to predict SOC stock and GWRK should be the recommended approach for the DSM of SOC. The methodology presented in this thesis beginning with preparing KSSL data and ending with an interpolated GWRK model with 95% prediction intervals depicting the SOC stock of the upper 1 m of soil in MLRA 127, is recommended to the NRCS as a guideline for future DSM research.

Recommendations for the NRCS

NRCS Soil Survey Products

NRCS soil scientists are currently devoting most of their time to harmonizing legacy soil survey data in the National Soil Information Database (NASIS) through the Soil Data Join Recorrelation (SDJR) project. SDJR is designed to consolidate similar map units in soil survey areas across a MLRA, evaluate and document each map unit, eliminate as many tabular join conflicts as possible, and populate NASIS with future field and spatial editing projects (USDA-NRCS, 2013). DSM techniques can be used in current SDJR harmonization efforts to help create future spatial and field projects, determine which map units should be harmonized, and help with map unit component composition. When the tabular harmonization phase is complete, soil scientists can spatially disaggregate gridded SSURGO (gSSURGO) data into individual soil components and/or properties using DSM techniques. This will enable soil scientists to create pixel-based, multi-resolution raster products to coincide with their limitation/suitability STATSGO2 and SSURGO products. Vector products allow area calculations, provide users with crisp boundaries, and allow for easy attribute and line editing. Raster products, like the SOC map created with this research, can be used in DSM, provide more detailed and reliable soil data, are quick to process, and better represent soil variability across a landscape (Thompson et al., 2010). With diverse soil data products, NRCS will be able to better serve their customers and global community (Stolt et al., 2010; Grunwald et al., 2011).

Legacy Lab Data

There is an apparent need to update the KSSL database given that half of the KSSL pedons within MLRA 127 were correlated to the incorrect soil series, many pedons had incorrect depths and horizon designations due to organic horizons, half of the KSSL horizons in MLRA 127 lacked bulk density data, 13% lacked SOC data, and there were two different laboratory methods used for measuring carbon. Through the SDJR process, NRCS is currently working on updating KSSL pedons to current soil taxonomic classification and adjusting horizon depths and

designations. Future workload should include developing or using an existing carbon-equivalent correction factor like the one used in Chapter 2 to ensure that carbon values have the same interpretability in the KSSL database. There is a future need to populate missing data, especially bulk density and carbon data. Whether it is best determined by the National Soil Survey Center to leave missing legacy data as is with the understanding that more field studies are needed or predict missing data from legacy KSSL data and environmental covariates like what was done in Chapter 2, this database deficiency needs to be addressed before DSM techniques can be utilized. Chapter 2 in this study has provided methodology for populating missing KSSL data and correcting carbon data for methodological errors.

Future Research

Although SOC was the dynamic soil property chosen to be modeled in this study, the methodology is applicable to modeling all soil properties. It is important to keep in mind that modeling can never be a complete substitute for detailed, ongoing field data collection (Elith et al., 2006), but it can be used to aid in management decisions, update soil survey data, and direct future field data acquisition. Future data collection sampling should be geostatistically designed and field bulk density methods (such as those used in the RaCA project and frame bulk density) should be explored because clod bulk densities may be inaccurate in some soils (Jenkins, 2001). Because most soil data are not normally distributed even with common transformations, nonparametric techniques such as RF, GWR, and GWRK should be used to predict soil properties and classes (Jobbágy and Jackson, 2000; Minasny et al., 2008; Keller et al., 2012; Pan et al., 2013; Razafimbelo et al., 2013). Future research is needed to better assess the statistical validation of nonparametric models and account for model over-fitting.

Given this time of changing climate and increased demand for soil productivity (crop yields), it is imperative that NRCS continue efforts to research and model land use change impacts on soil carbon sequestration and carbon greenhouse gas fluxes in and out of ecosystems. Currently the NRCS has provided the following programs/models to address carbon accounting and land use conversion: RaCA, COMET-FARM, Greenhouse Gas (GHG) and Carbon Sequestration Ranking Tool, Cover Crop Termination Guidelines, and Conservation Innovation Grants. Other agencies like the U.S. Forest Service, U.S. Geological Survey, and U.S. Environmental Protection Agency have also developed and are currently developing models and programs in support of GHG emissions and carbon sequestration efforts required by Executive

Order 13514, signed by President Obama in 2009 (U.S.EPA, 2012). Collaboration between NRCS and these agencies has been established through the U.S. Carbon Cycle Science Program aimed at determining the magnitudes and distributions of carbon sinks and sources in North America. Further collaboration is imperative in order to quantify biosphere carbon and GHG fluxes within an ecosystem, sustain the nation's environmental resources, and reduce human impacts on climate change.

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Appendix A: Kellogg Soil Survey Laboratory Site Data for Pedons in MLRA

127

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
60WV093001	-79.460111	39.140222	Brinkerton		Brinkerton Taxadjunct	Fine-silty, mixed, active, mesic Typic Fragiaquepts
60WV093002	-79.482972	39.119639	Brinkerton		Brinkerton Taxadjunct	Fine-silty, mixed, active, mesic Typic Fragiaqucls
61WV083006	-79.668083	38.940389	Ernest		Ernest Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudepts
61WV093003	-79.484556	39.171972	Ernest		Ernest	Fine-loamy, mixed, active, mesic Aquic Fragiudults
62WV083005	-79.848611	38.822778	Monongahela		Monongahela	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
64PA051007	-79.449722	39.9375	Wharton	Cruze	Cruz Taxadjunct	Fine, mixed, semiactive, mesic Mollic Oxyaquic Hapludalfs
64PA051008	-79.42	39.884167	Dekalb	Hazleton	Hazleton Taxadjunct	Coarse-loamy, siliceous, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
64PA051009	-79.379444	39.826389	Sequatchie/ Chavies	Chavies	Chavies Taxadjunct	Coarse-loamy, mixed, active, mesic Fragic Dystrudepts
64PA051010	-79.511667	39.781389	Dekalb	Hazleton	Hazleton	Loamy- skeletal, siliceous, active, mesic Typic Dystrudepts
64PA051011	-79.516667	39.730556	Purdy	Ginat	Ginat Taxadjunct	Fine-loamy, mixed, active, mesic Typic Endoaquults
67PA123001	-79.257778	41.720833	Dekalb	Hazelton	Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
67PA123002	-79.238611	41.706389	Dekalb	Hazelton	Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
67PA123003	-79.147222	41.670278	Dekalb	Dekalb	Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
67PA123004	-79.134167	41.6375	Cookport	Cookport	Cookport	Fine-loamy, mixed, active, mesic Aquic Fragiudults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
67PA123005	-78.984444	41.798056	Dekalb	Dekalb	Dekalb Taxadjunct	Loamy- skeletal, siliceous, active, mesic Spodic Dystrudepts
67PA123006	-78.990278	41.809444	Cookport	Cookport	Cookport	Fine-loamy, mixed, active, mesic Aquic Fragiudults
67PA123013	-79.272222	41.825	Lobdell	Philo	Philo	Coarse-loamy, mixed, active, mesic Fluvaquentic Dystrudepts
71PA021001	-78.389444	40.681111	Blandburg	Blandburg	Blandburg	Loamy- skeletal, mixed, semiactive, frigid Typic Haplorthods
71PA021002	-78.385556	40.698056	Blandburg	Blandburg	Blandburg	Loamy- skeletal, mixed, semiactive, frigid Typic Haplorthods
71PA021003	-78.37	40.698611	Blandburg	Blandburg	Blandburg Taxadjunct	Loamy- skeletal, mixed, semiactive, frigid Ultic Haplorthods
71PA111001	-79.061944	40.048611	Rayne	Hartleton	Rayne	Fine-loamy, mixed, active, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
71PA111002	-79.11	40.024167	Rayne	Rayne	Rayne Taxadjunct	Fine, mixed, active, mesic Typic Hapludults
71PA111003	-79.180556	39.995	Rayne	Hartleton	Rayne	Fine-loamy, mixed, active, mesic Typic Hapludults
71PA111004	-79.176667	39.786389	Leetonia	Blandburg	Blandburg Taxadjunct	Loamy- skeletal, mixed, semiactive, frigid Typic Fragiorthods
72PA129018	-79.269444	40.174722	Cavode	Cavode	Cavode Taxadjunct	Clayey, mixed, active, mesic Aeric Endoaquults
72PA129019	-79.279444	40.1675	Wharton	Blairton	Blairton Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Hapludalfs
72PA129020	-79.275833	40.166667	Wharton	Wharton	Wharton Taxadjunct	Fine, mixed, active, mesic Aquic Hapludults
72PA129021	-79.273889	40.166667	Gilpin	Gilpin	Gilpin Taxadjunct	Fine-loamy, mixed, active, mesic Mollic Hapludalfs
73PA033012	-78.549167	41.186389	Rayne	Brownsville	Brownsville	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
73PA033013	-78.531389	41.181389	Rayne	Brownsville	Brownsville	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
73PA033014	-78.545	41.186667	Ernest	Ernest	Ernest	Fine-loamy, mixed, superactive, mesic Aquic Fragiudults
73PA033015	-78.538889	41.178333	Ernest	Buchanan	Buchanan	Fine-loamy, mixed, semiactive, mesic Aquic Fragiudults
73PA033016	-78.411944	41.2075	Wharton	Cruze	Cruze	Fine, mixed, semiactive, mesic Aquic Hapludults
73PA033017	-78.405278	41.195833	Wharton	Wharton	Wharton	Fine-loamy, mixed, active, mesic Aquic Hapludults
73PA033018	-78.519444	41.101667	Nolo	Nolo	Nolo Taxadjunct	Coarse-loamy, mixed, superactive, mesic Typic Fragiaquults
73PA033019	-78.546389	41.078056	Nolo	Nolo	Nolo	Fine-loamy, mixed, superactive, mesic Aquic Fragiudults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
75WV061001	-79.816667	39.658333	Dekalb	Dekalb	Gilpin	Fine-loamy, mixed, active, mesic Typic Hapludults
78PA105007	-78.001389	41.751667	Hazleton	Hazleton	Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
78PA105008	-78.033333	41.789167	Hazleton	Hazleton	Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
78PA111005	-78.783056	40.038333	Hazelton	Hazelton	Hazelton Taxadjunct	Loamy- skeletal, siliceous, active, mesic Spodic Dystrudepts
78PA111006	-78.764167	40.036389	Hazelton	Leetonia	Blandburg Taxadjunct	Loamy- skeletal, mixed, semiactive, frigid Ultic Fragiorthods
78WV083001	-79.575	38.875	Cheat	Cheat	Gilpin	Fine-loamy, mixed, active, mesic Typic Hapludults
78WV083002	-79.666667	38.916667	Cheat	Cheat	Gilpin	Fine-loamy, mixed, active, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
78WV083003	-80.175	38.533333	Cheat	Cheat	Berks	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
78WV089007	-80.825	37.572222	Gilpin	Calvin	Cliff-top taxadjunct	Fine, mixed, semiactive, mesic Typic Hapludults
78WV089008	-80.908333	37.680556	Gilpin	Calvin	Cliff-top	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
78WV089009	-80.7625	37.645833	Kanawha	Kanawha	Kanawha Taxadjunct	Fine-loamy, mixed, semiactive, mesic Ultic Hapludalfs
78WV089010	-80.786111	37.6125	Kanawha		Kanawha Taxadjunct	Fine-loamy, mixed, semiactive, mesic Ultic Hapludalfs
79PA083006	-78.953056	41.647222	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, superactive, mesic Aquic Fragiudepts
79PA083007	-78.949444	41.6475	Hazleton	Hazleton	Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
79PA083008	-78.941667	41.626667	Clymer	Clymer	Lily Taxadjunct	Fine-loamy, siliceous, superactive, mesic Inceptic Hapludults
79PA083009	-78.949444	41.641389	Ernest	Ernest	Ernest	Fine-loamy, mixed, superactive, mesic Aquic Fragiudults
79PA083010	-78.946667	41.643056	Ernest	Ernest	Ernest	Fine-loamy, mixed, superactive, mesic Aquic Fragiudults
79PA083011	-78.943056	41.628056	Brinkerton	Brinkerton	Nolo	Fine-loamy, mixed, superactive, mesic Typic Fragiaquults
79PA083012	-78.936111	41.650278	Nolo	Nolo	Nolo	Fine-loamy, mixed, superactive, mesic Typic Fragiaquults
79WV067001	-80.881944	38.179167	Dekalb	Dekalb	Dekalb Taxadjunct	Loamy- skeletal, siliceous, active, mesic Typic Hapludults
79WV067002	-80.593333	38.241667	Ernest		Ernest Taxadjunct	Fine-loamy, mixed, active, mesic Typic Fragiudults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
79WV067006	-80.531389	38.3	Laidig		Laidig Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
79WV067007	-80.527778	38.3	Ernest		Ernest Taxadjunct	Fine-loamy, mixed, semiactive, mesic Aquic Fragiudults
79WV067008	-80.633333	38.303333	Buchanan	Buchanan	Buchanan Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
79WV067010	-80.868056	38.172222	Buchanan		Buchanan Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Typic Fragiudepts
79WV067011	-80.734444	38.281944	Gilpin		Cliff-top Taxadjunct	Clayey, mixed, semiactive, mesic Typic Hapludults
80WV067005	-80.883889	38.160556	Clymer	Clymer	Clymer Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Typic Dystrudepts
80WV067006	-80.865278	38.163889	Clymer	Clymer	Clymer Taxadjunct	Fine-loamy, siliceous, semiactive, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
81WV067001	-80.502222	38.255556	Laidig		Laidig Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Fragiudepts
81WV067002	-80.573333	38.256111	Laidig		Laidig Taxadjunct	Fine-loamy, mixed, active, mesic Typic Fragiudults
81WV101001	-80.489722	38.341111	Cookport		Cookport Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudepts
82PA047009	-78.891667	41.591667	Ernest	Ernest	Cookport Taxadjunct	Fine-loamy, mixed, active, mesic Typic Fragiudepts
82PA083004	-78.8725	41.720278	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Aquic Fragiudults
82PA083005	-78.871389	41.696667	Ernest	Ernest	Buchanan Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudults
82PA105001	-77.88	41.756667	Ernest	Ernest	Buchanan Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
82PA105002	-77.833333	41.808611	Buchanan	Buchanan	Buchanan Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Aquic Fragiudults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
82PA117017	-77.481389	41.543333	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Fragiudults
82PA117018	-77.482778	41.526667	Nolo	Nolo	Nolo Taxadjunct	Coarse-loamy, mixed, superactive, mesic Typic Fragiaquults
82PA117019	-77.4825	41.541667	Cookport	Cookport	Cookport Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudepts
82PA117020	-77.482778	41.527778	Nolo	Nolo	Nolo	Fine-loamy, mixed, superactive, mesic Typic Fragiaquults
83PA105003	-77.907778	41.808333	Sweden	Sweden	Leck Kill	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
83PA105004	-77.619722	41.525	Sweden	Sweden	Leck Kill Taxadjunct	Fine, mixed, semiactive, mesic Typic Hapludults
83PA105005	-77.62	41.524444	Sweden	Sweden	Leck Kill	Fine-loamy, mixed, semiactive, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
83PA117021	-77.481389	41.529722	Dekalb	Dekalb	Dekalb Taxadjunct	Coarse-loamy, siliceous, active, mesic Typic Dystrudepts
83PA117022	-77.481389	41.528056	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Fragiudults
83PA117023	-77.481389	41.528611	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Fragiudults
83PA117027	-77.42	41.558333	Sweden	Sweden	Ungers	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
83PA117028	-77.42	41.559167	Sweden	Sweden	Ungers	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
87PA027082	-78.211944	40.851667	Cookport	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Fragiudepts
87PA027083	-78.209722	40.851667	Clymer	Clymer	Cookport Taxadjunct	Fine-loamy, mixed, active, mesic Ultic Haplothods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
88PA021011	-78.766111	40.517778	SND	Gilpin	Berks Taxadjunct	Loamy- skeletal, mixed, superactive, mesic Typic Dystrudepts
88PA021012	-78.786667	40.505833	SND	Dekalb	Gilpin Taxadjunct	Loamy- skeletal, mixed, superactive, mesic Typic Hapludults
88PA021013	-78.751667	40.517778	SND	SND	Cavode Taxadjunct	Fine-loamy, mixed, active, mesic Aeric Endoaquults
88PA021014	-78.778611	40.495278	SND	Cavode	Cavode Taxadjunct	Fine-loamy, mixed, active, mesic Aeric Endoaquults
88PA021015	-78.773333	40.511944	SND	Wharton	Wharton Taxadjunct	Fine, mixed, active, mesic Aquic Hapludults
88PA021016	-78.752778	40.546111	SND	Brinkerton	Andover Taxadjunct	Fine-loamy, mixed, semiactive, mesic Aeric Fragiaquults
88PA033031	-78.55	41.138333	Gilpin	Gilpin	Gilpin Taxadjunct	Coarse-loamy, mixed, active, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
88PA033032	-78.580278	41.1375	SND	Buchanan	Buchanan Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudepts
88PA033033	-78.575278	41.1325	SND	Clymer	Rayne	Fine-loamy, mixed, active, mesic Typic Hapludults
88PA033034	-78.586944	41.135278	SND	Brinkerton	Ernest Taxadjunct	Fine, mixed, active, mesic Aquic Fragiudults
88PA033035	-78.420278	41.133611	SND	Hazleton	Hazleton Taxadjunct	Coarse-loamy, siliceous, active, mesic Typic Dystrudepts
88PA033036	-78.4375	41.122778	SND	Cookport	Cookport Taxadjunct	Coarse-loamy, mixed, active, mesic Aquic Fragiudults
88PA033037	-78.445278	41.134167	SND	Nolo	Cookport Taxadjunct	Fine-loamy, mixed, active, mesic Typic Fragiudults
88PA033038	-78.434167	41.141944	SND	Dekalb	Dekalb Taxadjunct	Loamy- skeletal, siliceous, superactive, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
88PA033039	-78.566944	41.03	SND	Hazleton	Hazleton	Loamy- skeletal, siliceous, active, mesic Typic Dystrudepts
88PA033040	-78.584444	41.059444	SND	Buchanan	Buchanan Taxadjunct	Fine, mixed, active, mesic Aquic Fragiudults
88PA033041	-78.566111	41.021111	SND	Dekalb	Clymer Taxadjunct	Loamy- skeletal, siliceous, superactive, mesic Typic Hapludults
88PA051021	-79.434167	39.934444	SND	Clymer	Clymer	Coarse-loamy, siliceous, active, mesic Typic Hapludults
88PA051022	-79.436944	39.937778	SND	Nolo	Nolo Taxadjunct	Fine-loamy, mixed, active, mesic Aeric Fragiaquults
88PA105011	-77.7575	41.660833	SND	Leck Kill	Lehew Taxadjunct	Loamy- skeletal, siliceous, superactive, mesic Typic Dystrudepts
88PA105012	-77.774444	41.673611	SND	Craigsville	Craigsville Taxadjunct	Loamy- skeletal, mixed, superactive, mesic Typic Hapludalfs

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
88PA105013	-77.771944	41.666944	SND	Hazelton	Hazelton Taxadjunct	Loamy- skeletal, siliceous, superactive, mesic Dystric Eutrudepts
93NY009001	-78.558889	42.045278	Brinkerton		Brinkerton Taxadjunct	Fine-loamy, mixed, active, mesic Fragic Endoaquepts
93NY009002	-78.558611	42.045833	Comly		Comly Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudults
93NY009003	-78.770833	42.056389	Carrollton		Carrollton Taxadjunct	Loamy- skeletal, mixed, active, frigid Aquic Dystrudepts
93NY009004	-78.721111	42.0025	Leetonia		Gauley Taxadjunct	Coarse-loamy, siliceous, superactive, frigid Typic Haplorthods
93NY009005	-78.729167	42.045833	Brinkerton		Brinkerton Taxadjunct	Clayey, mixed, active, mesic Aeric Fragiaqualfs
93NY009006	-78.446111	42.025833	Hazelton	Knapp Creek	Gauley Taxadjunct	Loamy- skeletal, siliceous, active, frigid Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
93NY009007	-78.445	42.023056	Hazleton	Flatiron	Flatiron Taxadjunct	Coarse-loamy, siliceous, active, mesic Typic Dystrudepts
93NY009008	-78.470278	42.016944	Onoville		Onoville Taxadjunct	Coarse-loamy, mixed, active, mesic Oxyaquic Dystrudepts
93NY009009	-78.4675	42.016667	Onoville		Onoville Taxadjunct	Fine-loamy, mixed, active, mesic Typic Fragiudepts
95WV075001	-80.253889	38.301944	Gauley		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
95WV075002	-79.9325	38.448611	Gauley		Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
95WV083001	-79.696333	38.97975	Snowdog		Snowdog Taxadjunct	Fine-loamy, mixed, superactive, frigid Typic Fragiudepts
95WV083002	-79.704056	38.938917	snd		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
95WV083003	-79.359	38.963778	Gauley		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
95WV083004	-79.369167	38.951111	Snowdog		Snowdog Taxadjunct	Fine-loamy, mixed, active, frigid Typic Fragiudepts
95WV083005	-79.695833	38.983889	Mandy		Mandy Taxadjunct	Loamy- skeletal, mixed, active, frigid Spodic Dystrudepts
95WV083006	-79.693611	38.983889	snd		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
95WV083007	-79.703056	38.946389	Mandy		Mandy Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Spodic Dystrudepts
95WV083008	-79.696389	38.983056	snd		Simoda Taxadjunct	Loamy- skeletal, mixed, active, frigid Aquic Fragiudepts
95WV093001	-79.599139	39.107833	snd		Snowdog Taxadjunct	Loamy- skeletal, siliceous, active, frigid Aquic Fragiudults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
95WV093002	-79.455861	39.087861	snd		Gauley Taxadjunct	Coarse-loamy, siliceous, superactive, frigid Typic Haplorthods
95WV093003	-79.461111	39.083444	snd		Gauley Taxadjunct	Coarse-loamy, siliceous, superactive, frigid Typic Haplorthods
95WV093004	-79.428333	38.994722	Mandy		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
95WV093005	-79.429444	38.991944	Mandy		Mandy Taxadjunct	Loamy- skeletal, mixed, active, frigid Spodic Dystrudepts
95WV093006	-79.427222	38.996389	Snowdog		Blandburg Taxadjunct	Fine-loamy, mixed, superactive, frigid Typic Fragiorthods
95WV093007	-79.429722	38.993889	Gauley		Gauley Taxadjunct	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
95WV093008	-79.398611	38.992222	Snowdog		Snowdog Taxadjunct	Fine-loamy, mixed, superactive, frigid Typic Fragiudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
97WV093001	-79.5975	39.171111	Berks		Berks Taxadjunct	Loamy- skeletal, mixed, active, mesic Typic Hapludults
97WV093002	-79.775278	39.041667	Gilpin		Berks	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
97WV093003	-79.775	39.0425	Shelocta-like		Shelocta Taxadjunct	Fine-loamy, mixed, superactive, mesic Typic Dystrudepts
97WV093004	-79.597778	39.186944	Highsplint		Highsplint	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
97WV093005	-79.597222	39.185833	Highsplint		Highsplint	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
97WV093006	-79.625278	39.201111	Berks		Berks	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
97WV093007	-79.718611	39.093333	Macove		Macove	Loamy- skeletal, mixed, active, mesic Typic Hapludults
97WV093008	-79.602778	39.185	Berks		Berks	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
98NY009001	-78.708889	42.001111	Cookport		Cookport Taxadjunct	Fine-loamy, mixed, semiactive, mesic Aquic Fragiudults
98NY009002	-78.724722	42.000833	Cookport		Cookport Taxadjunct	Coarse-loamy, mixed, superactive, mesic Aquic Fragiudults
98PA129121	-79.020833	40.335556	Clymer		Clymer	Coarse-loamy, siliceous, active, mesic Typic Hapludults
98PA129123	-79.023611	40.340278	Clymer		Hazleton	Loamy- skeletal, siliceous, active, mesic Typic Dystrudepts
S06WV071- 001	-79.535419	38.684833	Gauley		Gauley	Loamy- skeletal, siliceous, superactive, frigid Typic Haplorthods
S06WV081- 002	-80.208278	38.30375	Meckesville		Leck Kill Taxadjunct	Fine-loamy, mixed, semiactive, mesic Aquic Hapludults
S06WV093- 008	-79.698056	38.991111	SND		Gauley Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S01PA-031-010	-79.233778	41.329194	Laidig	Laidig	Laidig Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Typic Fragiudepts
S01PA-031-050	-79.241444	41.369861	Buchanan	Buchanan	Ernest Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudults
S01PA-031-053	-79.344028	41.40625	Tilsit	SND	Ernest Taxadjunct	Fine, mixed, semiactive, mesic Aquic Fragiudults
S01WV-019-001	-80.975833	37.881944	Highsplint	Layland	Layland Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Dystrudepts
S01WV-019-002	-80.922817	38.114933	Gilpin		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S01WV-019-003	-80.924667	38.113694	Lily		Nallen	Coarse-loamy, siliceous, semiactive, mesic Inceptic Hapludults
S01WV-019-004	-80.940811	38.048383	Matewan		Dekalb Taxadjunct	Loamy- skeletal, siliceous, semiactive, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S01WV-019-005	-80.941183	38.049883	Lily		Lily	Fine-loamy, siliceous, semiactive, mesic Typic Hapludults
S01WV-019-006	-81.075	38.091667	Matewan		Dekalb Taxadjunct	Loamy- skeletal, siliceous, semiactive, mesic Typic Dystrudepts
S01WV-019-007	-80.951	38.0383	Gilpin		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S01WV-019-008	-80.949183	38.036717	Highsplint	Layland	Layland Taxadjunct	Loamy- skeletal, siliceous, semiactive, mesic Typic Hapludults
S01WV-019-009	-80.920483	38.1155	Buchannon		Buchanan	Fine-loamy, mixed, semiactive, mesic Aquic Hapludults
S01WV-019-010	-81.078117	38.091767	Lily	Nallen	Nallen Taxadjunct	Coarse-loamy, siliceous, semiactive, mesic Typic Dystrudepts
S01WV-019-011	-81.154367	37.917533	Lily		Nallen Taxadjunct	Coarse-loamy, siliceous, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S01WV025002	-80.373889	37.92			Frankstown Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Paleudults
S01WV025003	-80.503028	37.839778	Frederick		Caneyville Taxadjunct	Fine, mixed, semiactive, mesic Typic Paleudalfs
S01WV025004	-80.503	37.839611	Caneyville		Caneyville	Fine, mixed, active, mesic Typic Hapludalfs
S01WV063005	-80.534278	37.608167	Frederick		Frederick	Fine, mixed, semiactive, mesic Typic Paleudults
S01WV063006	-80.508556	37.637472	Pickaway		Guernsey Taxadjunct	Fine, mixed, semiactive, mesic Aquic Hapludalfs
S01WV063007	-80.475972	37.692806	Caneyville		Caneyville	Fine, mixed, active, mesic Typic Hapludalfs
S01WV063008	-80.476222	37.692639	Frederick		Caneyville Taxadjunct	Fine-silty, mixed, semiactive, mesic Typic Hapludalfs
S01WV-081- 001	-80.977028	37.755389	Gilpin		Cliff-top taxadjunct	Fine-loamy, siliceous, semiactive, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S01WV-081-002	-81.011867	37.728333	Matewan		Dekalb Taxadjunct	Loamy- skeletal, siliceous, semiactive, mesic Typic Dystrudepts
S01WV-081-003	-81.010667	37.7314	Highsplint		Highsplint Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Dystrudepts
S01WV-081-004	-81.174733	37.8158	Lily		Nallen Taxadjunct	Coarse-loamy, siliceous, semiactive, mesic Typic Dystrudepts
S01WV-081-005	-81.173283	37.8175	Cookport		Cookport Taxadjunct	Coarse-loamy, siliceous, semiactive, mesic Aquic Fragiudepts
S01WV-081-006	-81.359767	37.80335	Highsplint		Highsplint	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S01WV-081-007	-81.359767	37.80335	Matewan		Matewan	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S02PA-031-008	-79.4745	41.273361	Atkins	SND	Atkins Taxadjunct	Fine-loamy, mixed, semiactive, acid, mesic Fluvaquentic Endoaquults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S02PA-065-004	-79.064333	41.317917	Cookport	Cookport	Cookport Taxadjunct	Fine-loamy, mixed, semiactive, mesic Aquic Fragiudults
S02WV-019-001	-81.19725	37.901333	Berks		Berks Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Dystrudepts
S02WV-019-006	-81.198639	37.89525	Matewan		Matewan Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Dystrudepts
S02WV-019-007	-81.221889	37.89025	Muskingum		Hazelton Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Hapludults
S02WV-019-008	-81.221806	37.889194	Guyandotte	Sharondale	Sharondale Taxadjunct	Loamy- skeletal, mixed, active, mesic Typic Humudepts
S02WV-019-012	-81.066389	38.175833	Berks		Berks	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S02WV-019-013	-81.066267	38.175867	Highsplint		Highsplint	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S02WV-081-002	-81.295611	37.873083	Matewan		Matewan Taxadjunct	Loamy- skeletal, mixed, superactive, mesic Dystric Eutrudepts
S02WV-081-004	-81.295056	37.875083	Highsplint		Highsplint	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S02WV-081-005	-81.294056	37.875444	Matewan		Matewan	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S03WV-025-001	-80.684639	37.977139	Cateache		Shouns Taxadjunct	Fine, mixed, semiactive, mesic Typic Rhodudults
S03WV-025-002	-80.628889	37.99975	Shouns		Shouns	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S03WV-071-001	-79.54925	38.679111	Shouns		Shouns Taxadjunct	Fine-loamy, mixed, active, mesic Typic Hapludults
S03WV-075-001	-79.855	38.549167	Cateache		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S03WV-077-001	-79.766808	39.250169	Calvin		Ungers Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Typic Hapludults
S03WV-081-001	-81.049889	37.831583	Shouns		Pipestem	Fine, mixed, active, mesic Dystric Eutrudepts
S03WV-081-002	-81.059667	37.834889	Cateache	Cateache	Pipestem Taxadjunct	Loamy- skeletal, mixed, active, mesic Dystric Eutrudepts
S03WV-083-001	-79.733492	38.966717	Hampshire		Ungers	Fine- loamy,mixed, semiactive, mesic Typic Hapludults
S03WV-083-002	-79.745083	38.947667	Cateache		Ungers	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S03WV-083-003	-79.746683	38.951433	Cateache		Ungers Taxadjunct	Fine-loamy, mixed, active, mesic Typic Hapludults
S03WV-083-004	-79.600017	38.950117	Calvin		Calvin Taxadjunct	Clayey- skeletal, mixed, active, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S03WV-083-005	-79.554028	38.997139	Hampshire		Hazleton Taxadjunct	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S03WV-083-006	-79.550031	38.983581	Calvin		Calvin Taxadjunct	Loamy- skeletal, mixed, active, mesic Typic Hapludults
S03WV-083-007	-79.603056	38.945	Escatawba		Meckesville Taxadjunct	Fine-loamy, mixed, semiactive, mesic Fragic Hapludults
S03WV-083-008	-79.915278	38.657222	Cateache		Leck Kill	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S03WV-089-001	-80.90125	37.752611	Shouns		Pipestem Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Dystrudepts
S03WV-089-002	-80.899389	37.833444	Cateache	Cateache Taxadjunct	Shouns Taxadjunct	Fine-loamy, mixed, active, mesic Typic Hapludults
S03WV-089-003	-80.899389	37.833444	Cateache	Cateache Taxadjunct	Pipestem Taxadjunct	Fine-loamy, mixed, semiactive, mesic Dystric Eutrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S03WV-089-004	-80.913722	37.8185	Shouns		Shouns Taxadjunct	Fine, mixed, semiactive, mesic Typic Rhodudults
S03WV-089-005	-80.874944	37.531889	Shouns		Pipestem Taxadjunct	Fine-loamy, mixed, active, mesic Dystric Eutrudepts
S03WV-089-006	-80.762222	37.78	Cateache	Cateache	Cateache Taxadjunct	Fine, mixed, semiactive, mesic Ultic Hapludalfs
S03WV-089-007	-80.761972	37.779694	Shouns	Pipestem Taxadjunct	Cateache Taxadjunct	Fine, mixed, semiactive, mesic Typic Hapludalfs
S03WV-093-001	-79.666914	39.050194	Calvin		Calvin Taxadjunct	Loamy- skeletal, mixed, active, mesic Typic Hapludults
S03WV-093-002	-79.666847	39.050219	Calvin		Calvin	Loamy- skeletal, mixed, active, mesic Typic Dystrudepts
S03WV-101-001	-80.296972	38.481333	Shouns		Pipestem Taxadjunct	Fine-loamy, mixed, semiactive, mesic Dystric Eutrudepts
S03WV-101-002	-80.297194	38.479583	Cateache		Pipestem Taxadjunct	Fine-loamy, mixed, active, mesic Typic Dystrudepts

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S04WV-001-002	-79.561667	39.076111	Brinkerton		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S04WV-093-001	-79.543056	39.324167	Gilpin		Gilpin	Fine-loamy, mixed, active, mesic Typic Hapludults
S04WV-093-002	-79.443611	39.15	Ernest		Buchanan Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudults
S04WV-093-003	-79.443889	39.140278	Brinkerton		Cavode Taxadjunct	Fine-loamy, mixed, active, mesic Aeris Endoaquults
S04WV-093-004	-79.443611	39.134167	Brinkerton		Buchanan Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiorthods
S04WV-093-005	-79.566667	39.08	Trussel		Snowdog Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudepts
S04WV-093-006	-79.561722	39.077139	Gilpin		Gilpin Taxadjunct	Fine, mixed, active, mesic Typic Hapludults
S04WV-093-007	-79.563611	39.078333			Gauley Taxadjunct	Fine-loamy, mixed, superactive, mesic Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S04WV-093-008	-79.565278	39.079444	Ernest		Ernest Taxadjunct	Fine, mixed, active, mesic Ultic Fragiorthods
S06WV019-001	-80.970278	38.015	Laidig	Laidig	Laidig Taxadjunct	Fine-loamy, mixed, semiactive, mesic Fragic Hapludults
S06WV019-002	-81.119444	37.93	Cookport		Cookport Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
S06WV019-004	-81.032778	38.000556	Laidig		Laidig Taxadjunct	Fine-loamy, mixed, semiactive, mesic Fragic Hapludults
S06WV019-005	-81.195278	37.941944	Gilpin		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults
S06WV025-001	-80.59	37.746667	Cookport		Cookport Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Typic Fragiudults
S06WV067-001	-80.808972	38.342944	Gilpin		Clifftop	Fine-loamy, mixed, semiactive, mesic Typic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S06WV067-002	-80.660583	38.204	Fenwick		Fenwick	Fine-loamy, mixed, semiactive, mesic Aquic Hapludults
S06WV067-003	-80.669361	38.206972	Laidig		Laidig Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Fragic Hapludults
S06WV067-004	-80.558889	38.259417	Fenwick		Fenwick	Fine-loamy, mixed, semiactive, mesic Aquic Hapludults
S06WV067-005	-80.577444	38.255583	Laidig		Laidig Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
S06WV067-006	-80.868333	38.261389	Gilpin	Clifftop	Clifftop taxadjunct	Fine, mixed, semiactive, mesic Typic Hapludults
S06WV081-001	-81.062917	37.695833	Cookport		Cookport Taxadjunct	Coarse-loamy, mixed, semiactive, mesic Typic Fragiudults
S06WV101-001	-80.609167	38.404444	Gilpin		Clifftop Taxadjunct	Fine-loamy, mixed, semiactive, mesic Oxyaquic Hapludults

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S06WV101-002	-79.78975	39.651806	Fenwick		Cookport Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
S09WV167500	-80.491111	38.355	Fenwick		Fenwick Taxadjunct	Loamy- skeletal, mixed, semiactive, mesic Aquic Hapludults
S09WV167510	-79.789778	39.650444	Buchanan		Buchanan Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Fragiudults
S09WV167515	-79.790111	39.649944	Buchanan		Buchanan	Fine-loamy, mixed, semiactive, mesic Aquic Fragiudults
S09WV167530	-79.7915	39.64775	Buchanan		Buchanan Taxadjunct	Fine-loamy, mixed, active, mesic Aquic Fragiudults
S09WV167540	-79.791361	39.646778	Gilpin		Clifftop Taxadjunct	Fine-loamy, mixed, semiactive, mesic Typic Dystrudepts
S12WV071001	-79.573269	38.707322	Mandy		Wildell Taxadjunct	Loamy- skeletal, mixed, active, frigid Typic Haplorthods

PedonID	Longitude	Latitude	Series Sampled As	Series Correlated As	Series Correlated To	Taxonomic Classification
S12WV075001	- 79.70592713	38.47024552	Mandy		Wildell	Loamy- skeletal, mixed, superactive, frigid Typic Haplorthods
S12WV075002	- 79.70154108	38.47320687	Wildell		Wildell Taxadjunct	Fine-loamy, mixed, superactive, frigid Typic Haplorthods
S12WV075003	- 79.74244996	38.60650192	Wildell		Wildell Taxadjunct	Fine-loamy, mixed, superactive, frigid Typic Haplorthods
S12WV075004	-79.740297	38.71701256	Mandy		Mandy Taxadjunct	Loamy- skeletal, mixed, active, frigid Spodic Dystrudepts
S12WV075005	-79.7521504	38.71467058	Wildell		Wildell	Loamy- skeletal, mixed, superative, frigid Typic Haplorthods
S12WV083001	-79.6554495	38.8565603	Mandy		Mandy Taxadjunct	Loamy- skeletal, mixed, active, frigid Spodic Dystrudepts

Appendix B: Kellogg Soil Survey Laboratory Pedon Data for Sites in MLRA 127

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm ⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm ⁻³)	SOC Stock (kg m ⁻²)
60WV093001	0	5	A	19.31		0	19.31	1.08	10.40
60WV093001	5	13	E	4.39		0	4.39	1.26	4.43
60WV093001	13	43	Bg1	0.53		0	0.53	1.21	1.91
60WV093001	43	66	Bg2	0.33		0	0.33	1.40	1.05
60WV093001	66	97	Bx1	0.24		0	0.24	1.67	1.25
60WV093001	97	135	Bx2	0.20		3	0.20	1.67	1.22
60WV093001	135	224	C	0.18		3	0.18	1.63	2.60
60WV093002	0	5	A	11.06		0	11.06	0.98	5.40
60WV093002	5	8	E	7.36		0	7.36	1.29	2.84
60WV093002	8	28	Btg1	0.88		0	0.88	1.36	2.39
60WV093002	28	36	Btg2	0.23		0	0.23	1.38	0.25
60WV093002	36	61	Btx1	0.18		0	0.18	1.51	0.70
60WV093002	61	84	Btx2	0.14		0	0.14	1.56	0.51
60WV093002	84	99	C	0.10		60	0.10	1.51	0.09
61WV083006	0	5	Oi			0	38.45	0.45	8.60
61WV083006	5	8	Oe			0	28.40	0.57	4.87
61WV083006	8	13	A	9.12		0	9.12	1.10	5.00
61WV083006	13	23	E	6.30	1.13	0	6.30	1.13	7.12
61WV083006	23	49	Bw1	3.00	1.09	0	3.00	1.09	8.49
61WV083006	49	67	Bw2	1.29	1.53	0	1.29	1.53	3.56
61WV083006	67	102	Bx1	0.67	1.70	0	0.67	1.70	3.97

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
61WV083006	102	153	Bx2	0.62	1.67	55	0.62	1.67	2.39
61WV083006	153	191	Cx	0.80		37	0.80	1.60	3.05
61WV093003	0	3	Oi			0	44.18	0.37	4.84
61WV093003	3	8	Oe			0	34.73	0.49	8.53
61WV093003	8	13	A	16.47	0.94	0	16.47	0.94	7.74
61WV093003	13	18	E	8.09	1.23	15	8.09	1.23	4.23
61WV093003	18	41	Bw1	2.47	1.43	0	2.47	1.43	8.13
61WV093003	41	66	Bw2	2.24	1.72	12	2.24	1.72	8.49
61WV093003	66	84	Bx	2.94	1.76	0	2.94	1.76	9.31
61WV093003	84	122	Btx	2.02		0	2.02	1.72	13.17
62WV083005	0	15	Ap	2.98		0	2.98	1.18	5.27
62WV083005	15	30	Bt1	0.21		0	0.21	1.36	0.43
62WV083005	30	56	Bt2	0.38		0	0.38	1.42	1.41
62WV083005	56	79	Btx1	0.06		0	0.06	1.51	0.20
62WV083005	79	107	Btx2	0.09		0	0.09	1.54	0.37
62WV083005	107	132	Btx3	0.13		25	0.13	1.55	0.37
62WV083005	132	165	2C	0.13		35	0.13	1.50	0.41
64PA051007	0	18	Ap	2.30	1.37	2	2.30	1.37	5.56
64PA051007	18	33	Bt1	0.68	1.44	2	0.68	1.44	1.44
64PA051007	33	48	Bt2	0.53	1.42	2	0.53	1.42	1.10
64PA051007	48	64	Bt3	0.37	1.55	2	0.37	1.55	0.90
64PA051007	64	76	Bt4	0.18	1.46	5	0.18	1.46	0.31
64PA051007	76	91	Bt5	0.11	1.66	2	0.11	1.66	0.28

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
64PA051007	91	107	BCg1	0.11	1.63	1	0.11	1.63	0.29
64PA051007	107	127	BCg2	0.07	1.39	30	0.07	1.39	0.14
64PA051008	0	18	Ap	2.97	1.17	20	2.97	1.17	5.00
64PA051008	18	28	BE	1.05	1.23	20	1.05	1.23	1.03
64PA051008	28	46	Bw1	0.38	1.29	20	0.38	1.29	0.71
64PA051008	46	64	Bw2	0.09	1.40	20	0.09	1.40	0.17
64PA051008	64	79	BC	0.09	1.47	22	0.09	1.47	0.15
64PA051008	79	99	C1	0.10	1.44	50	0.10	1.44	0.14
64PA051008	99	127	C2	0.14	1.52	20	0.14	1.52	0.48
64PA051008	127	150	C3	0.11	1.33	60	0.11	1.33	0.14
64PA051009	0	20	Ap	2.98	1.28	0	2.98	1.28	7.63
64PA051009	20	38	BA	1.11	1.32	0	1.11	1.32	2.63
64PA051009	38	53	Bw1	0.60	1.34	0	0.60	1.34	1.20
64PA051009	53	81	Bw2	0.45	1.30	0	0.45	1.30	1.65
64PA051009	81	102	Bw3	0.57	1.42	0	0.57	1.42	1.69
64PA051009	102	124	Bw4	0.38	1.40	0	0.38	1.40	1.18
64PA051009	124	163	Bx1	0.55	1.50	0	0.55	1.50	3.24
64PA051009	163	203	Bx2	0.43	1.56	0	0.43	1.56	2.66
64PA051010	0	23	Ap	3.55	1.16	20	3.55	1.16	7.58
64PA051010	23	38	BA	0.68	1.41	20	0.68	1.41	1.15
64PA051010	38	66	Bw	0.24	1.46	50	0.24	1.46	0.49
64PA051010	66	86	BC	0.13		50	0.13	1.57	0.20
64PA051011	0	20	Ap	6.13	0.92	0	6.13	0.92	11.29

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
64PA051011	20	46	Eg	3.48	0.82	0	3.48	0.82	7.42
64PA051011	46	69	Btg1	1.83	0.95	0	1.83	0.95	4.00
64PA051011	69	99	Btg2	1.49	1.03	0	1.49	1.03	4.61
64PA051011	99	114	Btg3	0.74	1.51	1	0.74	1.51	1.66
64PA051011	114	135	Btg4	0.68	1.69	15	0.68	1.69	2.06
64PA051011	135	157	2BCg	0.80	1.65	15	0.80	1.65	2.45
64PA051011	157	183	2Cg	0.65	1.59	10	0.65	1.59	2.43
67PA123001	0	3	Oi			15	43.21	0.44	4.90
67PA123001	3	8	Oa	55.83		15	55.83	0.59	14.01
67PA123001	8	13	E	2.04	1.35	15	2.04	1.35	1.17
67PA123001	13	18	Bhs	3.25		15	3.25	1.27	1.76
67PA123001	18	23	Bs	4.44		15	4.44	1.19	2.24
67PA123001	23	46	Bw1	1.01	1.17	25	1.01	1.17	2.03
67PA123001	46	64	Bw2	0.30	1.49	45	0.30	1.49	0.44
67PA123001	64	89	Bw3	0.27	1.82	60	0.27	1.82	0.49
67PA123001	89	117	C1	0.13	1.86	80	0.13	1.86	0.13
67PA123001	117	150	C2	0.10		95	0.10	1.75	0.03
67PA123002	0	2	Oi			0	42.22	0.45	3.76
67PA123002	2	5	Oa	35.78		0	35.78	0.60	6.44
67PA123002	5	8	E	3.18		20	3.18	1.48	1.13
67PA123002	8	10	Bhs	2.24		20	2.24	1.28	0.46
67PA123002	10	20	Bs	2.38	0.92	25	2.38	0.92	1.64
67PA123002	20	30	Bw1	0.66	1.07	30	0.66	1.07	0.49

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
67PA123002	30	48	Bw2	0.56	1.50	30	0.56	1.50	1.06
67PA123002	48	76	Bw3	0.21	1.65	50	0.21	1.65	0.48
67PA123002	76	112	BC1	0.04		80	0.04	1.72	0.05
67PA123002	112	135	BC2	0.07		75	0.07	1.67	0.06
67PA123002	135	162	C1	0.08	1.73	30	0.08	1.73	0.25
67PA123002	162	180	C2	0.03	1.70	40	0.03	1.70	0.06
67PA123002	180	208	C3	0.12		50	0.12	1.75	0.30
67PA123003	0	2	Oi			0	43.31	0.43	3.72
67PA123003	2	5	Oa	17.27		0	17.27	1.01	5.21
67PA123003	5	23	E	0.43	1.62	20	0.43	1.62	1.00
67PA123003	23	28	Bhs	2.06		25	2.06	1.29	1.00
67PA123003	28	48	Bs	1.20	1.30	30	1.20	1.30	2.18
67PA123003	48	79	Bw	0.47	1.49	50	0.47	1.49	1.09
67PA123003	79	96	C1	0.26		70	0.26	1.65	0.22
67PA123003	96	119	C2	0.10		85	0.10	1.66	0.06
67PA123004	0	2	Oi			0	42.07	0.44	3.72
67PA123004	2	5	Oa	32.94		0	32.94	0.62	6.11
67PA123004	5	8	A	9.68		10	9.68	0.89	2.32
67PA123004	8	13	E	1.14		10	1.14	1.40	0.72
67PA123004	13	15	Bhs	3.35		10	3.35	1.23	0.74
67PA123004	15	28	Bw	3.31		15	3.31	1.33	4.85
67PA123004	28	51	Bt	1.35	1.23	20	1.35	1.23	3.05
67PA123004	51	76	Btgx1	0.27	1.53	20	0.27	1.53	0.83

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
67PA123004	76	86	Btgx2	0.20	1.69	25	0.20	1.69	0.25
67PA123004	86	104	Btgx3	0.33	1.78	30	0.33	1.78	0.73
67PA123004	104	114	Btgx4	0.92	1.67	30	0.92	1.67	1.08
67PA123004	114	135	2Bgx5	9.66	1.51	70	9.66	1.51	9.19
67PA123004	135	150	2Bgx6	2.24	1.59	60	2.24	1.59	2.14
67PA123004	150	183	2Cx	0.43		80	0.43	1.66	0.47
67PA123005	0	2	Oi			0	37.40	0.38	2.88
67PA123005	2	5	Oa	29.93		0	29.93	0.51	4.62
67PA123005	5	15	E	2.04		35	2.04	1.34	1.77
67PA123005	15	18	Bh	2.49		35	2.49	1.15	0.56
67PA123005	18	20	Bs	2.06		35	2.06	1.14	0.31
67PA123005	20	48	Bw1	1.51		35	1.51	1.27	3.47
67PA123005	48	74	Bw2	0.89		60	0.89	1.40	1.30
67PA123005	74	94	C	0.61		90	0.61	1.47	0.18
67PA123006	0	3	A	7.38		0	7.38	0.84	1.87
67PA123006	3	5	E			0	6.78	1.28	1.74
67PA123006	5	13	EB	3.22	1.01	0	3.22	1.01	2.60
67PA123006	13	23	BA		1.10	0	1.96	1.10	2.16
67PA123006	23	33	Bt1	0.81	1.33	0	0.81	1.33	1.08
67PA123006	33	46	Bt2	0.38	1.43	0	0.38	1.43	0.71
67PA123006	46	58	Bt3	0.24	1.54	0	0.24	1.54	0.45
67PA123006	58	81	Btx1	0.26	1.63	0	0.26	1.63	0.96
67PA123006	81	102	Btx2	0.60	1.80	5	0.60	1.80	2.14

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
67PA123006	102	137	Btx3	0.33	1.81	20	0.33	1.81	1.66
67PA123006	137	170	Btx4	0.62	1.74	75	0.62	1.74	0.90
67PA123013	0	10	Ap1	1.89	1.23	0	1.89	1.23	2.32
67PA123013	10	20	Ap2	1.62	1.32	0	1.62	1.32	2.14
67PA123013	20	53	Bw1	0.23	1.39	0	0.23	1.39	1.04
67PA123013	53	69	Bw2	0.33	1.48	0	0.33	1.48	0.77
67PA123013	69	94	Bwg1	0.16	1.42	0	0.16	1.42	0.55
67PA123013	94	127	Bwg2	0.14	1.43	0	0.14	1.43	0.67
67PA123013	127	152	Bwg3	0.11	1.46	0	0.11	1.46	0.41
67PA123013	152	165	2C	0.07		0	0.07	1.44	0.13
71PA021001	0	5	Oi	46.82		0	46.82	0.41	9.52
71PA021001	5	10	Oa	16.50		0	16.50	1.13	9.29
71PA021001	10	15	A	10.56		60	10.56	1.16	2.44
71PA021001	15	33	E	0.53		60	0.53	1.60	0.61
71PA021001	33	41	Bh	3.20	1.30	30	3.20	1.30	2.33
71PA021001	41	46	Bs1	2.33	1.18	30	2.33	1.18	0.96
71PA021001	46	53	Bs2	0.84	1.25	10	0.84	1.25	0.66
71PA021001	53	76	Bw1	0.57	1.64	55	0.57	1.64	0.97
71PA021001	76	96	Bw2	0.33	1.66	60	0.33	1.66	0.44
71PA021001	96	112	BC	0.09	1.78	65	0.09	1.78	0.09
71PA021001	112	168	C1	0.13	1.79	65	0.13	1.79	0.46
71PA021001	168	221	C2	0.11		85	0.11	1.74	0.15
71PA021002	0	2	Oi	44.56		0	44.56	0.35	3.12

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
71PA021002	2	5	Oa	40.34		0	40.34	1.05	12.74
71PA021002	5	8	A	18.87		75	18.87	1.07	1.52
71PA021002	8	33	E	0.47		75	0.47	1.58	0.47
71PA021002	33	46	Bh	0.78		75	0.78	1.41	0.36
71PA021002	46	53	Bhs	4.08		65	4.08	1.33	1.33
71PA021002	53	61	Bs	4.21		75	4.21	1.32	1.11
71PA021002	61	69	Bw1	1.42		70	1.42	1.58	0.54
71PA021002	69	91	Bw2	0.30	1.55	70	0.30	1.55	0.30
71PA021002	91	109	Bw3	0.29	1.62	70	0.29	1.62	0.25
71PA021002	109	142	Bw4	0.17	1.73	70	0.17	1.73	0.28
71PA021002	142	157	Bw5	0.09	1.51	70	0.09	1.51	0.06
71PA021002	157	198	C	0.08	1.79	80	0.08	1.79	0.11
71PA021003	0	2	Oi			0	39.21	0.34	2.70
71PA021003	2	5	Oa	31.11		0	31.11	1.00	9.34
71PA021003	5	13	A	0.72		10	0.72	1.02	0.52
71PA021003	13	38	E	1.19		70	1.19	1.56	1.39
71PA021003	38	46	Bh	8.83		70	8.83	1.40	2.96
71PA021003	46	51	Bs1	7.06	1.51	80	7.06	1.51	1.07
71PA021003	51	58	Bs2	3.70	1.28	70	3.70	1.28	0.99
71PA021003	58	81	Bw1	0.74	1.71	65	0.74	1.71	1.01
71PA021003	81	119	Bw2	0.15		75	0.15	1.65	0.24
71PA021003	119	145	Bt1	0.26	1.77	30	0.26	1.77	0.85
71PA021003	145	170	Bt2	0.11	1.72	50	0.11	1.72	0.24

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
71PA021003	170	195	Bt3	0.11	1.80	50	0.11	1.80	0.25
71PA111001	0	23	Ap	2.60	1.29	10	2.60	1.29	6.94
71PA111001	23	48	Bt1	0.55	1.28	15	0.55	1.28	1.51
71PA111001	48	71	Bt2	0.21	1.54	17	0.21	1.54	0.63
71PA111001	71	94	Bt3	0.14	1.42	60	0.14	1.42	0.19
71PA111001	94	117	Bt4	0.10	1.51	75	0.10	1.51	0.09
71PA111001	117	152	BC	0.09		75	0.09	1.54	0.11
71PA111001	152	178	C1	0.06		75	0.06	1.50	0.06
71PA111001	178	208	C2	0.06		75	0.06	1.46	0.06
71PA111002	0	23	Ap	2.60	1.41	10	2.60	1.41	7.58
71PA111002	23	43	Bt1	0.53	1.48	30	0.53	1.48	1.09
71PA111002	43	66	Bt2	0.26	1.63	25	0.26	1.63	0.72
71PA111002	66	97	Bt3	0.07	1.63	30	0.07	1.63	0.25
71PA111002	97	130	Bt4	0.07	1.68	20	0.07	1.68	0.31
71PA111002	130	168	BC	0.11	1.53	80	0.11	1.53	0.13
71PA111002	168	208	C1	0.04		80	0.04	1.49	0.05
71PA111002	208	305	C2	0.13		40	0.13	1.52	1.13
71PA111003	0	20	Ap	2.64	1.30	10	2.64	1.30	6.18
71PA111003	20	51	Bt1	0.50	1.43	25	0.50	1.43	1.65
71PA111003	51	86	Bt2	0.24	1.36	40	0.24	1.36	0.69
71PA111003	86	109	Bt3	0.18	1.42	30	0.18	1.42	0.42
71PA111003	109	140	Bt4	0.13	1.52	5	0.13	1.52	0.57
71PA111003	140	160	BC	0.14	1.45	5	0.14	1.45	0.39

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
71PA111003	160	196	C1	0.21		95	0.21	1.47	0.06
71PA111003	196	236	C2	0.14		80	0.14	1.47	0.17
71PA111004	0	1	Oi	48.54		0	48.54	0.49	2.37
71PA111004	1	6	Oa	56.35		0	56.35	0.84	23.56
71PA111004	6	11	A	17.92		0	17.92	1.21	10.83
71PA111004	11	26	E	1.09	1.54	55	1.09	1.54	1.14
71PA111004	26	31	Bh	5.34	1.33	35	5.34	1.33	2.31
71PA111004	31	52	Bhs	1.82	1.31	35	1.82	1.31	3.25
71PA111004	52	59	Bw	0.81	1.60	35	0.81	1.60	0.59
71PA111004	59	85	Bx1	0.80	1.69	35	0.80	1.69	2.27
71PA111004	85	110	Bx2	0.77	1.75	40	0.77	1.75	2.01
71PA111004	110	138	Bx3	0.99	1.50	85	0.99	1.50	0.63
71PA111004	138	166	Bx4	0.89		85	0.89	1.68	0.63
72PA129018	0	23	Ap	2.94	1.30	0	2.94	1.30	8.79
72PA129018	23	30	Bt1	1.31	1.47	5	1.31	1.47	1.28
72PA129018	30	43	Bt2	0.72	1.48	5	0.72	1.48	1.32
72PA129018	43	66	Bt3	0.26	1.68	5	0.26	1.68	0.94
72PA129018	66	74	C	0.23		5	0.23	1.42	0.25
72PA129019	0	20	Ap	0.94	1.44	5	0.94	1.44	2.56
72PA129019	20	38	Bt	0.38	1.49	5	0.38	1.49	0.98
72PA129019	38	53	BCt	0.31		50	0.31	1.45	0.34
72PA129019	53	71	C	0.20		90	0.20	1.43	0.05
72PA129020	0	18	Ap	3.20	1.38	5	3.20	1.38	7.54

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
72PA129020	18	36	Bt1	0.75	1.46	5	0.75	1.46	1.88
72PA129020	36	51	Bt2	0.43	1.57	5	0.43	1.57	0.95
72PA129020	51	69	Bt3	0.26	1.57	5	0.26	1.57	0.69
72PA129020	69	84	Bt4	0.09	1.67	5	0.09	1.67	0.20
72PA129020	84	117	BC	0.14	1.80	5	0.14	1.80	0.80
72PA129021	0	25	Ap	2.94	1.25	15	2.94	1.25	7.81
72PA129021	25	46	Bt	0.36	1.52	10	0.36	1.52	1.02
72PA129021	46	58	BCt	0.74		80	0.74	1.45	0.26
72PA129021	86	157	C	0.10		50	0.10	1.44	0.51
73PA033013	0	8	Oa	8.61		0	17.17	0.47	4.07
73PA033013	8	23	BA	2.57	1.10	10	3.76	0.97	1.37
73PA033013	23	46	Bw1	0.58	1.29	15	1.97	1.12	2.65
73PA033013	46	72	Bw2	0.37	1.41	20	1.10	1.27	1.18
73PA033013	72	99	Bw3	0.13	1.37	50	0.56	1.49	1.87
73PA033013	99	148	BC	0.18		70	0.25	1.54	0.44
73PA033013	148	173	C	0.21		85	0.30	1.52	0.57
73PA033012	0	5	Oa	17.17		0	0.24	1.45	0.28
73PA033012	5	10	A	3.76		25	0.28	1.65	0.84
73PA033012	10	25	BA	1.97	1.12	20	0.32	1.52	0.44
73PA033012	25	38	Bw1	1.10	1.27	35	8.61	0.50	3.42
73PA033012	38	66	Bw2	0.56	1.49	20	2.57	1.10	3.82
73PA033012	66	81	Bw3	0.25	1.54	25	0.58	1.29	1.47
73PA033012	81	109	Bw4	0.30	1.52	55	0.37	1.41	1.08

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
73PA033012	109	132	Bw5	0.24	1.45	65	0.13	1.37	0.24
73PA033012	132	185	Bw6	0.28	1.65	65	0.18	1.49	0.40
73PA033012	185	211	C	0.32		65	0.21	1.48	0.12
73PA033014	0	3	Oi	14.71		0	14.71	0.41	1.83
73PA033014	3	8	Oa	10.80		0	10.80	0.55	2.95
73PA033014	8	13	A	6.23		0	6.23	1.11	3.44
73PA033014	13	24	BA	0.83	1.29	10	0.83	1.29	1.05
73PA033014	24	38	Bt1	0.56	1.49	20	0.56	1.49	0.94
73PA033014	38	49	Bt2	0.32	1.43	20	0.32	1.43	0.40
73PA033014	49	82	Btx1	0.31	1.38	10	0.31	1.38	1.26
73PA033014	82	120	Btx2	0.15	1.54	35	0.15	1.54	0.59
73PA033014	120	158	2Bx3	2.19	1.65	10	2.19	1.65	12.35
73PA033014	158	191	2Bx4	0.64	1.44	10	0.64	1.44	2.73
73PA033015	0	5	A	8.45		5	8.45	0.96	3.86
73PA033015	5	15	BA	3.29	1.02	10	3.29	1.02	3.02
73PA033015	15	25	Bt1	1.33	1.45	15	1.33	1.45	1.65
73PA033015	25	38	Bt2	1.35	1.49	10	1.35	1.49	2.35
73PA033015	38	58	Btx1	0.45	1.58	15	0.45	1.58	1.22
73PA033015	58	84	Btx2	0.36	1.62	20	0.36	1.62	1.20
73PA033015	84	119	Btx3	0.72	1.86	25	0.72	1.86	3.54
73PA033015	119	147	Btx4	0.64	1.71	30	0.64	1.71	2.14
73PA033015	147	165	Btx5	0.64	1.64	40	0.64	1.64	1.13
73PA033016	0	5	Oa	46.01		0	46.01	0.62	14.17

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
73PA033016	5	15	A	8.62	1.07	0	8.62	1.07	9.22
73PA033016	15	33	Bt1	1.33	1.27	0	1.33	1.27	3.05
73PA033016	33	61	Bt2	0.55	1.43	0	0.55	1.43	2.22
73PA033016	61	91	Btg1	0.36	1.61	0	0.36	1.61	1.71
73PA033016	91	132	Btg2	0.28	1.67	0	0.28	1.67	1.94
73PA033016	132	160	BC	0.23	1.58	30	0.23	1.58	0.70
73PA033016	160	195	C	0.37		60	0.37	1.58	0.82
73PA033017	0	3	Oa	7.76		0	7.76	0.60	1.39
73PA033017	3	11	A	1.36		0	1.36	1.00	1.09
73PA033017	11	28	Bt1	0.69	1.29	5	0.69	1.29	1.44
73PA033017	28	49	Bt2	0.37	1.49	5	0.37	1.49	1.11
73PA033017	49	74	Btg1	0.22	1.72	5	0.22	1.72	0.90
73PA033017	74	94	Btg2	0.23	1.73	5	0.23	1.73	0.76
73PA033017	94	112	Btg3	0.22		5	0.22	1.65	0.62
73PA033017	112	138	Btg4	0.19	1.58	10	0.19	1.58	0.69
73PA033018	0	5	Oa	27.34		0	27.34	0.55	7.58
73PA033018	5	18	A	2.67	1.53	0	2.67	1.53	5.31
73PA033018	18	30	Btg1	0.71	1.48	0	0.71	1.48	1.26
73PA033018	30	48	Btg2	0.51	1.46	0	0.51	1.46	1.34
73PA033018	48	81	Bgx1	0.26	1.49	15	0.26	1.49	1.07
73PA033018	81	129	Bgx2	0.31	1.57	0	0.31	1.57	2.35
73PA033018	129	175	Bgx3	0.21	1.60	0	0.21	1.60	1.57
73PA033019	0	8	Oa	33.09		0	33.09	0.62	16.47

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
73PA033019	8	18	A	4.71	1.29	0	4.71	1.29	6.08
73PA033019	18	36	E	1.78	1.39	0	1.78	1.39	4.44
73PA033019	36	44	Btg	0.98	1.46	5	0.98	1.46	1.09
73PA033019	44	87	Bgx1	0.78	1.74	10	0.78	1.74	5.26
73PA033019	87	132	Bgx2	1.01	1.81	10	1.01	1.81	7.39
73PA033019	132	163	Bgx3	1.02	1.76	30	1.02	1.76	3.90
73PA033019	163	201	Bgx4	0.37	1.86	30	0.37	1.86	1.83
75WV061001	0	5	Oe	21.74		0	21.74	0.91	9.93
75WV061001	5	8	A	9.36	1.01	20	21.74	0.92	10.01
75WV061001	8	13	E	4.53		20	9.36	1.01	2.27
75WV061001	13	23	Bt1	1.85		20	9.36	1.01	2.27
75WV061001	23	46	Bt2	1.29	1.28	35	4.53	1.16	2.10
75WV061001	46	69	BC/C	0.68		70	4.49	1.16	2.08
78PA105007	0	1	Oi			60	42.83	0.45	0.77
78PA105007	1	4	Oa			60	36.33	0.58	2.51
78PA105007	4	24	E	0.29		60	0.29	1.37	0.31
78PA105007	24	27	Bhs1	2.75		60	2.75	1.28	0.42
78PA105007	27	34	Bhs2	1.82		60	1.82	1.28	0.65
78PA105007	34	103	BC	0.96		60	0.96	1.56	4.12
78PA105007	103	128	C	0.25		60	0.25	1.56	0.40
78PA105008	0	4	Oi			0	44.62	0.32	5.66
78PA105008	4	5	Oa			0	34.86	0.49	1.72
78PA105008	5	8	A	8.79		10	8.79	1.04	2.46

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
78PA105008	8	20	E	0.64		20	0.64	1.30	0.80
78PA105008	20	23	Bhs	4.98		20	4.98	1.27	1.52
78PA105008	23	30	Bs	4.31		25	4.31	1.23	2.79
78PA105008	30	35	Bw	1.84		40	1.84	1.31	0.72
78PA105008	35	53	BC	0.94		60	0.94	1.37	0.92
78PA105008	53	86	C	0.57		90	0.57	1.39	0.26
78PA111005	0	3	Oi			0	37.99	0.45	5.16
78PA111005	3	6	Oa			0	25.78	0.53	4.10
78PA111005	6	11	A	17.88		35	17.88	1.10	6.41
78PA111005	11	26	E	1.28		60	1.28	1.28	0.98
78PA111005	26	29	Bhs	5.69		45	5.69	1.27	1.19
78PA111005	29	34	Bs	2.50		50	2.50	1.18	0.74
78PA111005	34	59	Bw	0.98		60	0.98	1.41	1.38
78PA111005	59	72	BC1	0.44		65	0.44	1.51	0.30
78PA111005	72	97	BC2	0.55		75	0.55	1.50	0.51
78PA111006	0	2	Oi			0	33.79	0.49	3.30
78PA111006	2	8	Oa			0	24.56	0.54	7.96
78PA111006	8	11	A	9.06		25	9.06	1.23	2.50
78PA111006	11	26	E	0.48		50	0.48	1.50	0.54
78PA111006	26	33	Bhs	7.77		30	7.77	1.31	4.99
78PA111006	33	46	Bs	1.93		30	1.93	1.30	2.28
78PA111006	46	59	Bt	0.50		30	0.50	1.53	0.69
78PA111006	59	79	Btx1	0.21		40	0.21	1.66	0.43

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
78PA111006	79	107	Btx2	0.38		30	0.38	1.61	1.21
78PA111006	107	135	Btx3	0.17		30	0.17	1.70	0.57
78PA111006	135	163	Btx4	0.28		30	0.28	1.69	0.94
78WV083001	0	5	Ap1	7.51		5	7.51	1.22	4.34
78WV083001	5	15	Ap2	5.07		5	5.07	1.30	6.27
78WV083001	15	30	Bt1	1.52		10	1.52	1.44	2.95
78WV083001	30	43	Bt2	0.55		15	0.55	1.48	0.90
78WV083001	43	58	Bt3	0.28		20	0.28	1.44	0.49
78WV083001	58	71	C	0.13		15	0.13	1.41	0.20
78WV083002	0	15	A			10	5.44	1.14	8.34
78WV083002	15	36	Bt1			15	1.21	1.46	3.14
78WV083002	36	64	Bt2			25	0.62	1.54	1.99
78WV083002	64	84	C			80	0.63	1.53	0.39
78WV083003	0	20	A			15	6.86	1.09	12.73
78WV083003	20	36	Bw1			25	1.51	1.36	2.47
78WV083003	36	56	Bw2			30	1.01	1.42	2.02
78WV083003	56	69	C			65	0.69	1.43	0.45
78WV089007	0	23	Ap			0	2.91	1.28	8.60
78WV089007	23	38	Bt1			0	0.76	1.45	1.66
78WV089007	38	56	Bt2			25	0.51	1.47	1.01
78WV089007	56	76	C			50	0.38	1.47	0.56
78WV089008	0	20	Ap			0	2.51	1.28	6.44
78WV089008	20	41	Bt1			0	0.80	1.46	2.44

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
78WV089008	41	56	Bt2			30	0.50	1.49	0.78
78WV089008	56	79	C			55	0.47	1.39	0.68
78WV089009	0	20	Ap			0	2.66	1.26	6.73
78WV089009	20	33	Bt1			0	0.86	1.46	1.63
78WV089009	33	71	Bt2			0	0.51	1.50	2.89
78WV089009	71	137	Bt3			0	0.34	1.53	3.40
78WV089009	137	190	BC			0	0.29	1.52	2.34
78WV089010	0	18	Ap			5	2.81	1.25	6.03
78WV089010	18	30	BA			5	1.17	1.30	1.74
78WV089010	30	56	Bt1			5	0.49	1.48	1.79
78WV089010	56	102	Bt2			5	0.28	1.53	1.86
78WV089010	102	132	Bt3			5	0.33	1.52	1.43
78WV089010	132	157	C			0	0.45	1.48	1.67
79PA083006	0	2	Oi			0	37.11	0.43	3.18
79PA083006	2	4	Oe			0	29.26	0.52	3.06
79PA083006	4	6	Oa	23.94		0	23.94	0.59	2.83
79PA083006	6	12	E	1.23	1.54	5	1.23	1.54	1.08
79PA083006	12	17	Bhs	2.97		5	2.97	1.25	1.76
79PA083006	17	33	Bw1	1.94	1.16	10	1.94	1.16	3.23
79PA083006	33	49	Bw2	1.10	1.53	15	1.10	1.53	2.29
79PA083006	49	64	Bw3	0.39	1.53	15	0.39	1.53	0.75
79PA083006	64	86	Bx1	0.39	1.69	25	0.39	1.69	1.07
79PA083006	86	108	Bx2	0.20	1.69	25	0.20	1.69	0.55

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79PA083006	108	131	C	0.32	1.77	60	0.32	1.77	0.52
79PA083007	0	2	Oi			0	46.01	0.37	3.43
79PA083007	2	4	Oe			0	40.72	0.54	4.41
79PA083007	4	6	Oa	37.52		10	37.52	0.60	4.05
79PA083007	6	23	E	0.39		30	0.39	1.54	0.71
79PA083007	23	28	Bhs1	3.37		40	3.37	1.26	1.27
79PA083007	28	44	Bhs2	2.00		35	2.00	1.34	2.79
79PA083007	44	63	Bs	0.78		40	0.78	1.49	1.32
79PA083007	63	84	Bw	0.45		45	0.45	1.65	0.86
79PA083007	84	102	BC	0.20		60	0.20	1.68	0.24
79PA083007	102	151	C	0.32		80	0.32	1.70	0.53
79PA083008	0	4	Oi			0	42.54	0.36	6.16
79PA083008	2	4	Oe			0	36.26	0.48	3.51
79PA083008	4	6	Oa	33.32		0	33.32	0.55	3.69
79PA083008	6	12	E	1.36	1.45	0	1.36	1.45	1.19
79PA083008	12	16	Bhs	4.40	0.90	0	4.40	0.90	1.58
79PA083008	16	29	2Bt1	2.46	1.20	10	2.46	1.20	3.46
79PA083008	29	45	2Bt2	1.94	1.17	15	1.94	1.17	3.08
79PA083008	45	61	2BC	0.65	1.40	15	0.65	1.40	1.24
79PA083008	61	95	2C	0.39		75	0.39	1.40	0.46
79PA083009	0	1	Oi			0	38.65	0.44	1.70
79PA083009	1	3	Oe			0	38.40	0.51	3.90
79PA083009	3	5	Oa	47.87		5	47.87	0.62	5.66

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79PA083009	5	15	E	1.68	1.52	10	1.68	1.52	2.30
79PA083009	15	18	Bhs	5.05		10	5.05	1.21	1.65
79PA083009	18	30	Bt1	2.65	1.14	15	2.65	1.14	3.08
79PA083009	30	51	Bt2	1.17	1.25	11	1.17	1.25	2.72
79PA083009	51	95	2Bx1	0.58	1.69	60	0.58	1.69	1.73
79PA083009	95	143	2Bx2	0.74	1.79	65	0.74	1.79	2.22
79PA083010	0	2	Oi			0	38.92	0.44	3.43
79PA083010	2	5	Oe			0	38.62	0.51	5.91
79PA083010	5	7	Oa	47.87		0	47.87	0.63	6.00
79PA083010	7	13	E	1.75	1.44	5	1.75	1.44	1.44
79PA083010	13	18	Bhs	3.42		8	3.42	1.22	1.92
79PA083010	18	29	Bt1	2.40	1.04	10	2.40	1.04	2.47
79PA083010	29	52	Bt2	1.17	1.33	10	1.17	1.33	3.21
79PA083010	52	102	Bx1	0.26	1.71	20	0.26	1.71	1.81
79PA083010	102	137	Bx2	0.65	1.74	10	0.65	1.74	3.56
79PA083011	0	3	Oi			0	38.96	0.39	4.55
79PA083011	3	4	Oe			0	36.16	0.43	1.57
79PA083011	4	6	Oa	45.94		0	45.94	0.54	4.97
79PA083011	6	14	E	2.84	1.57	0	2.84	1.57	3.57
79PA083011	14	30	Btg1	1.83	1.63	5	1.83	1.63	4.54
79PA083011	30	56	Btg2	0.58	1.60	10	0.58	1.60	2.18
79PA083011	56	80	2Bgx1	0.50	1.67	15	0.50	1.67	1.69
79PA083011	80	119	2Bgx2	0.33	1.72	30	0.33	1.72	1.53

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79PA083011	119	141	2Bgx3	0.33	1.79	15	0.33	1.79	1.09
79PA083012	0	4	Oi			0	43.47	0.44	7.72
79PA083012	4	17	Oe			0	37.49	0.55	26.66
79PA083012	17	19	Oa	40.12		0	40.12	0.67	5.34
79PA083012	19	26	E	1.62	1.76	5	1.62	1.76	1.89
79PA083012	26	38	Bt	2.52	1.06	5	2.52	1.06	3.04
79PA083012	38	51	Btg	0.84	1.30	5	0.84	1.30	1.34
79PA083012	51	69	Btx1	0.39	1.73	12	0.39	1.73	1.06
79PA083012	69	87	Btx2	0.32	1.73	12	0.32	1.73	0.87
79PA083012	87	125	Btx3	0.19	1.80	15	0.19	1.80	1.09
79PA083012	125	144	Btx4	0.32	1.79	30	0.32	1.79	0.76
79WV067001	0	5	Oe	41.54		0	41.54	0.96	19.98
79WV067001	5	9	A	14.80		25	14.80	1.08	4.78
79WV067001	9	13	E	5.37		20	5.37	1.29	2.21
79WV067001	13	20	Bt1	2.49		25	2.49	1.39	1.81
79WV067001	20	43	Bt2	1.21	1.07	40	1.21	1.07	1.78
79WV067001	43	56	Bt3	0.60	1.39	60	0.60	1.39	0.43
79WV067001	56	76	C	0.67		75	0.67	1.43	0.48
79WV067002	0	5	Oi			0	46.86	0.45	10.61
79WV067002	5	8	Oe			0	41.65	0.59	7.36
79WV067002	8	13	A	8.02		15	8.02	1.06	3.60
79WV067002	13	28	Bt1	1.28	1.29	15	1.28	1.29	2.10
79WV067002	28	53	Bt2	0.91	1.39	20	0.91	1.39	2.53

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79WV067002	53	79	Btx1	0.41	1.45	30	0.41	1.45	1.09
79WV067002	79	136	Btx2	0.20	1.60	35	0.20	1.60	1.18
79WV067002	136	171	Btx3	0.16	1.58	30	0.16	1.58	0.60
79WV067006	0	5	Oi			0	47.74	0.47	11.34
79WV067006	5	8	Oe			0	44.37	0.61	8.15
79WV067006	8	13	A	35.50		25	35.50	1.15	15.35
79WV067006	13	18	E	8.83		25	8.83	1.35	4.48
79WV067006	18	33	Bt1	2.31		20	2.31	1.45	4.03
79WV067006	33	69	Bt2	0.53	1.48	20	0.53	1.48	2.24
79WV067006	69	81	Bt3	0.23	1.66	20	0.23	1.66	0.36
79WV067006	81	109	Bx1	0.14	1.68	30	0.14	1.68	0.47
79WV067006	109	142	Bx2	0.13	1.76	30	0.13	1.76	0.52
79WV067006	142	158	Bx3	0.16	1.78	30	0.16	1.78	0.31
79WV067007	0	7	Oi			0	45.37	0.51	16.06
79WV067007	7	10	Oe			0	44.11	0.63	8.36
79WV067007	10	13	A	40.46		50	40.46	1.00	6.09
79WV067007	13	20	E	7.94		50	7.94	1.31	3.65
79WV067007	20	40	Bt1	1.69	1.38	25	1.69	1.38	3.50
79WV067007	40	71	Bt2	0.54	1.52	15	0.54	1.52	2.16
79WV067007	71	91	Bt3	0.48	1.47	15	0.48	1.47	1.21
79WV067007	91	137	Btx1	0.81	1.38	40	0.81	1.38	3.08
79WV067007	137	163	Btx2	0.60	1.69	3	0.60	1.69	2.54
79WV067008	0	7	Oi			0	47.42	0.48	16.03

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79WV067008	7	10	Oe			0	43.67	0.62	8.11
79WV067008	10	17	A	35.94		20	35.94	1.27	25.57
79WV067008	17	28	E	5.62		20	5.62	1.37	6.77
79WV067008	28	40	Bt1	1.68		20	1.68	1.46	2.34
79WV067008	40	61	Bt2	0.61	1.34	25	0.61	1.34	1.29
79WV067008	61	81	Bx1	0.18	1.58	30	0.18	1.58	0.41
79WV067008	81	163	Bx2	0.17	1.70	40	0.17	1.70	1.43
79WV067010	0	5	Oi			0	44.94	0.46	10.29
79WV067010	5	8	Oe			0	34.24	0.57	5.90
79WV067010	8	11	A	43.38		5	43.38	1.23	15.23
79WV067010	11	16	E	6.75		5	6.75	1.31	4.21
79WV067010	16	33	Bw1	1.49		5	1.49	1.39	3.34
79WV067010	33	56	Bw2	0.75	1.51	10	0.75	1.51	2.35
79WV067010	56	74	Bw3	0.23	1.62	15	0.23	1.62	0.56
79WV067010	74	112	Bx1	0.10	1.57	2	0.10	1.57	0.58
79WV067010	112	161	Bx2	0.13	1.84	20	0.13	1.84	0.92
79WV067011	0	5	Oi			0	40.59	0.40	8.05
79WV067011	5	8	Oe			0	39.74	0.52	6.25
79WV067011	8	11	A	33.77		5	33.77	1.07	10.29
79WV067011	11	16	E	6.15		5	6.15	1.16	3.39
79WV067011	16	33	Bw	1.16	1.28	20	1.16	1.28	2.03
79WV067011	33	54	Bt1	0.37	1.36	15	0.37	1.36	0.90
79WV067011	54	64	Bt2	0.40	1.27	45	0.40	1.27	0.28

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
79WV067011	64	74	C	0.34	1.46	65	0.34	1.46	0.17
80WV067005	0	15	Ap	2.75	1.36	0	2.75	1.36	5.62
80WV067005	15	28	Bw1	0.77	1.57	0	0.77	1.57	1.57
80WV067005	28	53	Bw2	0.37	1.55	5	0.37	1.55	1.36
80WV067005	53	81	Bw3	0.14	1.75	25	0.14	1.75	0.52
80WV067005	81	104	C	0.16	1.75	40	0.16	1.75	0.38
80WV067006	0	23	Ap	4.09	1.40	0	4.09	1.40	13.17
80WV067006	23	38	Bt1	0.88	1.56	0	0.88	1.56	2.06
80WV067006	38	63	Bt2	0.24	1.65	5	0.24	1.65	0.95
80WV067006	63	79	Bt3	0.16	1.67	30	0.16	1.67	0.29
80WV067006	79	104	C	0.09	1.29	65	0.09	1.29	0.10
81WV067001	0	7	Oi			0	43.54	0.44	13.56
81WV067001	7	9	Oe			0	33.38	0.56	3.71
81WV067001	9	14	A	14.64		30	14.64	1.17	5.98
81WV067001	14	22	E	5.51		25	5.51	1.34	4.44
81WV067001	22	34	Bw1	2.49	1.26	20	2.49	1.26	3.01
81WV067001	34	49	Bw2	1.05	1.36	25	1.05	1.36	1.61
81WV067001	49	84	Bw3	0.64	1.49	30	0.64	1.49	2.33
81WV067001	84	112	Bx1	0.34	1.73	40	0.34	1.73	0.99
81WV067001	112	159	Bx2	0.34	1.69	35	0.34	1.69	1.76
81WV067002	0	5	Oi			0	46.86	0.45	10.61
81WV067002	5	8	Oe			0	41.65	0.59	7.36
81WV067002	8	11	A	21.91		20	21.91	1.04	5.46

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
81WV067002	11	16	E	6.72		20	6.72	1.23	3.31
81WV067002	16	31	Bt1	2.16	1.08	15	2.16	1.08	2.97
81WV067002	31	83	Bt2	0.74		15	0.74	1.49	4.85
81WV067002	83	106	Bx1	0.60		20	0.60	1.61	1.76
81WV067002	106	160	Bx2	0.55		25	0.55	1.63	3.65
81WV101001	0	5	Oi			0	37.50	0.44	8.32
81WV101001	5	8	Oe			0	29.60	0.57	5.08
81WV101001	8	11	A	30.50		10	30.50	1.11	9.18
81WV101001	11	16	E	10.99		15	10.99	1.21	5.67
81WV101001	16	28	Bw1	3.91	1.15	15	3.91	1.15	4.58
81WV101001	28	46	Bw2	0.88	1.43	20	0.88	1.43	1.81
81WV101001	46	61	Bw3	0.71	1.50	20	0.71	1.50	1.28
81WV101001	61	111	Bx	0.48	1.52	20	0.48	1.52	2.94
82PA047009	0	5	Oi			0	45.01	0.43	9.63
82PA047009	5	13	A	4.91		0	4.91	1.13	4.45
82PA047009	13	30	Bw1	2.67		0	2.67	1.36	6.17
82PA047009	30	53	Bw2	0.38	1.60	0	0.38	1.60	1.41
82PA047009	53	86	Bx1	0.23	1.57	0	0.23	1.57	1.18
82PA047009	86	114	Bx2	0.16	1.70	0	0.16	1.70	0.74
82PA047009	114	140	Bx3	0.07	1.68	0	0.07	1.68	0.31
82PA047009	140	157	2B't1	0.06	1.71	0	0.06	1.71	0.17
82PA047009	157	170	2B't2	0.13		0	0.13	1.61	0.27
82PA047009	170	208	2B't3	0.10		0	0.10	1.63	0.62

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
82PA083004	0	3	Oi			0	40.99	0.45	5.58
82PA083004	3	11	A	5.52		0	5.52	1.07	4.72
82PA083004	11	28	BA	2.13		0	2.13	1.24	4.51
82PA083004	28	41	Bw	0.92	1.45	0	0.92	1.45	1.74
82PA083004	41	51	Bt	0.61	1.61	0	0.61	1.61	0.98
82PA083004	51	72	Btx1	0.64	1.74	0	0.64	1.74	2.33
82PA083004	72	89	Btx2	0.85	1.76	0	0.85	1.76	2.55
82PA083004	89	110	BCx	1.07	1.77	0	1.07	1.77	3.96
82PA083004	110	150	C1	0.98	1.72	0	0.98	1.72	6.74
82PA083004	150	176	C2	0.89	1.70	0	0.89	1.70	3.95
82PA083005	0	1	Oi			0	37.74	0.38	1.45
82PA083005	1	5	Oe			0	34.16	0.46	6.31
82PA083005	5	10	A	18.67		0	18.67	0.95	8.90
82PA083005	10	18	E	2.53	1.07	0	2.53	1.07	2.16
82PA083005	18	33	BE	1.28	1.49	0	1.28	1.49	2.86
82PA083005	33	48	Bt1	1.08	1.54	0	1.08	1.54	2.49
82PA083005	48	66	Bt2	0.38	1.62	0	0.38	1.62	1.12
82PA083005	66	91	Btx1	0.57	1.69	0	0.57	1.69	2.40
82PA083005	91	104	Btx2	0.23	1.74	0	0.23	1.74	0.51
82PA083005	104	124	2Btx3	0.16	1.77	0	0.16	1.77	0.55
82PA083005	124	137	2BC	0.14	1.80	0	0.14	1.80	0.33
82PA083005	137	168	2C1	0.14	1.74	0	0.14	1.74	0.77
82PA083005	168	195	2C2	0.16	1.82	0	0.16	1.82	0.77

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
82PA105001	0	3	Oi			0	42.50	0.51	6.48
82PA105001	3	8	Oe			0	39.26	0.58	11.35
82PA105001	8	11	A	7.89		0	7.89	1.13	2.68
82PA105001	11	13	E	1.06		0	1.06	1.34	0.28
82PA105001	13	31	BE	0.81		0	0.81	1.34	1.96
82PA105001	31	49	Bw	1.00	1.56	0	1.00	1.56	2.81
82PA105001	49	72	Btx1	0.08	1.86	0	0.08	1.86	0.33
82PA105001	72	92	Btx2	0.28	1.89	0	0.28	1.89	1.04
82PA105001	92	117	Btx3	0.07	1.91	0	0.07	1.91	0.32
82PA105001	117	143	Btx4	0.42	1.88	0	0.42	1.88	2.04
82PA105002	0	3	Oi			0	38.75	0.47	5.47
82PA105002	3	8	Oe			0	35.74	0.51	9.13
82PA105002	8	13	A	15.51		0	15.51	1.17	9.05
82PA105002	13	31	AE	3.31		0	3.31	1.41	8.37
82PA105002	31	51	Bw	0.44	1.77	0	0.44	1.77	1.56
82PA105002	51	66	Bt1	0.41	1.73	0	0.41	1.73	1.07
82PA105002	66	82	Btx1	0.21	1.80	0	0.21	1.80	0.61
82PA105002	82	102	Btx2	0.11	1.76	0	0.11	1.76	0.40
82PA105002	102	132	Btx3	0.10	1.81	0	0.10	1.81	0.54
82PA105002	132	150	2Bt2	0.06	1.82	0	0.06	1.82	0.19
82PA105002	150	176	2Bt3	0.06	1.76	0	0.06	1.76	0.26
82PA105002	176	193	2BC	0.04		0	0.04	1.74	0.13
82PA117017	0	2	Oi	23.10		25	23.10	1.04	3.62

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
82PA117017	2	5	Oe	35.31		25	35.31	0.52	4.15
82PA117017	5	8	A	1.54		25	1.54	1.22	0.42
82PA117017	8	15	E	0.11	1.85	25	0.11	1.85	0.11
82PA117017	15	30	BE		1.63	15	0.95	1.63	1.97
82PA117017	30	51	Bt1		1.71	20	0.50	1.71	1.42
82PA117017	51	66	Bt2		1.64	15	0.30	1.64	0.62
82PA117017	66	71	E'			15	0.80	1.71	0.58
82PA117017	71	91	Btx1		1.83	10	0.23	1.83	0.77
82PA117017	91	114	Btx2		1.84	15	0.24	1.84	0.86
82PA117017	114	137	Btx3		1.81	15	0.33	1.81	1.18
82PA117017	137	155	2Btb1			50	0.22	1.73	0.34
82PA117017	155	170	2Btb2			50	0.24	1.70	0.31
82PA117017	170	208	2Btb3			50	0.24	1.70	0.77
82PA117017	208	259	2Btb4			50	0.21	1.72	0.90
82PA117018	0	5	Oi	44.11		0	44.11	1.00	21.97
82PA117018	5	10	Oa	36.85		0	36.85	0.54	9.92
82PA117018	10	13	A	7.37		0	7.37	1.26	2.77
82PA117018	13	23	Eg	1.10	1.56	0	1.10	1.56	1.72
82PA117018	23	33	BEg	0.33	1.67	0	0.33	1.67	0.55
82PA117018	33	48	Btg1		1.72	0	0.58	1.72	1.49
82PA117018	48	76	Btg2		1.72	0	0.50	1.72	2.43
82PA117018	76	99	Bx1		1.93	0	0.26	1.93	1.14
82PA117018	99	124	Btx1		1.82	0	0.43	1.82	1.94

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
82PA117018	124	145	2Btx2		1.79	5	0.45	1.79	1.61
82PA117018	145	160	2Bt1		1.81	5	0.49	1.81	1.28
82PA117018	160	193	2Bt2		1.80	10	0.29	1.80	1.57
82PA117018	193	193	2Bt3			15	0.31	1.71	0.31
82PA117019	0	5	Oi	41.69		0	41.69	0.97	20.23
82PA117019	5	8	Oe	25.19		0	25.19	0.55	4.12
82PA117019	8	13	A	6.49		10	6.49	1.15	3.37
82PA117019	13	31	BA	1.98	1.24	10	1.98	1.24	3.98
82PA117019	31	46	Bw1		1.27	10	1.05	1.27	1.80
82PA117019	46	64	Bw2		1.49	10	0.63	1.49	1.51
82PA117019	64	82	Bx1		1.69	10	0.31	1.69	0.84
82PA117019	82	97	Bx2		1.69	10	0.23	1.69	0.53
82PA117019	97	115	Bx3		1.74	10	0.23	1.74	0.63
82PA117019	115	135	Bx4		1.72	15	0.22	1.72	0.64
82PA117019	135	148	Bx5		1.74	15	0.35	1.74	0.67
82PA117019	148	171	BC1			15	0.20	1.76	0.69
82PA117019	171	186	BC2			15	0.20	1.76	0.45
82PA117019	186	211	BC3			15	0.21	1.78	0.79
82PA117019	211	226	C1			15	0.32	1.72	0.69
82PA117019	226	267	C2			15	0.31	1.72	1.87
82PA117019	267	313	2Cg1			25	0.57	1.62	3.22
82PA117019	313	374	2Cg2			10	0.65	1.61	5.74
82PA117020	0	12	Oi	44.55		25	44.55	1.08	43.32

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
82PA117020	12	15	Oa	22.77		20	22.77	0.61	3.33
82PA117020	15	25	Eg	0.99	1.29	30	0.99	1.29	0.89
82PA117020	25	35	Btg1		1.57	0	1.02	1.57	1.60
82PA117020	35	48	Btg2		1.62	0	0.63	1.62	1.33
82PA117020	48	58	Bx1		1.72	15	0.65	1.72	0.95
82PA117020	58	76	Bx2		1.68	15	0.41	1.68	1.04
82PA117020	76	91	Bx3		1.79	15	0.31	1.79	0.71
82PA117020	91	114	Bx4		1.68	15	0.25	1.68	0.82
82PA117020	114	134	Bx5		1.68	30	0.25	1.68	0.59
82PA117020	134	152	2Cg1			65	0.27	1.73	0.30
82PA117020	152	167	2Cg2			75	0.26	1.74	0.17
82PA117020	167	203	2Cg3			70	0.26	1.74	0.49
82PA117020	203	233	2Cg4			70	0.42	1.73	0.66
83PA105003	0	5	Oa	54.44		10	54.44	0.53	13.03
83PA105003	5	13	A	12.17	1.17	15	12.17	1.17	9.68
83PA105003	13	28	Bw1	3.41	1.19	15	3.41	1.19	5.17
83PA105003	28	53	Bw2	1.35	1.78	10	1.35	1.78	5.40
83PA105003	53	79	Bw3	0.38	1.71	35	0.38	1.71	1.11
83PA105003	79	96	Bt1	0.20	1.58	35	0.20	1.58	0.35
83PA105003	96	122	Bt2	0.27	1.57	35	0.27	1.57	0.72
83PA105003	122	147	Bt3	0.20	1.59	40	0.20	1.59	0.47
83PA105003	147	168	2Btb1	0.21	1.52	10	0.21	1.52	0.61
83PA105003	168	185	2Btb2	0.18	1.52	10	0.18	1.52	0.43

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
83PA105003	185	203	2Btb3	0.18	1.55	5	0.18	1.55	0.49
83PA105003	203	236	2Btb4	0.14	1.53	10	0.14	1.53	0.65
83PA105003	236	267	2BC1	0.07	1.54	25	0.07	1.54	0.25
83PA105003	267	300	2BC2	0.09	1.51	45	0.09	1.51	0.23
83PA105003	300	345	2BC3	0.07		45	0.07	1.57	0.28
83PA105004	0	5	Oi	49.39		10	49.39	0.41	9.10
83PA105004	5	10	Oe	46.65		10	46.65	0.46	9.60
83PA105004	10	13	Oa	30.51		10	30.51	0.58	4.82
83PA105004	13	16	E	2.51	1.56	10	2.51	1.56	1.06
83PA105004	16	26	Bt1	0.91	1.57	10	0.91	1.57	1.29
83PA105004	26	38	Bt2	0.79	1.60	10	0.79	1.60	1.37
83PA105004	38	59	Bt3	0.42	1.58	10	0.42	1.58	1.25
83PA105004	59	71	2Btb1	0.32	1.56	5	0.32	1.56	0.57
83PA105004	71	89	2Btb2	0.26		5	0.26	1.55	0.70
83PA105004	89	110	2Btb3	0.20		15	0.20	1.56	0.55
83PA105004	110	140	2Btb4	0.24		15	0.24	1.57	0.97
83PA105004	140	165	2Btb5	0.23		15	0.23	1.58	0.77
83PA105005	0	5	Oi			10	47.82	0.41	8.88
83PA105005	5	10	Oe			10	38.92	0.46	8.13
83PA105005	10	15	Oa			10	29.35	0.59	7.79
83PA105005	15	18	E			20	1.49	1.40	0.50
83PA105005	18	33	Bt1			20	1.29	1.45	2.23
83PA105005	33	51	Bt2			20	0.64	1.47	1.37

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
83PA105005	51	73	Bt3			20	0.37	1.53	1.00
83PA105005	73	104	Bt4			25	0.36	1.56	1.30
83PA105005	104	132	2Btb1			30	0.24	1.55	0.72
83PA105005	132	162	2Btb2			30	0.28	1.55	0.91
83PA105005	162	185	2Btb3			30	0.23	1.56	0.58
83PA105005	185	200	2Btb4			30	0.23	1.54	0.37
83PA105005	200	226	2Btb5			70	0.22	1.56	0.26
83PA105005	226	251	3C1			70	0.23	1.52	0.27
83PA105005	251	274	3C2			70	0.16	1.55	0.17
83PA105005	274	302	3C3			80	0.18	1.56	0.15
83PA117021	0	7	Oi	49.94		25	49.94	0.35	9.21
83PA117021	7	10	Oa	16.61		15	16.61	0.43	1.80
83PA117021	10	20	E	0.66	1.56	25	0.66	1.56	0.77
83PA117021	20	23	Bhs	1.98		20	1.98	1.28	0.61
83PA117021	23	40	Bw1	0.77	1.45	20	0.77	1.45	1.52
83PA117021	40	56	Bw2		1.49	20	0.58	1.49	1.10
83PA117021	56	66	Bw3		1.58	20	0.40	1.58	0.51
83PA117021	66	76	2C1			75	0.44	1.44	0.16
83PA117021	76	91	2C2			95	0.36	1.46	0.04
83PA117022	0	5	Oi	52.47		15	0.27	1.69	1.13
83PA117022	5	8	Oa	22.44		15	0.25	1.70	0.61
83PA117022	8	18	BA	1.76		10	0.24	1.71	0.55
83PA117022	18	38	Bw1		1.47	15	0.23	1.73	0.65

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
83PA117022	38	54	Bw2		1.52	15	48.62	1.02	9.90
83PA117022	54	69	Bw3		1.64	15	25.96	0.50	3.92
83PA117022	69	94	Bx1		1.89	20	0.99	1.46	1.04
83PA117022	94	112	Bx2		1.86	20	1.98	1.30	1.53
83PA117022	112	130	Bx3		1.85	20	1.38	1.45	2.55
83PA117022	130	150	Btx		1.87	20	0.57	1.36	1.38
83PA117022	150	165	2Btb1		1.73	10	0.36	1.61	1.31
83PA117022	165	181	2Btb2		1.76	10	0.29	1.83	1.05
83PA117022	181	209	2Btb3		1.69	10	0.27	1.85	0.93
83PA117022	209	226	2Btb4		1.70	15	0.25	1.88	0.49
83PA117022	226	242	2Btb5			15	0.18	1.66	0.19
83PA117022	242	262	2Btb6			20	0.18	1.71	0.16
83PA117023	0	2	Oi	48.62		0	52.47	0.39	8.66
83PA117023	2	5	Oa	25.96		0	22.44	0.52	2.99
83PA117023	5	13	E	0.99		10	1.76	1.25	1.98
83PA117023	13	20	Bs	1.98		15	1.14	1.47	2.85
83PA117023	20	35	Bt1			15	0.46	1.52	0.95
83PA117023	35	56	Bt2		1.36	15	0.34	1.64	0.72
83PA117023	56	84	Bx1		1.61	20	0.24	1.89	0.89
83PA117023	84	109	Bx2		1.83	20	0.21	1.86	0.57
83PA117023	109	132	Bx3		1.85	20	0.16	1.85	0.43
83PA117023	132	145	BC		1.88	20	0.18	1.87	0.53
83PA117023	145	157	2C1			45	0.29	1.73	0.69

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
83PA117023	157	183	2C2			80	0.31	1.76	0.80
83PA117027	0	5	Oi	52.58		0	52.58	0.47	12.44
83PA117027	5	8	Oa	22.55		25	22.55	0.62	3.13
83PA117027	8	16	E	1.32		15	1.32	1.45	1.31
83PA117027	16	18	Bhs	2.86		10	2.86	1.26	0.65
83PA117027	18	31	Bw	0.77		20	0.77	1.45	1.16
83PA117027	31	44	Bt1			20	0.73	1.49	1.12
83PA117027	44	56	Bt2			20	0.44	1.53	0.65
83PA117027	56	66	2Btb1			15	0.35	1.56	0.47
83PA117027	66	79	2Btb2			15	0.31	1.55	0.54
83PA117027	79	97	2Btb3			30	0.25	1.58	0.50
83PA117027	97	110	2Btb4			30	0.31	1.59	0.45
83PA117027	110	130	2Btb5			35	0.36	1.61	0.74
83PA117027	130	148	2Btb6			35	0.35	1.59	0.65
83PA117027	148	176	2Btb7			40	0.34	1.59	0.92
83PA117027	176	191	2Btb8			40	0.34	1.60	0.49
83PA117027	191	216	2Btb9			45	0.35	1.59	0.78
83PA117027	216	226	2BC			35	0.30	1.64	0.32
83PA117027	226	242	2C1			90	0.31	1.58	0.08
83PA117027	242	257	2C2			90	0.37	1.60	0.09
83PA117028	0	5	Oi	73.70		10	73.70	1.11	36.80
83PA117028	5	8	Oa	39.90		20	39.90	1.00	9.58
83PA117028	8	16	E	0.99		20	0.99	1.48	0.94

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
83PA117028	16	26	Bw	1.14		10	1.14	1.51	1.55
83PA117028	26	33	Bt1			5	0.87	1.50	0.87
83PA117028	33	46	Bt2			5	0.50	1.55	0.96
83PA117028	46	56	Bt3			15	0.51	1.54	0.67
83PA117028	56	69	2Btb1			10	0.36	1.56	0.65
83PA117028	69	84	2Btb2			10	0.32	1.56	0.68
83PA117028	84	110	2Btb3			10	0.40	1.53	1.42
83PA117028	110	132	2Btb4			10	0.28	1.56	0.87
83PA117028	132	160	2Btb5			15	0.28	1.57	1.06
83PA117028	160	173	2BC1			20	0.18	1.67	0.31
83PA117028	173	183	2BC2			70	0.30	1.65	0.15
83PA117028	183	232	C			0	0.21	1.61	1.68
87PA027082	0	8	A	13.21		15	13.21	1.06	9.48
87PA027082	8	23	E	0.80	1.58	15	0.80	1.58	1.60
87PA027082	23	41	Bw1	0.30	1.64	15	0.30	1.64	0.75
87PA027082	41	61	Bw2	0.20	1.65	15	0.20	1.65	0.56
87PA027082	61	79	Bx1	0.80	1.67	20	0.80	1.67	1.91
87PA027082	79	104	Bx2		1.86	25	0.30	1.86	1.06
87PA027082	104	132	Bx3	0.20	1.86	30	0.20	1.86	0.72
87PA027082	132	158	Bx4	0.11	1.88	30	0.11	1.88	0.39
87PA027082	158	203	Bx5	0.23	1.94	20	0.23	1.94	1.59
87PA027082	203	243	Bx6	0.38	1.89	15	0.38	1.89	2.46
87PA027082	243	305	2C	0.13	1.81	35	0.13	1.81	0.93

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
87PA027083	0	2	Oi			10	42.37	0.39	2.96
87PA027083	2	4	Oa			10	31.02	0.57	3.21
87PA027083	4	12	E	0.47		10	0.47	1.51	0.51
87PA027083	12	17	Bhs	1.68		10	1.68	1.35	1.02
87PA027083	17	27	Bs	0.92	1.36	10	0.92	1.36	1.13
87PA027083	27	47	Bt1	0.13	1.75	10	0.13	1.75	0.40
87PA027083	47	75	Bt2	0.01	1.78	20	0.01	1.78	0.06
87PA027083	75	98	Bt3	0.01	1.69	45	0.01	1.69	0.03
87PA027083	98	126	Bt4		1.80	25	0.15	1.80	0.58
87PA027083	126	141	BC		1.75	30	0.12	1.75	0.23
87PA027083	141	172	C1			65	2.86	1.65	5.12
87PA027083	172	207	C2	0.04		80	0.04	1.73	0.05
88PA021011	0	6	Oe	27.35	0.26	5	27.35	0.26	4.05
88PA021011	6	20	Ap	3.94	1.02	15	3.94	1.02	4.78
88PA021011	20	48	Bw	1.47	1.42	25	1.47	1.42	4.40
88PA021011	48	68	CB1	0.36	1.43	40	0.36	1.43	0.62
88PA021011	68	94	CB2	0.35	1.48	40	0.35	1.48	0.81
88PA021012	0	8	Oe	27.11	0.37	25	27.11	0.37	6.02
88PA021012	8	14	AE	2.50	1.55	20	2.50	1.55	1.86
88PA021012	22	33	Bt1	2.78	1.24	45	2.78	1.24	2.09
88PA021012	41	60	Bt2	2.98	1.27	50	2.98	1.27	3.60
88PA021012	68	77	C	2.80	0.49	70	2.80	0.49	0.37
88PA021013	0	3	Oe	48.71	0.48	5	48.71	0.48	6.66

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA021013	3	19	AE	3.32	1.44	8	3.32	1.44	7.04
88PA021013	19	34	Bw	0.43	1.83	15	0.43	1.83	0.99
88PA021013	34	60	Bt1	0.33	1.58	15	0.33	1.58	1.14
88PA021013	60	86	Bt2	0.26	1.73	20	0.26	1.73	0.92
88PA021013	86	131	Bt3	0.17	1.81	20	0.17	1.81	1.11
88PA021013	131	193	Bt4	0.30	1.61	50	0.30	1.61	1.49
88PA021014	0	3	Oe			2	39.13	0.44	5.12
88PA021014	3	20	AE	2.31	1.56	4	2.31	1.56	5.89
88PA021014	20	28	Bw	1.28	1.41	4	1.28	1.41	1.38
88PA021014	28	42	Bt1	1.29	1.35	6	1.29	1.35	2.30
88PA021014	42	61	Bt2	3.17	1.15	6	3.17	1.15	6.50
88PA021014	61	98	Bt3	0.78	1.50	10	0.78	1.50	3.90
88PA021014	98	131	Bt4	0.50	1.66	10	0.50	1.66	2.45
88PA021014	131	203	Bt5	0.31	1.62	13	0.31	1.62	3.17
88PA021015	0	3	Oe			0	30.95	0.46	4.27
88PA021015	3	20	AB	2.32	1.25	5	2.32	1.25	4.69
88PA021015	20	42	Bt1	0.75	1.43	5	0.75	1.43	2.24
88PA021015	42	72	Bt2	0.42	1.47	5	0.42	1.47	1.75
88PA021015	72	99	Bt3	0.19	1.68	15	0.19	1.68	0.72
88PA021015	99	123	Bt4	0.14	1.73	15	0.14	1.73	0.50
88PA021015	123	157	Bt5	0.17	1.70	15	0.17	1.70	0.81
88PA021015	157	203	C	0.11	1.70	15	0.11	1.70	0.73
88PA021016	0	7	Ap1	9.97	1.67	2	0.31	1.42	1.13

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA021016	7	18	Ap2	3.25	1.60	3	0.31	1.69	1.44
88PA021016	18	32	Bt1	1.04	1.72	5	0.27	1.18	1.38
88PA021016	32	49	Bt2	0.38	1.70	20	0.28	1.42	1.02
88PA021016	49	79	Btx1	0.31	1.42	15	20.59	0.26	2.68
88PA021016	79	111	Btx2	0.31	1.69	15	5.96	0.56	2.19
88PA021016	111	164	Btx3	0.27	1.18	18	1.68	1.34	5.19
88PA021016	164	200	C	0.28	1.42	30	0.50	1.65	0.83
88PA033031	0	5	Oe	20.59	0.26	0	9.97	1.67	11.42
88PA033031	5	13	E	5.96	0.56	18	3.25	1.60	5.55
88PA033031	13	43	Bt	1.68	1.34	23	1.04	1.72	2.37
88PA033031	43	72	BC	0.50	1.65	65	0.38	1.70	0.89
88PA033032	0	3	Oa			0	24.64	0.54	3.98
88PA033032	3	19	E	2.68	1.29	5	2.68	1.29	5.26
88PA033032	19	47	Bw1	1.19	1.52	10	1.19	1.52	4.57
88PA033032	47	60	Bw2	1.09	1.72	10	1.09	1.72	2.20
88PA033032	60	89	Bx	0.80	1.84	20	0.80	1.84	3.39
88PA033032	89	126	C	0.33	1.33	65	0.33	1.33	0.56
88PA033033	0	3	Oi			0	33.99	0.42	4.32
88PA033033	3	13	A	5.20	0.66	10	5.20	0.66	3.09
88PA033033	13	27	Bt1	2.70	1.53	15	2.70	1.53	4.91
88PA033033	27	55	Bt2	0.95	1.44	20	0.95	1.44	3.07
88PA033033	55	82	Bt3	0.61	1.48	30	0.61	1.48	1.71
88PA033033	82	109	BC	0.68	1.50	50	0.68	1.50	1.38

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA033033	109	154	C	0.67	1.20	95	0.67	1.20	0.18
88PA033034	0	8	Oa	45.40	0.67	0	45.40	0.67	24.33
88PA033034	8	17	EA	6.40	1.48	0	6.40	1.48	8.53
88PA033034	17	39	Bt1	2.78	1.32	0	2.78	1.32	8.08
88PA033034	39	68	Bt2	1.32	1.44	0	1.32	1.44	5.51
88PA033034	68	93	Btx	1.02	1.67	0	1.02	1.67	4.27
88PA033034	93	124	Btgx	0.95	1.68	25	0.95	1.68	3.72
88PA033034	124	165	2C	0.78	1.00	90	0.78	1.00	0.32
88PA033035	0	3	Oe			0	31.48	0.47	4.40
88PA033035	3	6	A			5	12.66	1.00	3.60
88PA033035	6	9	E			8	3.87	1.34	1.43
88PA033035	9	37	Bw1	1.92	1.30	10	1.92	1.30	6.28
88PA033035	37	67	Bw2	0.31	1.70	14	0.31	1.70	1.37
88PA033035	67	92	Bw3	0.14	1.71	14	0.14	1.71	0.52
88PA033035	92	117	BC	0.16	1.67	35	0.16	1.67	0.42
88PA033035	117	145	C	0.14	1.24	75	0.14	1.24	0.12
88PA033036	0	3	Oe			0	36.06	0.52	5.59
88PA033036	3	12	E	1.79	1.51	15	1.79	1.51	2.07
88PA033036	12	27	Bt1	1.72	1.19	15	1.72	1.19	2.61
88PA033036	27	49	Bt2	0.87	1.40	15	0.87	1.40	2.27
88PA033036	49	71	Bt3	0.21	1.76	15	0.21	1.76	0.70
88PA033036	71	93	Bgx1	0.11	1.82	20	0.11	1.82	0.36
88PA033036	93	116	Bgx2	0.10	1.92	20	0.10	1.92	0.35

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA033036	116	150	BC	0.11	1.99	15	0.11	1.99	0.65
88PA033036	150	185	C	0.13	1.82	15	0.13	1.82	0.69
88PA033036	185	203	2Bt3	0.14	1.93	15	0.14	1.93	0.42
88PA033037	0	3	Oe			0	37.84	0.55	6.21
88PA033037	3	6	A			8	6.28	1.08	1.87
88PA033037	6	32	Bt1	1.62	1.43	0	1.62	1.43	6.02
88PA033037	32	49	Bt2	0.13	1.80	0	0.13	1.80	0.39
88PA033037	49	79	Bgx1	0.13	1.85	5	0.13	1.85	0.67
88PA033037	79	98	Bgx2	7.10	1.84	8	7.10	1.84	22.84
88PA033037	98	119	Bx3	0.13	1.84	5	0.13	1.84	0.47
88PA033037	119	173	BC	0.09	1.97	0	0.09	1.97	0.91
88PA033037	173	203	2Bt3	0.16	1.85	19	0.16	1.85	0.70
88PA033038	0	3	Oe			0	31.45	0.39	3.69
88PA033038	3	8	A	7.04	0.46	20	7.04	0.46	1.30
88PA033038	8	27	Bw1	2.19	1.51	40	2.19	1.51	3.76
88PA033038	27	57	Bw2	0.91	1.03	50	0.91	1.03	1.40
88PA033038	57	73	Bw3	0.38	0.96	65	0.38	0.96	0.21
88PA033038	73	97	Bw4	0.31		65	0.31	1.37	0.36
88PA033039	0	3	Oe			14	32.98	0.49	4.21
88PA033039	3	5	Oa			0	24.52	0.54	2.65
88PA033039	5	9	E			40	4.86	1.40	1.63
88PA033039	9	20	Bw1	1.75	1.12	25	1.75	1.12	1.61
88PA033039	20	49	Bw2	0.58	1.48	30	0.58	1.48	1.75

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA033039	49	75	Bw3	0.37	1.62	55	0.37	1.62	0.70
88PA033039	75	105	C1	0.20	1.66	60	0.20	1.66	0.40
88PA033039	105	165	C2	0.11	1.78	75	0.11	1.78	0.30
88PA033040	0	4	Oe	47.98	0.49	5	47.98	0.49	8.93
88PA033040	4	9	A	18.01	0.20	3	18.01	0.20	1.75
88PA033040	9	34	Bt1	2.87	1.34	3	2.87	1.34	9.33
88PA033040	34	45	Bt2	1.94	1.44	5	1.94	1.44	2.91
88PA033040	45	58	Btg	0.51	1.62	7	0.51	1.62	0.99
88PA033040	58	87	Bgx	0.17	1.96	10	0.17	1.96	0.84
88PA033040	87	133	Bx1	0.14	1.95	8	0.14	1.95	1.18
88PA033040	133	153	Bx2	0.14	2.00	10	0.14	2.00	0.51
88PA033041	0	5	Oi			20	35.17	0.41	5.74
88PA033041	5	12	E	2.64	0.87	50	2.64	0.87	0.80
88PA033041	12	34	Bt1	1.60	1.20	40	1.60	1.20	2.54
88PA033041	34	55	Bt2	0.58	1.57	40	0.58	1.57	1.15
88PA033041	55	76	Bt3	0.41	1.69	55	0.41	1.69	0.66
88PA033041	76	95	BC	0.44	1.74	70	0.44	1.74	0.44
88PA051021	0	16	A	7.77	1.19	30	7.77	1.19	10.35
88PA051021	16	43	Bt1	1.45	1.69	10	1.45	1.69	5.95
88PA051021	43	67	Bt2	0.28	1.85	10	0.28	1.85	1.13
88PA051021	67	85	Bt3	0.11	1.76	15	0.11	1.76	0.31
88PA051021	85	132	C	0.17	1.72	55	0.17	1.72	0.62
88PA051022	0	10	AE	2.67	1.50	15	2.67	1.50	3.40

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley- Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA051022	10	33	Bt	0.74	1.72	8	0.74	1.72	2.69
88PA051022	33	58	Btg	0.44	1.81	10	0.44	1.81	1.79
88PA051022	58	87	Btx1	0.30	1.89	10	0.30	1.89	1.47
88PA051022	87	132	Btx2	0.34	1.88	15	0.34	1.88	2.45
88PA051022	132	200	Btg	0.34	1.86	11	0.34	1.86	3.84
88PA105011	0	2	Oe			15	31.47	0.42	2.25
88PA105011	2	8	A	3.39	1.14	20	3.39	1.14	1.86
88PA105011	8	24	BA	1.76	1.28	20	1.76	1.28	2.88
88PA105011	24	41	Bw1	1.02	1.26	35	1.02	1.26	1.42
88PA105011	41	66	Bw2	0.94	1.28	55	0.94	1.28	1.35
88PA105011	66	85	C1	0.43	1.20	80	0.43	1.20	0.19
88PA105011	85	124	C2	0.26	1.78	80	0.26	1.78	0.35
88PA105012	0	23	Ap	4.25	0.96	20	4.25	0.96	7.50
88PA105012	23	48	BE	1.28	1.70	55	1.28	1.70	2.44
88PA105012	48	76	Bt1	1.16	1.38	55	1.16	1.38	2.02
88PA105012	76	105	Bt2	0.84	1.43	60	0.84	1.43	1.39
88PA105012	105	128	Bt3	0.54	1.38	65	0.54	1.38	0.60
88PA105012	128	164	BC	0.41	1.32	70	0.41	1.32	0.59
88PA105013	0	3	Oa			10	26.66	0.47	3.41
88PA105013	3	10	E	2.98	1.36	13	2.98	1.36	2.47
88PA105013	10	33	Bs	2.81	1.22	25	2.81	1.22	5.92
88PA105013	33	57	Bw1	1.33	1.40	40	1.33	1.40	2.69
88PA105013	57	85	Bw2	0.54	1.55	70	0.54	1.55	0.70

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
88PA105013	85	148	BC	0.23	1.70	85	0.23	1.70	0.36
93NY009001	0	23	Ap	3.27		5	3.27	1.22	8.72
93NY009001	23	56	BE	0.25		10	0.25	1.36	1.01
93NY009001	56	76	Bw1	0.16	1.75	15	0.16	1.75	0.48
93NY009001	76	102	Bw2	0.18	1.65	25	0.18	1.65	0.58
93NY009001	102	140	Bx	0.10		30	0.10	1.59	0.42
93NY009001	140	178	C	0.13		30	0.13	1.60	0.55
93NY009002	0	20	Ap	2.44		10	2.44	1.25	5.50
93NY009002	20	41	Bw1	0.83		10	0.83	1.40	2.20
93NY009002	41	61	Bw2	0.27	1.54	15	0.27	1.54	0.71
93NY009002	61	97	Bt	0.17	1.69	20	0.17	1.69	0.83
93NY009002	97	157	Btx	0.10		25	0.10	1.64	0.74
93NY009002	157		C	0.08		50	0.08	1.61	0.28
93NY009003	0	3	Oa	27.05		0	27.05	0.43	3.47
93NY009003	3	13	A	5.68		20	5.68	0.94	4.28
93NY009003	13	41	Bw	1.37		30	1.37	1.32	3.54
93NY009003	41	66	Bt	0.38		40	0.38	1.40	0.80
93NY009004	0	8	Oe	46.89		0	46.89	0.40	14.91
93NY009004	8	20	E	0.25		4	0.25	1.46	0.42
93NY009004	20	25	Bhs			1	1.63	1.37	1.10
93NY009004	25	48	Bh	0.88		5	0.88	1.35	2.60
93NY009004	48	91	BC1	0.26		10	0.26	1.59	1.60
93NY009004	91	119	BC2	0.14		20	0.14	1.61	0.50

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
93NY009004	119	147	C	0.06		10	0.06	1.60	0.24
93NY009005	0	15	Ap	2.81		0	2.81	1.23	5.19
93NY009005	15	36	Btg1	1.97		1	1.97	1.40	5.72
93NY009005	36	61	Btg2	0.63		5	0.63	1.45	2.17
93NY009005	61	79	Btg3	0.16		20	0.16	1.48	0.34
93NY009005	79	124	Btxg	0.14		30	0.14	1.56	0.69
93NY009005	124	152	Cg	0.48		25	0.48	1.50	1.52
93NY009006	0	8	Oe	40.89		0	40.89	0.42	13.71
93NY009006	8	28	E	0.22		25	0.22	1.28	0.42
93NY009006	28	41	Bs1	0.41		25	0.41	1.28	0.51
93NY009006	41	56	Bs2	0.90		40	0.90	1.35	1.10
93NY009006	56	122	BC	0.24		70	0.24	1.62	0.77
93NY009007	0	3	Oe	27.83		0	27.83	0.43	3.55
93NY009007	3	5	E			10	4.47	1.33	1.07
93NY009007	5	64	Bw1	0.41		15	0.41	1.39	2.87
93NY009007	64	91	Bw2	0.14		32	0.14	1.53	0.39
93NY009007	91	119	C1			50	0.15	1.58	0.34
93NY009007	119	152	C2			10	0.15	1.55	0.68
93NY009007	152	203	C3			20	0.32	1.57	2.06
93NY009008	0	20	Ap	5.24		5	5.24	1.14	11.34
93NY009008	20	48	Bw1	0.32		10	0.32	1.37	1.10
93NY009008	48	74	Bw2	0.23		15	0.23	1.49	0.76
93NY009008	74	91	BC	0.12		10	0.12	1.54	0.28

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
93NY009008	91	117	C	0.14		10	0.14	1.51	0.50
93NY009009	0	3	Oe	35.64		0	35.64	0.48	5.09
93NY009009	3	10	A	4.12		1	4.12	1.03	2.94
93NY009009	10	46	Bw1	0.70		2	0.70	1.38	3.41
93NY009009	46	56	Bw2	0.14		5	0.14	1.52	0.20
93NY009009	56	69	E / Btx	0.08	1.65	5	0.08	1.65	0.16
93NY009009	69	119	2Btx1	0.06	1.65	15	0.06	1.65	0.42
93NY009009	119	165	2Btx2	0.12	1.73	15	0.12	1.73	0.81
95WV075001	0	1	Oi1	53.18		0	53.18	0.35	1.85
95WV075001	1	4	Oi2	50.14		0	50.14	0.37	5.52
95WV075001	4	8	Oa	36.30		25	36.30	0.62	6.70
95WV075001	8	12	A	13.83		40	13.83	1.18	3.91
95WV075001	12	27	E	0.53	1.74	50	0.53	1.74	0.69
95WV075001	27	39	Bh / Bhs	3.40	1.30	35	3.40	1.30	3.45
95WV075001	39	61	Bw	0.97	1.51	45	0.97	1.51	1.77
95WV075001	61	94	BC	0.33	1.50	50	0.33	1.50	0.82
95WV075001	94	124	C	0.17	1.65	50	0.17	1.65	0.42
95WV075002	0	1	Oi1	51.42		0	51.42	0.33	1.71
95WV075002	1	4	Oi2	51.68		0	51.68	0.35	5.45
95WV075002	4	9	Oe	50.59		0	50.59	0.54	13.60
95WV075002	9	14	Oa	43.59		25	43.59	0.61	9.94
95WV075002	14	26	E	1.61	1.71	35	1.61	1.71	2.15
95WV075002	26	34	Bhs	2.36	1.62	25	2.36	1.62	2.29

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV075002	34	42	Bs	1.02	1.29	30	1.02	1.29	0.74
95WV075002	42	63	Bw	0.53	1.69	50	0.53	1.69	0.94
95WV075002	63	94	C	0.83		70	0.83	1.60	1.23
95WV083001	0	5	Oi1	51.26		0	51.26	0.43	10.95
95WV083001	5	8	Oi2	42.90		0	42.90	0.44	5.66
95WV083001	8	9	Oa	25.26		0	25.26	0.60	1.52
95WV083001	9	23	A	18.70		30	18.70	1.06	19.41
95WV083001	23	33	AB	6.34		30	6.34	1.25	5.55
95WV083001	33	61	Bw	2.98		30	2.98	1.42	8.27
95WV083001	61	107	Bx1	0.45	1.83	10	0.45	1.83	3.41
95WV083001	107	165	Bx2	0.31	1.80	25	0.31	1.80	2.43
95WV083001	165	267	2C1	0.91	1.69	30	0.91	1.69	10.98
95WV083001	267	307	2C2	2.91	1.74	10	2.91	1.74	18.23
95WV083001	307	376	2C3	0.26	1.75	10	0.26	1.75	2.83
95WV083001	376	404	2C4	0.24	1.33	45	0.24	1.33	0.49
95WV083002	0	4	Oi	49.06		0	49.06	0.35	6.89
95WV083002	4	8	Oe	47.52		0	47.52	0.54	10.27
95WV083002	8	13	Oa / A	33.96		5	33.96	0.59	9.59
95WV083002	13	21	AE	1.26	1.54	40	1.26	1.54	0.93
95WV083002	21	32	E	0.36	1.90	40	0.36	1.90	0.45
95WV083002	32	40	Bh	2.80	1.43	20	2.80	1.43	2.56
95WV083002	40	52	Bh / Bs	1.14	1.42	30	1.14	1.42	1.36
95WV083002	52	57	Bs	0.34	1.60	60	0.34	1.60	0.11

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV083002	57	71	C	0.15	1.71	75	0.15	1.71	0.09
95WV083003	0	1	Oi1	54.23		0	0.41	1.74	0.32
95WV083003	1	6	Oi2	51.85		0	51.40	0.35	2.51
95WV083003	6	9	Oe	49.61		0	39.72	0.37	5.95
95WV083003	9	14	A	16.54		70	11.56	1.16	4.36
95WV083003	14	18	AE	2.42		70	5.46	1.26	5.51
95WV083003	18	29	E	0.17	1.66	60	2.77	0.98	5.29
95WV083003	29	35	Bh	0.47	1.35	50	1.45	1.21	3.16
95WV083003	35	41	Bhs	2.32	1.33	50	0.94	1.75	1.78
95WV083003	41	54	Bhs / BC	0.97	1.63	60	0.73	1.84	7.02
95WV083003	54	69	C	0.41	1.74	70	0.88	1.71	2.77
95WV083004	0	2	Oi1	51.40		30	54.23	0.26	1.43
95WV083004	2	6	Oi2	39.72		0	51.85	0.29	7.51
95WV083004	6	11	A	11.56		35	49.61	0.43	6.39
95WV083004	11	19	AB	5.46		0	16.54	1.13	2.80
95WV083004	19	45	Bw1	2.77	0.98	25	2.42	1.47	0.43
95WV083004	45	69	Bw2	1.45	1.21	25	0.17	1.66	0.12
95WV083004	69	87	Bx1	0.94	1.75	40	0.47	1.35	0.19
95WV083004	87	182	Bx2	0.73	1.84	45	2.32	1.33	0.93
95WV083004	182	205	BC	0.88		20	0.97	1.63	0.82
95WV083005	0	1	Oi1	50.30		0	50.30	0.32	1.61
95WV083005	1	3	Oi2	49.03		0	49.03	0.34	3.29
95WV083005	3	5	Oe	48.24		0	48.24	0.47	4.57

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV083005	5	14	A	10.27	1.03	35	10.27	1.03	6.19
95WV083005	14	26	BA	2.85	1.14	30	2.85	1.14	2.73
95WV083005	26	47	Bw1	1.52	1.22	40	1.52	1.22	2.34
95WV083005	47	80	Bw2	1.92	1.27	55	1.92	1.27	3.62
95WV083005	80	98	C	0.87	1.36	80	0.87	1.36	0.43
95WV083006	0	1	Oi1	53.44		0	53.44	0.33	1.77
95WV083006	1	4	Oi2	52.62		0	52.62	0.35	5.53
95WV083006	4	11	Oe	45.39		0	45.39	0.53	16.94
95WV083006	11	18	Oa	15.59		0	15.59	0.60	6.57
95WV083006	18	24	A	12.72		20	12.72	1.28	7.83
95WV083006	24	31	E	0.24	1.49	30	0.24	1.49	0.18
95WV083006	31	45	EB	0.35	1.90	30	0.35	1.90	0.65
95WV083006	45	60	Bh	0.14	1.51	60	0.14	1.51	0.13
95WV083006	60	81	C	0.14	1.75	50	0.14	1.75	0.26
95WV083007	0	1	Oi1	5.41		0	5.41	0.32	0.17
95WV083007	1	4	Oi2	17.68		30	17.68	0.34	1.26
95WV083007	4	7	Oe	15.61		30	15.61	0.49	1.62
95WV083007	7	19	A	10.82	0.73	40	10.82	0.73	5.69
95WV083007	19	64	Bw	2.57	0.87	50	2.57	0.87	5.03
95WV083007	64	92	BC	0.92	1.07	70	0.92	1.07	0.83
95WV083008	0	2	Oi1	15.78		0	15.78	0.40	1.27
95WV083008	2	5	Oi2	13.29		0	13.29	0.43	1.70
95WV083008	5	8	Oe	15.01		0	15.01	0.55	2.49

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV083008	8	15	Oa	14.91		0	14.91	0.62	6.46
95WV083008	15	22	A	13.17	1.71	55	13.17	1.71	7.09
95WV083008	22	44	A / E	0.69	1.68	55	0.69	1.68	1.15
95WV083008	44	57	Bw	0.34	1.73	45	0.34	1.73	0.42
95WV083008	57	110	Bx	0.21	1.89	40	0.21	1.89	1.26
95WV083008	110	136	BCx	0.12	1.94	50	0.12	1.94	0.30
95WV093001	0	2	Oi1	50.37		0	50.37	0.39	3.97
95WV093001	2	5	Oi2	48.89		0	48.89	0.41	6.06
95WV093001	5	8	Oe	44.63		0	44.63	0.51	6.79
95WV093001	8	14	Oa	38.23		0	38.23	0.57	13.11
95WV093001	14	17	A	18.92		30	18.92	1.29	5.13
95WV093001	17	35	E	0.34	1.94	30	0.34	1.94	0.83
95WV093001	35	58	Btx1	0.27	1.98	35	0.27	1.98	0.80
95WV093001	58	87	Btx2	0.24	1.79	45	0.24	1.79	0.69
95WV093001	87	121	Cg	0.68	1.93	45	0.68	1.93	2.45
95WV093002	0	2	Oi1	45.76		0	45.76	0.33	3.04
95WV093002	2	5	Oi2	48.59		0	48.59	0.36	5.20
95WV093002	5	7	Oe	46.68		0	46.68	0.53	4.97
95WV093002	7	12	A	26.07		5	26.07	1.01	12.46
95WV093002	12	20	E	0.90	1.90	5	0.90	1.90	1.30
95WV093002	20	29	Bh	1.21	1.62	5	1.21	1.62	1.68
95WV093002	29	36	Bhs			5	3.44	1.39	3.17
95WV093002	36	43	Bsm	1.20	1.77	10	1.20	1.77	1.34

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV093002	43	60	Bs	0.73	1.75	25	0.73	1.75	1.63
95WV093002	60	92	C	0.46	2.01	15	0.46	2.01	2.51
95WV093003	0	2	Oi1	51.64		0	51.64	0.39	4.06
95WV093003	2	6	Oi2	49.34		0	49.34	0.36	7.09
95WV093003	6	9	Oe	46.79		0	46.79	0.53	7.37
95WV093003	9	11	Oa	35.31		0	35.31	0.59	4.13
95WV093003	11	13	A			0	19.10	1.22	4.65
95WV093003	13	26	E		1.81	0	0.97	1.81	2.29
95WV093003	26	31	Bh		1.74	0	2.32	1.74	2.02
95WV093003	31	45	Bw		1.67	10	0.85	1.67	1.78
95WV093003	45	54	BC			10	0.69	1.68	0.94
95WV093003	54	85	C		1.82	10	0.65	1.82	3.28
95WV093004	0	2	Oi1	46.19		0	46.19	0.35	3.22
95WV093004	2	5	Oi2	46.67		0	46.67	0.37	5.23
95WV093004	5	7	Oe	43.02		30	43.02	0.58	3.48
95WV093004	7	17	A	17.00	0.98	30	17.00	0.98	11.66
95WV093004	17	53	Bs	2.12	0.97	35	2.12	0.97	4.81
95WV093004	53	90	BC	1.10	1.42	60	1.10	1.42	2.31
95WV093004	90	110	2C	0.89	1.22	75	0.89	1.22	0.54
95WV093005	0	2	Oi1	47.00		0	47.00	0.32	3.02
95WV093005	2	5	Oi2	48.13		0	48.13	0.34	4.94
95WV093005	5	7	Oe	36.40		0	36.40	0.49	3.54
95WV093005	7	13	A	10.39	1.18	35	10.39	1.18	4.78

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV093005	13	26	Bhs	3.52	1.05	30	3.52	1.05	3.36
95WV093005	26	48	Bw	1.59	1.21	45	1.59	1.21	2.33
95WV093005	48	69	BC	0.73	1.68	45	0.73	1.68	1.42
95WV093005	69	102	C	1.44		80	1.44	1.44	1.37
95WV093006	0	2	Oi1	46.72		20	46.72	0.40	2.99
95WV093006	2	4	Oi2	47.12		0	47.12	0.42	3.96
95WV093006	4	6	Oe	13.20		0	13.20	0.58	1.54
95WV093006	6	18	A	12.91		30	12.91	1.05	11.40
95WV093006	18	26	Bhs	3.53		20	3.53	1.21	2.73
95WV093006	26	38	Bs1	2.04	1.17	15	2.04	1.17	2.43
95WV093006	38	50	Bs2	2.18	1.21	15	2.18	1.21	2.69
95WV093006	50	94	Bx	0.98	1.61	35	0.98	1.61	4.51
95WV093006	94	134	BC	0.44	1.74	40	0.44	1.74	1.84
95WV093006	134	202	2BC	0.35	1.55	45	0.35	1.55	2.03
95WV093007	0	1	Oi1	48.15		0	48.15	0.35	1.67
95WV093007	1	5	Oi2	50.99		0	50.99	0.37	7.49
95WV093007	5	7	Oe	49.06		0	49.06	0.58	5.67
95WV093007	7	13	Oa / A	42.50		75	42.50	0.62	3.97
95WV093007	13	16	AE	12.31		75	12.31	1.24	1.14
95WV093007	16	51	E	0.73	1.50	75	0.73	1.50	0.96
95WV093007	51	68	Bh / Bhs	6.52	1.04	45	6.52	1.04	6.34
95WV093007	68	94	Bw	1.37	1.16	75	1.37	1.16	1.03
95WV093007	94	114	C	1.00	1.32	55	1.00	1.32	1.19

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
95WV093008	0	2	Oi1	51.51		0	51.51	0.41	4.22
95WV093008	2	5	Oi2	49.88		0	49.88	0.44	6.52
95WV093008	5	8	Oe	38.96		0	38.96	0.57	6.64
95WV093008	8	16	A	16.02		25	16.02	1.09	10.52
95WV093008	16	34	A / E	3.05	1.34	25	3.05	1.34	5.52
95WV093008	34	57	Bw	1.10	1.08	20	1.10	1.08	2.19
95WV093008	57	102	Bx	0.59	1.56	30	0.59	1.56	2.90
95WV093008	102	133	2BC	0.54		65	0.54	1.69	0.99
95WV093008	133	167	2C	0.65		75	0.65	1.58	0.88
97WV093001	0	2	Oi	48.40		0	48.40	0.26	2.48
97WV093001	2	7	Oi / A	38.44		60	38.44	0.28	2.15
97WV093001	7	16	Oa / A	12.93		60	12.93	1.02	4.74
97WV093001	16	27	BA	2.65	1.11	50	2.65	1.11	1.62
97WV093001	27	63	Bw	0.38	1.40	40	0.38	1.40	1.15
97WV093001	63	100	BC	0.14	1.47	50	0.14	1.47	0.38
97WV093002	0	3	Oi	50.79		0	50.79	0.24	3.67
97WV093002	3	6	Oi / Oe	40.14		10	40.14	0.26	2.78
97WV093002	6	10	A	0.46		10	0.46	0.98	0.16
97WV093002	10	20	BA	1.84	1.18	15	1.84	1.18	1.85
97WV093002	20	41	Bt1	0.88	1.26	20	0.88	1.26	1.86
97WV093002	41	65	Bt2	0.18	1.38	20	0.18	1.38	0.48
97WV093002	65	82	Bt3	0.19	1.26	40	0.19	1.26	0.24
97WV093002	82	100	2C	0.19	0.83	60	0.19	0.83	0.11

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
97WV093003	0	4	Oi	50.48		0	50.48	0.29	5.92
97WV093003	4	7	Oi/E	39.90		10	39.90	0.31	3.33
97WV093003	7	13	A	9.54		20	9.54	1.05	4.83
97WV093003	13	25	BE	1.21	1.30	20	1.21	1.30	1.51
97WV093003	25	52	Bw1	0.32	1.44	20	0.32	1.44	1.00
97WV093003	52	74	Bw2	0.10	1.44	25	0.10	1.44	0.24
97WV093003	74	114	Bw3	0.10	1.46	30	0.10	1.46	0.41
97WV093003	114	142	Bw4	0.05	1.53	30	0.05	1.53	0.15
97WV093003	142	164	2BCx	0.04	1.39	40	0.04	1.39	0.07
97WV093004	0	4	Oi	46.98		0	46.98	0.28	5.21
97WV093004	4	8	Oa	23.72		30	23.72	0.46	3.07
97WV093004	8	17	A	10.28		30	10.28	0.99	6.39
97WV093004	17	28	AB	5.43		40	5.43	1.12	4.03
97WV093004	28	40	BA	1.44	0.97	40	1.44	0.97	1.01
97WV093004	40	66	Bw1	0.48		70	0.48	1.30	0.49
97WV093004	66	108	Bw2	0.28	1.40	50	0.28	1.40	0.82
97WV093004	108	133	Bw3	0.15	1.58	60	0.15	1.58	0.24
97WV093004	133	169	BCx	0.11	1.54	60	0.11	1.54	0.24
97WV093005	0	2	Oi	45.93		0	45.93	0.27	2.47
97WV093005	2	4	Oa	13.85		35	13.85	0.45	0.82
97WV093005	4	12	A	3.57		35	3.57	1.03	1.91
97WV093005	12	32	BA	0.99		30	0.99	1.19	1.65
97WV093005	32	72	Bw1	0.20		50	0.20	1.42	0.57

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
97WV093005	72	91	Bw2	0.08		60	0.08	1.47	0.09
97WV093005	91	124	BC	0.08		65	0.08	1.44	0.13
97WV093005	124	162	C	0.07		60	0.07	1.43	0.15
97WV093006	0	2	Oi1	46.18		40	46.18	0.23	1.29
97WV093006	2	4	Oi2	31.08		40	31.08	0.24	0.90
97WV093006	4	6	Oe	26.58		50	26.58	0.36	0.95
97WV093006	6	13	Oa/A	10.79		40	10.79	0.94	4.27
97WV093006	13	23	BA	3.97		35	3.97	1.05	2.71
97WV093006	23	38	Bw1	1.71		45	1.71	1.07	1.51
97WV093006	38	57	Bw2	1.02		80	1.02	1.03	0.40
97WV093007	0	2	Oi1	34.96		0	34.96	0.29	2.03
97WV093007	2	5	Oi2	44.46		20	44.46	0.31	3.26
97WV093007	5	10	Oe	41.62		20	41.62	0.41	6.85
97WV093007	10	15	Oa	30.70		40	30.70	0.50	4.65
97WV093007	15	27	A	7.67		40	7.67	1.07	5.89
97WV093007	27	35	BE	1.20	1.10	30	1.20	1.10	0.74
97WV093007	35	48	Bt1	0.70	1.14	35	0.70	1.14	0.67
97WV093007	48	80	Bt2	0.44	1.35	45	0.44	1.35	1.05
97WV093007	80	112	Bt3	0.14	1.28	50	0.14	1.28	0.29
97WV093007	112	129	2BCx	0.12	1.48	60	0.12	1.48	0.12
97WV093007	129	162	2C	0.07	1.57	60	0.07	1.57	0.15
97WV093008	0	3	Oi	51.54		0	51.54	0.24	3.72
97WV093008	3	6	Oi / E	31.56		30	31.56	0.30	2.01

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
97WV093008	6	15	A	8.60		40	8.60	1.02	4.74
97WV093008	15	24	BA	1.98		30	1.98	1.09	1.36
97WV093008	24	52	Bw1	0.76		40	0.76	1.07	1.36
97WV093008	52	93	Bw2	0.37		70	0.37	1.28	0.58
98NY009001	0	5	Oe			0	35.34	0.51	8.94
98NY009001	5	8	A	16.11		10	16.11	1.09	4.73
98NY009001	8	13	E	1.61		10	1.61	1.35	0.98
98NY009001	13	46	Bt1	0.60		10	0.60	1.43	2.55
98NY009001	46	69	Bt2	0.20		15	0.20	1.59	0.62
98NY009001	69	97	Btx1	0.05	1.98	20	0.05	1.98	0.22
98NY009001	97	147	Btx2	0.02	1.95	25	0.02	1.95	0.15
98NY009001	147	175	C	0.04		45	0.04	1.75	0.11
98NY009002	0	5	Oe			0	30.73	0.50	7.66
98NY009002	5	8	A	18.70		10	18.70	1.09	5.52
98NY009002	8	15	E	0.76		10	0.76	1.39	0.66
98NY009002	15	48	Bt1	0.17		15	0.17	1.45	0.69
98NY009002	48	66	Bt2	1.39		15	1.39	1.60	3.40
98NY009002	66	107	Btx1	0.06		30	0.06	1.77	0.30
98NY009002	107	163	Btx2	0.05	1.96	35	0.05	1.96	0.36
98NY009002	163	191	C	0.21		60	0.21	1.73	0.41
98PA129121	0	3	Oi			0	40.49	0.37	4.47
98PA129121	3	5	Oe			0	36.77	0.51	3.73
98PA129121	5	6	Oa			0	28.71	0.55	1.58

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
98PA129121	6	9	A			0	12.08	1.19	4.32
98PA129121	9	11	E	2.36		25	2.36	1.45	0.51
98PA129121	11	17	Bs			25	2.91	1.29	1.69
98PA129121	17	43	Bt	0.33		20	0.33	1.43	0.98
98PA129121	43	79	BC	0.18		25	0.18	1.63	0.79
98PA129121	79	114	C			30	0.21	1.62	0.84
98PA129123	0	3	Oi			0	41.47	0.36	4.43
98PA129123	3	5	Oe			5	33.41	0.50	3.19
98PA129123	5	13	A	5.37		15	5.37	1.08	3.93
98PA129123	13	38	Bw	0.74		35	0.74	1.32	1.59
98PA129123	38	76	BC	0.26		55	0.26	1.47	0.65
98PA129123	76	114	C			35	0.33	1.48	1.20
S06WV071001	0	2	Oi	51.25		0	51.25	0.27	2.74
S06WV071001	2	4	Oe	49.47		0	49.47	0.45	4.49
S06WV071001	4	13	Oa/A	21.59		90	21.59	0.88	1.71
S06WV071001	13	26	E	6.44		75	6.44	1.30	2.72
S06WV071001	26	42	Bhs	9.64		70	9.64	1.27	5.88
S06WV071001	42	57	Bs	5.75		0	5.75	1.31	11.27
S06WV071001	57	75	C	4.17		75	4.17	1.52	2.84
S06WV081002	0	3	Oe	47.87		0	47.87	0.52	7.48
S06WV081002	3	8	Oa/A	34.85		5	34.85	0.58	9.59
S06WV081002	8	25	AB	2.34	1.45	5	2.34	1.45	5.48
S06WV081002	25	51	Bt1	0.82	1.49	5	0.82	1.49	3.02

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV081002	51	74	2Bt2	0.27	1.64	10	0.27	1.64	0.92
S06WV081002	74	97	2Bt3	0.15	1.67	25	0.15	1.67	0.43
S06WV081002	97	130	2Bt4	0.20	1.66	35	0.20	1.66	0.71
S06WV093008	0	1	Oi	44.19		0	44.19	0.30	1.32
S06WV093008	1	3	Oe	36.25		0	36.25	0.50	3.62
S06WV093008	3	15	Oa/A	6.90		10	6.90	1.10	8.16
S06WV093008	15	33	AE	5.53	0.83	15	5.53	0.83	7.02
S06WV093008	33	51	Bs1	2.56	1.37	55	2.56	1.37	2.84
S06WV093008	51	69	Bs2	1.18	1.50	55	1.18	1.50	1.43
S06WV093008	69	137	Bs3	0.70	1.30	75	0.70	1.30	1.55
S06WV093008	137		BC	0.45		75	0.45	1.62	1.15
S01PA031010	0	3	Oe			0	30.35	0.46	4.20
S01PA031010	3	6	A	1.47		15	1.47	1.03	0.39
S01PA031010	6	10	E	0.55		10	0.55	1.42	0.28
S01PA031010	10	28	BE	0.21		10	0.21	1.37	0.47
S01PA031010	28	58	Bw1	0.13		20	0.13	1.51	0.47
S01PA031010	58	97	Bw2	0.15		40	0.15	1.66	0.58
S01PA031010	97	157	Bx	0.12		60	0.12	1.78	0.51
S01PA031-050	0	3	Oe			0	34.14	0.49	5.02
S01PA031-050	3	8	A	5.60		5	5.60	1.02	2.72
S01PA031-050	8	25	BE	1.24		5	1.24	1.28	2.57
S01PA031-050	25	46	Bt1	0.53		5	0.53	1.44	1.52
S01PA031-050	46	66	Bt2	0.27		10	0.27	1.57	0.76

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01PA031-050	66	127	Btx1	0.12		20	0.12	1.66	0.97
S01PA031-050	127	177	Btx2	0.16		35	0.16	1.76	0.91
S01PA031-050	177	200	BC	0.05		50	0.05	1.74	0.10
S01PA031-053	0	3	Oa			0	33.84	0.64	6.52
S01PA031-053	3	13	A	10.79		0	10.79	1.02	11.04
S01PA031-053	13	25	BA	2.40		0	2.40	1.21	3.49
S01PA031-053	25	50	Bt	0.63		0	0.63	1.38	2.18
S01PA031-053	50	75	Btg	0.47		0	0.47	1.58	1.86
S01PA031-053	75	117	Btx	0.45		10	0.45	1.68	2.85
S01PA031-053	117	150	C	0.41		35	0.41	1.61	1.41
S01WV019001	0	3	Oi2	44.69		0	44.69	0.42	5.66
S01WV019001	3	6	Oe	26.31		0	26.31	1.04	8.19
S01WV019001	6	18	A	4.05	1.04	40	4.05	1.04	3.03
S01WV019001	18	26	A/B	2.49	1.19	30	2.49	1.19	1.66
S01WV019001	26	39	Bw1	0.90	1.48	30	0.90	1.48	1.21
S01WV019001	39	74	Bw2	0.37	1.52	42	0.37	1.52	1.14
S01WV019001	74	120	Bw3	0.18	1.66	45	0.18	1.66	0.76
S01WV019001	120	148	BC	0.29	1.47	45	0.29	1.47	0.66
S01WV019001	148	168	C	0.32	1.68	45	0.32	1.68	0.59
S01WV019002	0	3	Oi1	49.86		0	49.86	0.41	6.07
S01WV019002	3	5	Oi2	49.16		0	49.16	0.42	4.08
S01WV019002	5	8	Oe	44.99		0	44.99	0.55	7.42
S01WV019002	8	14	A	6.75	1.03	10	6.75	1.03	3.75

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV019002	14	25	B/A	2.12	1.15	15	2.12	1.15	2.28
S01WV019002	25	38	Bt1	0.98	1.42	15	0.98	1.42	1.54
S01WV019002	38	65	Bt2	0.27	1.50	15	0.27	1.50	0.93
S01WV019002	65	91	BC	0.16	1.49	45	0.16	1.49	0.34
S01WV019003	0	3	Oi1	42.45		0	42.45	0.40	5.04
S01WV019003	3	5	Oi2	46.22		0	46.22	0.40	3.73
S01WV019003	5	7	Oe	41.60		0	41.60	0.52	4.36
S01WV019003	7	16	A	4.67	0.96	5	4.67	0.96	3.83
S01WV019003	16	27	BA	4.59	1.26	5	4.59	1.26	6.04
S01WV019003	27	51	Bt	1.14	1.37	5	1.14	1.37	3.56
S01WV019003	51	68	BC	0.20	1.66	10	0.20	1.66	0.51
S01WV019003	68	90	C	0.08	1.52	20	0.08	1.52	0.21
S01WV019004	0	3	Oe	50.30		0	50.30	0.52	7.81
S01WV019004	3	10	Oa			40	29.98	0.57	7.24
S01WV019004	3	10	A	36.11		40	36.11	0.99	15.02
S01WV019004	10	25	BA	3.76		40	3.76	1.17	3.96
S01WV019004	25	40	Bw1	1.72	1.11	50	1.72	1.11	1.43
S01WV019004	40	70	Bw2	1.72	1.25	50	1.72	1.25	3.23
S01WV019004	70	95	C	1.15		80	1.15	1.47	0.84
S01WV019005	0	2	Oi1	49.27		0	49.27	0.39	3.86
S01WV019005	2	3	Oi2	48.48		0	48.48	0.41	1.98
S01WV019005	3	5	Oe	33.74		0	33.74	0.55	3.70
S01WV019005	5	10	Oa	24.04		5	24.04	0.93	10.65

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV019005	5	10	A	6.44		5	6.44	0.98	2.99
S01WV019005	10	25	BA	1.98	1.20	5	1.98	1.20	3.39
S01WV019005	25	47	Bt1	0.53	1.30	5	0.53	1.30	1.44
S01WV019005	47	75	Bt2	0.16	1.49	10	0.16	1.49	0.60
S01WV019005	75	88	BC	0.10	1.52	15	0.10	1.52	0.17
S01WV019006	0	3	Oi1	47.60		0	47.60	0.36	5.19
S01WV019006	3	5	Oi2	47.95		0	47.95	0.37	3.58
S01WV019006	5	7	Oe	41.11		0	41.11	0.50	4.10
S01WV019006	7	14	Oa	36.32		55	36.32	0.58	6.69
S01WV019006	14	23	B/E	1.98		60	1.98	1.28	0.91
S01WV019006	23	40	Bw1	1.46	1.24	50	1.46	1.24	1.54
S01WV019006	40	57	Bw2	0.76		50	0.76	1.44	0.93
S01WV019006	57	70	BC	0.77	1.42	60	0.77	1.42	0.57
S01WV019007	0	2	Oi1	39.58		0	39.58	0.39	3.10
S01WV019007	2	4	Oi2	27.48		0	27.48	0.87	4.79
S01WV019007	4	9	A	5.33	0.81	15	5.33	0.81	1.83
S01WV019007	9	21	BA	1.61	1.15	10	1.61	1.15	2.00
S01WV019007	21	42	Bt1	0.67	1.45	15	0.67	1.45	1.73
S01WV019007	42	65	Bt2	0.41	1.43	15	0.41	1.43	1.15
S01WV019007	65	76	BC	0.45	1.40	20	0.45	1.40	0.55
S01WV019007	76	93	C	0.32	1.50	50	0.32	1.50	0.41
S01WV019008	0	1	Oi1	25.97		0	25.97	0.95	2.47
S01WV019008	117	171	2C	0.14	1.47	30	35.24	0.44	3.07

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV019008	1	3	Oi2	35.24		0	5.39	1.01	1.74
S01WV019008	3	7	A	5.39		20	2.01	1.18	0.95
S01WV019008	7	12	A/B	2.01		20	1.49	1.33	1.52
S01WV019008	12	21	B/A	1.49	1.33	15	0.69	1.44	2.38
S01WV019008	21	53	Bt1	0.69	1.44	25	0.27	1.47	0.26
S01WV019008	53	66	Bt2	0.27	1.47	50	0.13	1.43	0.25
S01WV019008	66	93	Bx	0.13	1.43	50	0.22	1.49	0.47
S01WV019008	93	117	2BC	0.22	1.49	40	0.14	1.47	0.78
S01WV019009	2	0	Oi1	35.22		0	35.22	0.95	6.66
S01WV019009	0	2	Oi2	46.11		0	49.42	0.61	5.99
S01WV019009	2	6	Oe	49.42		0	16.24	0.89	6.94
S01WV019009	6	14	Oa/A	16.24	0.89	40	3.99	1.14	2.39
S01WV019009	14	21	B/A	3.99	1.14	25	2.89	1.54	5.67
S01WV019009	21	38	Bw	2.89	1.54	25	0.51	1.53	1.37
S01WV019009	38	60	Bt1	0.51		20	0.25	1.45	0.84
S01WV019009	60	89	2Bt2	0.25	1.45	20	0.26	1.65	0.59
S01WV019009	89	112	2Btx1	0.26	1.65	40	0.20	1.70	0.39
S01WV019009	112	135	2Btx2	0.20	1.70	50	46.11	0.46	4.21
S01WV019010	0	2	Oi1	39.97		0	39.97	0.35	2.80
S01WV019010	2	4	Oi2	38.06		0	38.06	0.36	2.76
S01WV019010	4	7	Oe/Oa	31.81		10	31.81	0.47	4.01
S01WV019010	7	13	A	5.75		15	5.75	1.07	3.13
S01WV019010	13	22	B/A	2.48	1.18	15	2.48	1.18	2.24

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV019010	22	40	Bw1	0.54	1.36	30	0.54	1.36	0.93
S01WV019010	40	54	Bw2	0.30	1.39	90	0.30	1.39	0.06
S01WV019010	54	68	BC	0.13	1.63	70	0.13	1.63	0.09
S01WV019011	0	1	Oi1	49.06		0	49.06	0.32	1.59
S01WV019011	1	2	Oi2	43.98		0	43.98	0.34	1.49
S01WV019011	2	3	Oe	30.34		0	30.34	0.98	2.96
S01WV019011	3	10	A	3.85	0.90	10	3.85	0.90	2.18
S01WV019011	10	18	BE	0.88	1.29	5	0.88	1.29	0.86
S01WV019011	18	30	Bw1	0.59	1.26	10	0.59	1.26	0.80
S01WV019011	30	53	Bw2	0.38	1.29	15	0.38	1.29	0.96
S01WV019011	53	68	Bw3	0.25	1.53	25	0.25	1.53	0.43
S01WV019011	68	78	C	0.15	1.53	60	0.15	1.53	0.09
S01WV025002	0	5	A	4.07		0	4.07	1.03	2.10
S01WV025002	5	15	E	0.59		0	0.59	1.26	0.74
S01WV025002	15	30	BE	0.40		0	0.40	1.26	0.76
S01WV025002	30	64	Bt1	0.18		5	0.18	1.35	0.78
S01WV025002	64	109	Bt2	0.14		10	0.14	1.42	0.80
S01WV025002	109	137	Bt3	0.19		25	0.19	1.43	0.57
S01WV025002	137	201	BC	0.19		0	0.19	1.45	1.76
S01WV025002	201	216	C	0.14		0	0.14	1.41	0.30
S01WV025003	0	23	A	1.99		0	1.99	1.11	5.08
S01WV025003	23	56	BA	0.44		0	0.44	1.26	1.83
S01WV025003	56	87	Bt1	0.30		0	0.30	1.41	1.32

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV025003	87	145	Bt2	0.55		10	0.55	1.41	4.05
S01WV025003	145	183	Bt3	0.43		10	0.43	1.25	1.84
S01WV025003	183	203	Bt4	0.26		10	0.26	1.41	0.66
S01WV025004	0	15	A	3.05		0	3.05	1.03	4.71
S01WV025004	15	30	BA	0.73		0	0.73	1.22	1.33
S01WV025004	30	48	Bt1	0.39		0	0.39	1.36	0.96
S01WV025004	48	89	Bt2	0.59		0	0.59	1.41	3.40
S01WV063005	0	20	Ap	3.52		5	3.52	1.23	8.20
S01WV063005	20	36	BA	0.57		5	0.57	1.31	1.14
S01WV063005	36	71	Bt1	0.32		5	0.32	1.41	1.50
S01WV063005	71	107	Bt2	0.37		10	0.37	1.43	1.72
S01WV063005	107	132	Bt3	0.38		15	0.38	1.43	1.15
S01WV063005	132	155	Bt4	0.33		2	0.33	1.38	1.03
S01WV063005	155	188	C	0.28		5	0.28	1.43	1.26
S01WV063006	0	20	Ap	1.13		5	1.13	1.21	2.60
S01WV063006	20	30	BA	0.41		5	0.41	1.28	0.50
S01WV063006	30	51	Bt1	0.22		10	0.22	1.41	0.58
S01WV063006	51	97	Bt2	0.16		10	0.16	1.45	0.96
S01WV063006	97	132	Bt3	0.18		10	0.18	1.44	0.82
S01WV063006	132	155	C1	0.18		5	0.18	1.42	0.56
S01WV063006	155	191	C2	0.25		25	0.25	1.42	0.96
S01WV063007	0	13	A	2.09		5	2.09	1.04	2.68
S01WV063007	13	25	BA	0.81		2	0.81	1.27	1.21

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV063007	25	51	Bt1	0.53		0	0.53	1.38	1.90
S01WV063007	51	94	Bt2	0.54		0	0.54	1.43	3.32
S01WV063007	94	119	Bt3	0.62		0	0.62	1.41	2.19
S01WV063008	0	10	A	1.68		5	1.68	1.08	1.72
S01WV063008	10	23	AB	0.82		1	0.82	1.24	1.31
S01WV063008	23	36	BA	0.49		1	0.49	1.30	0.82
S01WV063008	36	56	Bt1	0.30		0	0.30	1.41	0.85
S01WV063008	56	79	Bt2	0.26		0	0.26	1.42	0.85
S01WV063008	79	112	Bt3	0.43		0	0.43	1.42	2.01
S01WV063008	112	140	Bt4	0.70		0	0.70	1.25	2.46
S01WV081001	0	3	Oi1	50.54		0	50.54	0.39	5.86
S01WV081001	3	5	Oi2	46.48		0	46.48	0.40	3.68
S01WV081001	5	6	Oe	22.39		15	22.39	0.94	1.79
S01WV081001	6	16	A	3.46	1.05	10	3.46	1.05	3.27
S01WV081001	16	22	A/B	2.48	1.18	5	2.48	1.18	1.67
S01WV081001	22	32	B/A	1.05	1.43	5	1.05	1.43	1.43
S01WV081001	32	59	Bt1	0.26	1.49	5	0.26	1.49	0.99
S01WV081001	59	81	Bt2	0.15	1.54	10	0.15	1.54	0.46
S01WV081001	81	105	BC	0.19	1.52	15	0.19	1.52	0.59
S01WV081002	0	1	Oi	40.02		15	40.02	0.30	1.01
S01WV081002	1	3	Oe	15.39		15	15.39	0.95	2.47
S01WV081002	3	8	A	10.83		15	10.83	1.05	4.82
S01WV081002	8	20	B/A	2.63	0.91	15	2.63	0.91	2.44

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV081002	20	30	Bw1	2.00	1.14	15	2.00	1.14	1.94
S01WV081002	30	54	Bw2	0.66	1.32	25	0.66	1.32	1.57
S01WV081002	54	65	Bw3	0.54	1.53	50	0.54	1.53	0.45
S01WV081002	65	80	BC	0.28	1.48	60	0.28	1.48	0.25
S01WV081003	0	2	Oi	43.66		0	43.66	0.33	2.88
S01WV081003	2	4	Oe	32.56		0	32.56	0.46	2.99
S01WV081003	4	13	A1	12.75		35	12.75	1.09	8.13
S01WV081003	13	23	A2	4.22	1.07	35	4.22	1.07	2.94
S01WV081003	23	33	B/A	1.24	1.26	25	1.24	1.26	1.17
S01WV081003	33	55	Bw1	0.43	1.57	25	0.43	1.57	1.11
S01WV081003	55	95	Bw2	0.33	1.56	40	0.33	1.56	1.24
S01WV081003	95	155	BC	0.23	1.31	70	0.23	1.31	0.54
S01WV081004	0	2	Oi1	45.64		0	45.64	0.35	3.20
S01WV081004	2	5	Oi2	35.52		0	35.52	0.37	3.94
S01WV081004	5	10	A	6.01		10	6.01	1.01	2.73
S01WV081004	10	17	A/B	2.30		10	2.30	1.15	1.66
S01WV081004	17	27	BA	0.90	1.31	5	0.90	1.31	1.12
S01WV081004	27	40	Bw1	0.44	1.38	10	0.44	1.38	0.71
S01WV081004	40	62	Bw2	0.19	1.50	10	0.19	1.50	0.56
S01WV081004	62	84	Bw3	0.15	1.66	20	0.15	1.66	0.44
S01WV081004	84	104	BC	0.12	1.57	30	0.12	1.57	0.26
S01WV081005	0	3	Oi1	50.28		0	50.28	0.44	6.67
S01WV081005	3	5	Oi2	40.03		0	40.03	0.45	3.63

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S01WV081005	5	7	Oe	25.23		0	25.23	1.00	5.04
S01WV081005	7	17	A	5.96	0.97	10	5.96	0.97	5.20
S01WV081005	17	30	BA	1.92	1.09	10	1.92	1.09	2.45
S01WV081005	30	59	Bw1	0.43	1.45	5	0.43	1.45	1.72
S01WV081005	59	74	Bw2	0.19	1.50	5	0.19	1.50	0.41
S01WV081005	74	110	Bx	0.07	1.53	10	0.07	1.53	0.35
S01WV081006	0	3	A	5.43		30	5.43	0.97	1.10
S01WV081006	3	12	BA	1.75	1.09	20	1.75	1.09	1.37
S01WV081006	12	27	Bw1	0.99	1.43	25	0.99	1.43	1.59
S01WV081006	27	52	Bw2	0.43	1.37	35	0.43	1.37	0.96
S01WV081006	52	70	Bw3	0.29	1.55	50	0.29	1.55	0.40
S01WV081006	70	106	BC	0.17	1.77	50	0.17	1.77	0.54
S01WV081006	106	130	C	0.24	1.41	80	0.24	1.41	0.16
S01WV081007	0	2	Oi1	50.15		0	50.15	0.33	3.27
S01WV081007	2	4	Oi2	47.47		0	47.47	0.34	3.23
S01WV081007	4	7	Oa	20.76		20	20.76	0.53	2.63
S01WV081007	7	17	BA	1.77		35	1.77	1.18	1.35
S01WV081007	17	36	Bw1	0.86	1.31	60	0.86	1.31	0.86
S01WV081007	36	67	Bw2	0.44		60	0.44	1.45	0.79
S01WV081007	67	92	C	0.16	1.53	70	0.16	1.53	0.18
S02PA031008	0	8	A1	2.60		0	2.60	1.01	2.10
S02PA031008	8	20	A2	4.94		0	4.94	1.10	6.55
S02PA031008	20	48	Bg1	1.48		0	1.48	1.19	4.94

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S02PA031008	48	71	Bg2	0.74		0	0.74	1.41	2.40
S02PA031008	71	94	BCg	0.40		0	0.40	1.53	1.41
S02PA031008	94	124	Cg	0.61		0	0.61	1.51	2.77
S02PA031008	124	165	2C	0.70		60	0.70	1.56	1.79
S02PA065004	0	3	Oe			0	40.60	0.58	7.01
S02PA065004	3	5	A	9.65		5	9.65	1.01	1.84
S02PA065004	5	20	BA	0.59		5	0.59	1.18	0.99
S02PA065004	20	43	Bt1	0.27		10	0.27	1.41	0.79
S02PA065004	43	61	Bt2	0.21		15	0.21	1.53	0.49
S02PA065004	61	142	Btx	0.25		25	0.25	1.72	2.61
S02WV019001	0	3	Oi1	41.99		0	41.99	0.36	4.57
S02WV019001	3	6	Oi2	37.20		0	37.20	0.38	4.21
S02WV019001	6	9	Oe	36.53		0	36.53	0.49	5.38
S02WV019001	9	21	A	5.15		25	5.15	1.05	4.87
S02WV019001	21	28	BA	1.76		25	1.76	1.26	1.17
S02WV019001	28	54	Bw1	0.75	1.50	30	0.75	1.50	2.05
S02WV019001	54	69	Bw2	0.56	1.30	50	0.56	1.30	0.55
S02WV019001	69	85	BC	0.46	1.63	70	0.46	1.63	0.36
S02WV019006	3	0	Oi1	47.88		0	32.17	0.49	4.48
S02WV019006	0	2	Oi2	46.78		0	47.88	0.36	3.47
S02WV019006	2	5	Oe	32.17		5	3.46	1.01	1.79
S02WV019006	5	11	A	3.46		15	1.26	1.01	0.76
S02WV019006	11	18	B/A	1.26	1.01	15	0.75	1.39	1.33

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S02WV019006	18	34	Bw1	0.75	1.39	20	0.36	1.48	0.86
S02WV019006	34	61	Bw2	0.36	1.48	40	0.24	1.56	0.46
S02WV019006	61	80	2Bw3	0.24	1.56	35	0.24	1.59	0.21
S02WV019006	80	94	2C	0.24	1.59	60	0.24	1.59	0.21
S02WV019007	0	5	A1	6.42		25	6.42	1.01	2.43
S02WV019007	5	15	A2	1.42	0.99	25	1.42	0.99	1.05
S02WV019007	15	30	B/A	0.82	1.26	20	0.82	1.26	1.24
S02WV019007	30	60	Bt1	0.29	1.49	30	0.29	1.49	0.91
S02WV019007	60	81	Bt2	0.27	1.18	40	0.27	1.18	0.40
S02WV019007	81	104	BC	0.20		50	0.20	1.45	0.33
S02WV019008	0	8	A1	3.45		20	3.45	1.03	2.28
S02WV019008	8	35	A2	1.64	1.05	20	1.64	1.05	3.72
S02WV019008	35	54	BA	0.65	1.34	40	0.65	1.34	0.99
S02WV019008	54	96	Bw4	0.61	1.48	40	0.61	1.48	2.28
S02WV019008	96	134	2Bw2	0.26	1.27	40	0.26	1.27	0.75
S02WV019008	134	190	2BC	0.34	1.06	30	0.34	1.06	1.41
S02WV019012	0	2	Oi	35.19		0	35.19	0.33	2.29
S02WV019012	2	5	A1	6.24		25	6.24	0.97	1.36
S02WV019012	5	19	A2	3.18	1.01	30	3.18	1.01	3.15
S02WV019012	19	28	BA	2.76	1.09	30	2.76	1.09	1.90
S02WV019012	28	41	Bw1	2.19	1.40	40	2.19	1.40	2.39
S02WV019012	41	56	Bw2	0.79	1.56	40	0.79	1.56	1.11
S02WV019012	56	76	Bw3	0.46	1.60	45	0.46	1.60	0.81

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S02WV019012	76	98	C	0.35	1.67	60	0.35	1.67	0.51
S02WV019013	0	18	A	4.13		30	4.13	1.06	5.50
S02WV019013	18	27	AB	1.13	1.44	30	1.13	1.44	1.03
S02WV019013	27	60	Bw1	0.67	1.41	35	0.67	1.41	2.03
S02WV019013	60	95	Bw2	0.30	1.46	40	0.30	1.46	0.92
S02WV019013	95	108	Bw3	0.22	1.51	45	0.22	1.51	0.24
S02WV019013	108	135	BC	0.21		50	0.21	1.48	0.42
S02WV019013	135	155	C	0.24		60	0.24	1.48	0.28
S02WV081002	3	0	Oi1	47.10		0	44.82	0.37	3.36
S02WV081002	0	2	Oi2	40.25		0	36.84	0.48	3.52
S02WV081002	2	4	Oe	36.84		0	47.10	0.36	3.38
S02WV081002	4	9	A1	5.33		0	5.33	1.12	2.98
S02WV081002	9	16	A2	3.44		0	3.44	1.13	2.71
S02WV081002	16	32	AB	2.13	1.06	0	2.13	1.06	3.61
S02WV081002	32	64	Bw1	0.76		0	0.76	1.47	3.57
S02WV081002	64	89	Bw2	0.61		0	0.61	1.50	2.28
S02WV081004	0	3	Oi1	48.95		0	48.95	0.38	5.53
S02WV081004	3	5	Oi2	46.98		0	46.98	0.39	3.63
S02WV081004	5	7	Oe	35.12		0	35.12	0.52	3.64
S02WV081004	7	13	A1	5.53		30	5.53	1.08	2.51
S02WV081004	13	25	A2	3.45	1.12	40	3.45	1.12	2.78
S02WV081004	25	34	BA	1.59	1.34	40	1.59	1.34	1.15
S02WV081004	34	76	Bw1	0.65	1.51	45	0.65	1.51	2.27

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S02WV081004	76	123	Bw2	0.35	1.59	50	0.35	1.59	1.31
S02WV081004	123	143	BC	0.55	1.54	60	0.59	1.54	0.46
S02WV081004	143	168	C	0.59		80	0.55	1.54	0.68
S02WV081005	0	4	Oi1	50.01		0	50.01	0.35	7.10
S02WV081005	4	6	Oi2	44.82		0	44.82	0.37	3.36
S02WV081005	6	12	Oe	48.12		0	48.12	0.51	14.76
S02WV081005	12	15	Oa/A	14.87		0	14.87	1.13	5.03
S02WV081005	15	22	A/E	2.40	1.19	0	2.40	1.19	2.00
S02WV081005	22	44	Bw1	0.91	0.84	0	0.91	0.84	1.68
S02WV081005	44	74	Bw2	0.59		0	0.59	1.49	2.64
S02WV081005	74	96	2BC	0.37		0	0.37	1.49	1.22
S02WV081005	96	112	2C	0.37		0	0.37	1.47	0.87
S03WV025001	0	1	Oi	37.36		0	37.36	1.06	3.95
S03WV025001	1	2	Oe	35.38		0	35.38	0.52	1.84
S03WV025001	2	5	A	4.44		5	4.44	1.07	1.36
S03WV025001	5	16	BA	1.49	1.41	5	1.49	1.41	2.20
S03WV025001	16	28	Bt1	1.08	1.48	5	1.08	1.48	1.82
S03WV025001	28	53	Bt2	0.65	1.42	5	0.65	1.42	2.19
S03WV025001	53	78	Bt3	0.45	1.52	15	0.45	1.52	1.45
S03WV025001	78	99	BC	0.23	1.61	15	0.23	1.61	0.66
S03WV025001	99	115	C	0.19		30	0.19	1.55	0.33
S03WV025002	0	2	Oi1	46.68		0	46.68	1.00	9.33
S03WV025002	2	3	Oi2	30.32		0	30.32	0.36	1.11

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV025002	3	9	A	5.49		5	5.49	1.12	3.49
S03WV025002	9	14	AB	2.86		5	2.86	1.32	1.79
S03WV025002	14	19	BA	1.68		5	1.68	1.29	1.03
S03WV025002	19	42	Bt1	0.72	1.53	15	0.72	1.53	2.15
S03WV025002	42	73	Bt2	0.45	1.62	25	0.45	1.62	1.69
S03WV025002	73	93	Bt3	0.19	1.68	30	0.19	1.68	0.45
S03WV025002	93	160	BC	0.24	1.67	60	0.24	1.67	1.07
S03WV071001	0	2	Oi	40.54		0	40.54	0.33	2.65
S03WV071001	2	4	Oe	30.76		0	10.39	1.04	2.60
S03WV071001	4	7	Oa/A	10.39		20	5.24	1.24	1.56
S03WV071001	7	10	AB	5.24		20	2.77	1.40	2.80
S03WV071001	10	19	Bt1/A	2.77		20	1.79	1.40	5.21
S03WV071001	19	45	Bt2	1.79	1.40	20	1.64	1.72	4.29
S03WV071001	45	64	Bt3	1.64	1.72	20	0.36	1.62	1.19
S03WV071001	64	98	Bt4	0.36	1.62	40	0.16	1.82	0.38
S03WV071001	98	120	Bt5	0.16	1.82	40	0.11	1.86	0.39
S03WV071001	120	155	BCt	0.11	1.86	45	30.76	0.48	2.97
S03WV075001	0	2	Oi	47.65		0	47.65	0.32	3.07
S03WV075001	2	12	A	10.10		20	10.10	0.95	7.65
S03WV075001	12	26	AB	5.65		20	5.65	1.22	7.70
S03WV075001	26	40	Bt1	0.84	1.21	20	0.84	1.21	1.14
S03WV075001	40	77	Bt2	0.79	1.32	25	0.79	1.32	2.89
S03WV075001	77	100	BC	0.40		50	0.40	1.44	0.66

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV077001	0	1	Oi	42.56		0	42.56	0.27	1.17
S03WV077001	1	2	Oe	35.80		0	35.80	0.40	1.42
S03WV077001	2	10	Oa/A	7.06		25	7.06	1.00	4.22
S03WV077001	10	20	BA	2.42		40	2.42	1.16	1.68
S03WV077001	20	35	Bt1	0.92		55	0.92	1.30	0.81
S03WV077001	35	60	Bt2	0.66		60	0.66	1.33	0.87
S03WV077001	60	72	CB	0.58		80	0.58	1.34	0.19
S03WV081001	0	11	A	2.80		15	2.80	1.27	3.32
S03WV081001	11	30	BA	0.59	1.43	20	0.59	1.43	1.28
S03WV081001	30	61	Bw1	0.54	1.52	20	0.54	1.52	2.04
S03WV081001	61	98	Bw2	0.51	1.58	25	0.51	1.58	2.24
S03WV081001	98	137	Bw3	0.46	1.49	25	0.46	1.49	2.00
S03WV081001	137	160	BC	0.52	1.54	35	0.52	1.54	1.20
S03WV081002	0	3	Oa/A	10.97		30	10.97	1.09	2.51
S03WV081002	3	16	A	6.39	1.07	30	6.39	1.07	6.22
S03WV081002	16	25	BA	2.23	1.22	40	2.23	1.22	1.47
S03WV081002	25	46	Bw1	1.01	1.57	35	1.01	1.57	2.16
S03WV081002	46	82	Bw2	0.84	1.45	65	0.84	1.45	1.53
S03WV083001	0	2	Oi	40.36		0	40.36	0.30	2.40
S03WV083001	2	10	A	7.26		20	7.26	0.96	4.44
S03WV083001	10	15	AB	2.11		20	2.11	1.20	1.02
S03WV083001	15	28	BA	0.83	1.20	20	0.83	1.20	1.04
S03WV083001	28	75	Bt1	0.43	1.41	30	0.43	1.41	1.99

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV083001	75	110	Bt2	0.25	1.51	45	0.25	1.51	0.73
S03WV083001	110	160	C	0.15	1.62	70	0.15	1.62	0.36
S03WV083002	0	3	Oa/A	13.57		40	13.57	0.91	2.21
S03WV083002	3	13	E	1.78		40	1.78	1.20	1.28
S03WV083002	13	26	BE	1.02		40	1.02	1.23	0.98
S03WV083002	26	49	Bt1	0.63	1.28	30	0.63	1.28	1.30
S03WV083002	49	57	Bt2	0.51	1.46	35	0.51	1.46	0.39
S03WV083002	57	77	BC	0.38	1.47	40	0.38	1.47	0.67
S03WV083002	77	95	C	0.28	1.45	65	0.28	1.45	0.26
S03WV083003	0	2	Oi			3	42.17	0.27	2.24
S03WV083003	2	3	Oe	37.32		3	37.32	0.43	1.56
S03WV083003	3	18	A	5.95		25	5.95	1.01	6.76
S03WV083003	18	26	BA	1.15	1.34	25	1.15	1.34	0.92
S03WV083003	26	39	Bt1	0.51	1.48	25	0.51	1.48	0.74
S03WV083003	39	69	Bt2	0.54	1.50	35	0.54	1.50	1.58
S03WV083003	69	97	BC	0.61	1.65	50	0.61	1.65	1.41
S03WV083004	0	2	Oi	24.55		0	24.55	0.23	1.15
S03WV083004	2	11	A	6.38		40	6.38	1.01	3.49
S03WV083004	11	20	BA	2.55		40	2.55	1.21	1.67
S03WV083004	20	36	Bt1	1.84		25	1.84	1.30	2.86
S03WV083004	36	59	2Bt2	1.21	1.20	35	1.21	1.20	2.17
S03WV083004	59	79	2Bt3	0.76	1.38	45	0.76	1.38	1.15
S03WV083004	79	99	2C	0.55		80	0.55	1.41	0.31

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV083005	0	1	Oi	34.77		0	34.77	0.25	0.85
S03WV083005	1	6	A	9.95		15	9.95	0.98	4.13
S03WV083005	6	10	AE	3.96		10	3.96	1.16	1.65
S03WV083005	10	35	BE	2.10	1.31	20	2.10	1.31	5.50
S03WV083005	36	60	Bw1	0.43	1.54	30	0.43	1.54	1.11
S03WV083005	60	95	Bw2	0.18	1.55	45	0.18	1.55	0.54
S03WV083005	95	130	2BC	0.12	1.74	60	0.12	1.74	0.29
S03WV083005	130	170	2C	0.13		60	0.13	1.53	0.32
S03WV083006	0	1	Oi	49.64		0	49.64	0.25	1.23
S03WV083006	1	2	Oe	42.38		0	42.38	0.43	1.82
S03WV083006	2	5	A	8.66		20	8.66	0.94	1.95
S03WV083006	5	13	E	3.57		25	3.57	1.17	2.51
S03WV083006	13	35	BE	1.57		25	1.57	1.26	3.27
S03WV083006	35	52	Bt1	0.62	1.42	35	0.62	1.42	0.97
S03WV083006	52	68	Bt2	0.47	1.48	40	0.47	1.48	0.67
S03WV083006	68	80	Bt3	0.23	1.56	50	0.23	1.56	0.22
S03WV083006	80	104	BC	0.17	1.65	40	0.17	1.65	0.40
S03WV083007	0	8	A	6.79		15	6.79	1.01	4.67
S03WV083007	8	28	BA	1.44	1.10	15	1.44	1.10	2.69
S03WV083007	28	65	Bw	0.36	1.21	20	0.36	1.21	1.29
S03WV083007	65	80	2Bt1	0.24	1.52	30	0.24	1.52	0.38
S03WV083007	80	103	2Bt2	0.11	1.60	30	0.11	1.60	0.28
S03WV083007	103	125	2Bt3	0.11	1.57	50	0.11	1.57	0.19

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV083007	125	150	2BCx	0.07	1.59	65	0.07	1.59	0.10
S03WV083008	0	11	A	5.91		30	5.91	1.07	4.88
S03WV083008	11	22	BA	2.19		20	2.19	1.31	2.52
S03WV083008	22	52	Bt1	0.52	1.59	30	0.52	1.59	1.74
S03WV083008	52	75	Bt2	0.17	1.63	20	0.17	1.63	0.51
S03WV083008	75	98	Bt3	0.12	1.63	20	0.12	1.63	0.36
S03WV083008	98	110	BCt	0.17	1.61	35	0.17	1.61	0.21
S03WV089001	0	1	Oi	38.13		0	38.13	1.05	3.99
S03WV089001	1	12	A	3.10	1.17	10	3.10	1.17	3.59
S03WV089001	12	27	BA	1.13	1.41	10	1.13	1.41	2.15
S03WV089001	27	53	Bw1	0.56	1.48	10	0.56	1.48	1.94
S03WV089001	53	93	Bw2	0.31	1.56	20	0.31	1.56	1.55
S03WV089001	93	146	Bw3	0.14	1.70	35	0.14	1.70	0.82
S03WV089001	146	165	BC	0.14	1.64	45	0.14	1.64	0.24
S03WV089002	0	3	Oi	46.44		0	46.44	1.02	14.18
S03WV089002	3	16	A	2.07	1.21	10	2.07	1.21	2.93
S03WV089002	16	34	BA	0.98	1.44	10	0.98	1.44	2.29
S03WV089002	34	67	Bt1	0.34	1.58	15	0.34	1.58	1.51
S03WV089002	67	101	Bt2	0.32	1.51	30	0.32	1.51	1.15
S03WV089002	101	122	C	0.31		50	0.31	1.56	0.51
S03WV089003	0	10	A	3.73	1.36	5	3.73	1.36	4.82
S03WV089003	10	16	AB	2.36	1.40	5	2.36	1.40	1.88
S03WV089003	16	25	BA	1.76		15	1.76	1.34	1.81

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV089003	25	48	Bt1	0.36	1.69	25	0.36	1.69	1.05
S03WV089003	48	66	Bt2	0.19	1.68	20	0.19	1.68	0.46
S03WV089003	66	90	BC	0.28	1.63	35	0.28	1.63	0.71
S03WV089004	0	2	Oi	40.50		0	40.50	1.10	8.93
S03WV089004	2	4	Oe	20.99		0	5.15	1.19	1.66
S03WV089004	4	7	A	5.15		10	2.33	1.39	1.75
S03WV089004	7	13	AE	2.33		10	1.25	1.55	1.74
S03WV089004	13	23	BE	1.25	1.55	10	0.69	1.40	1.83
S03WV089004	23	44	Bt1	0.69	1.40	10	0.20	1.63	0.97
S03WV089004	44	77	Bt2	0.20	1.63	10	0.12	1.64	0.55
S03WV089004	77	112	Bt3	0.12	1.64	20	0.09	1.62	0.26
S03WV089004	112	137	2Bt4	0.09	1.62	30	0.07	1.58	0.15
S03WV089004	137	160	2BCt	0.07	1.58	40	20.99	1.05	4.40
S03WV089005	0	10	A1	5.06		20	5.06	1.27	5.16
S03WV089005	10	24	A2	2.60		20	2.60	1.31	3.81
S03WV089005	24	38	BA	1.17	1.27	20	1.17	1.27	1.66
S03WV089005	38	61	Bw1	0.63	1.56	20	0.63	1.56	1.81
S03WV089005	61	106	Bw2	0.57	1.47	35	0.57	1.47	2.45
S03WV089005	106	160	2Bt	0.44	1.55	55	0.44	1.55	1.66
S03WV089006	0	9	A	3.08	1.04	22	3.08	1.04	2.25
S03WV089006	9	21	Bt1	0.79	1.46	38	0.79	1.46	0.86
S03WV089006	21	53	Bt2	0.42	1.49	32	0.42	1.49	1.36
S03WV089006	53	75	Bt3	0.38	1.54	10	0.38	1.54	1.16

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV089006	75	92	Bt4	0.35	1.58	21	0.35	1.58	0.74
S03WV089007	0	6	A	7.80		15	7.80	1.14	4.55
S03WV089007	6	18	BE	1.87		15	1.87	1.36	2.59
S03WV089007	18	45	Bt1	0.42	1.61	15	0.42	1.61	1.55
S03WV089007	45	70	Bt2	0.35	1.66	15	0.35	1.66	1.23
S03WV089007	70	110	2Bt3	0.36	1.44	25	0.36	1.44	1.56
S03WV089007	110	150	2Bt4	0.22	1.63	45	0.22	1.63	0.79
S03WV093001	0	1	Oi	42.93		0	42.93	0.29	1.26
S03WV093001	1	2	Oe	35.39		0	35.39	0.43	1.54
S03WV093001	2	10	A	5.26	0.92	20	5.26	0.92	3.10
S03WV093001	10	20	BA	1.73	1.52	20	1.73	1.52	2.10
S03WV093001	20	35	Bt1	0.49	1.54	35	0.49	1.54	0.74
S03WV093001	35	60	Bt2	0.20	1.55	40	0.20	1.55	0.47
S03WV093001	60	72	BC	0.22	1.59	60	0.22	1.59	0.17
S03WV093002	0	2	Oi	41.21		0	41.21	0.37	3.03
S03WV093002	2	23	A	5.65		25	5.65	1.11	9.85
S03WV093002	23	35	BA	2.83		30	2.83	1.23	2.93
S03WV093002	35	47	Bw1	1.82		45	1.82	1.35	1.62
S03WV093002	47	80	Bw2	0.68		45	0.68	1.41	1.75
S03WV093002	80	130	Bw3	0.31	1.49	55	0.31	1.49	1.04
S03WV093002	130	160	BC	0.25		70	0.25	1.52	0.34
S03WV101001	0	1	Oi	42.11		0	42.11	1.05	4.42
S03WV101001	1	3	Oa	20.49		25	20.49	1.12	3.45

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S03WV101001	3	10	A	2.91		25	2.91	1.23	1.88
S03WV101001	10	25	BA	0.89	1.52	30	0.89	1.52	1.42
S03WV101001	25	48	Bw1	0.59	1.58	25	0.59	1.58	1.61
S03WV101001	48	109	Bw2	0.48	1.64	30	0.48	1.64	3.36
S03WV101001	109	148	Bw3	0.47	1.55	40	0.47	1.55	1.70
S03WV101001	148	170	2BCt	0.19	1.62	60	0.19	1.62	0.27
S03WV101002	0	2	Oi	41.70		0	41.70	0.97	8.10
S03WV101002	2	12	A	5.92		15	5.92	1.16	5.86
S03WV101002	12	37	Bt1	0.81	1.53	15	0.81	1.53	2.63
S03WV101002	37	67	Bt2	0.60	1.67	20	0.60	1.67	2.40
S04WV001002	0	2	Oi	51.56		0	51.56	0.31	3.17
S04WV001002	2	5	A	11.06		0	11.06	0.97	3.21
S04WV001002	5	16	BA	1.28		5	1.28	1.15	1.54
S04WV001002	16	32	Bt1	1.16		10	1.16	1.40	2.34
S04WV001002	32	55	Bt2	0.55		10	0.55	1.47	1.67
S04WV001002	55	75	Bt3	0.52		30	0.52	1.54	1.12
S04WV093001	0	1	Oi	40.47		0	40.47	0.39	1.56
S04WV093001	1	2	Oe	48.85		0	48.85	0.59	2.90
S04WV093001	2	5	A	9.83		20	9.83	1.03	2.42
S04WV093001	5	19	Bt1	1.58	1.59	20	1.58	1.59	2.81
S04WV093001	19	38	Bt2	2.20	1.45	20	2.20	1.45	4.85
S04WV093001	38	55	Bt3	1.28	1.56	20	1.28	1.56	2.72
S04WV093001	55	71	BC	1.23	1.74	40	1.23	1.74	2.05

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S04WV093001	71	96	C1	1.28	1.57	53	1.28	1.57	2.36
S04WV093001	96	109	C2	0.66		80	0.66	1.51	0.26
S04WV093002	0	2	Oi	46.47		0	46.47	0.38	3.50
S04WV093002	2	4	Oe	26.85		0	26.85	0.49	2.65
S04WV093002	4	12	A	6.75		0	6.75	1.08	5.84
S04WV093002	12	22	BA	2.91		0	2.91	1.23	3.59
S04WV093002	22	43	Bw	1.42	1.44	0	1.42	1.44	4.29
S04WV093002	43	75	2Btx1	0.84	1.73	15	0.84	1.73	3.95
S04WV093002	75	117	2Btx2	0.55	1.80	17	0.55	1.80	3.45
S04WV093002	117	140	3BC	0.75	1.60	12	0.75	1.60	2.43
S04WV093002	140	160	3C	0.98	1.58	25	0.98	1.58	2.32
S04WV093003	0	3	Oi			0	40.76	0.36	4.41
S04WV093003	3	23	Ap	4.49		0	4.49	1.06	9.55
S04WV093003	23	33	Bg	0.75		40	0.75	1.26	0.57
S04WV093003	33	72	Btg	0.41		0	0.41	1.48	2.37
S04WV093003	72	110	Bt	0.39		0	0.39	1.47	2.17
S04WV093003	110	151	C1	1.03		10	1.03	1.54	5.86
S04WV093003	151	164	2C2	0.62		0	0.62	1.50	1.21
S04WV093003	164	183	2C3	0.30		0	0.30	1.54	0.88
S04WV093004	0	6	Oe1	32.72		0	32.72	0.58	11.30
S04WV093004	6	9	Oe2	14.44		0	14.44	0.96	4.16
S04WV093004	9	14	A	4.29		3	4.29	1.05	2.18
S04WV093004	14	21	AE	1.17		3	1.17	1.40	1.12

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S04WV093004	21	44	Bt	0.89		5	0.89	1.34	2.60
S04WV093004	44	82	Btg	0.84		15	0.84	1.48	4.01
S04WV093004	82	125	Btx	0.62		25	0.62	1.58	3.17
S04WV093005	0	2	Oi	49.93		0	49.93	0.37	3.67
S04WV093005	2	4	Oe	47.74		0	47.74	0.98	9.32
S04WV093005	4	9	Oa	20.52		0	20.52	0.53	5.48
S04WV093005	9	21	E/A	2.03	1.52	2	2.03	1.52	3.63
S04WV093005	21	42	Bw1	0.45	1.69	2	0.45	1.69	1.57
S04WV093005	42	67	Bw2	0.34	1.76	5	0.34	1.76	1.42
S04WV093005	67	121	Bx	0.27	2.00	5	0.27	2.00	2.77
S04WV093005	121	165	BCt	0.35	1.90	3	0.35	1.90	2.84
S04WV093006	0	2	Oi	48.80		0	48.80	0.28	2.77
S04WV093006	2	3	Oe	40.87		0	40.87	0.41	1.68
S04WV093006	3	10	A	6.84	0.90	5	6.84	0.90	4.09
S04WV093006	10	16	A/B	2.30	1.22	5	2.30	1.22	1.60
S04WV093006	16	38	Bt1	1.99	1.24	5	1.99	1.24	5.16
S04WV093006	38	51	Bt2	0.95	1.64	15	0.95	1.64	1.72
S04WV093006	51	70	BC	0.30	1.80	20	0.30	1.80	0.82
S04WV093007	0	4	Oi	35.40		0	35.40	0.30	4.25
S04WV093007	4	11	A	4.10		10	4.10	1.00	2.58
S04WV093007	11	16	E	4.69		16	4.69	1.32	2.59
S04WV093007	16	27	BE	1.71	1.44	20	1.71	1.44	2.17
S04WV093007	27	41	Bs1	1.94		28	1.94	1.23	2.41

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S04WV093007	41	67	Bs2	1.71	1.16	33	1.71	1.16	3.46
S04WV093007	67	95	Bw1	1.39	1.24	33	1.39	1.24	3.23
S04WV093007	95	122	Bw2	0.38	1.51	60	0.38	1.51	0.62
S04WV093007	122	147	2CB	0.33	1.76	55	0.33	1.76	0.65
S04WV093008	0	1	Oi	41.59		0	41.59	0.33	1.38
S04WV093008	1	2	Oe	29.44		0	9.56	1.08	2.79
S04WV093008	2	5	A	9.56		10	3.51	1.17	2.58
S04WV093008	5	12	A/B	3.51		10	2.70	1.20	3.69
S04WV093008	12	24	BA	2.70		5	1.72	1.41	4.61
S04WV093008	24	44	Bt1	1.72	1.41	5	0.25	1.73	0.53
S04WV093008	44	57	Bt2	0.25	1.73	5	0.18	1.76	0.86
S04WV093008	57	87	Btx1	0.18	1.76	10	0.16	1.73	0.82
S04WV093008	87	118	Btx2	0.16	1.73	5	0.21	1.49	0.03
S04WV093008	118	119	2Bt	0.21	1.49	5	29.44	0.46	1.36
S06WV019001	0	2	Oi	41.19		0	41.19	0.43	3.53
S06WV019001	2	8	A	3.28		15	3.28	0.99	1.65
S06WV019001	8	18	BA	1.24		15	1.24	1.19	1.26
S06WV019001	18	53	Bt1	0.29	1.60	10	0.29	1.60	1.46
S06WV019001	53	69	Bt2	0.16	1.67	15	0.16	1.67	0.36
S06WV019001	69	104	2Bt3	0.20	1.65	15	0.20	1.65	0.98
S06WV019001	104	141	3Bx	0.13	1.70	25	0.13	1.70	0.61
S06WV019001	141	165	3BC	0.12	1.67	40	0.12	1.67	0.29
S06WV019001	165	200	4C	0.12	1.66	55	0.12	1.66	0.31

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV019002	0	3	Oi	42.63		0	42.63	0.46	5.85
S06WV019002	3	12	A	4.20	0.97	0	4.20	0.97	3.67
S06WV019002	12	25	AE	1.08	1.40	0	1.08	1.40	1.97
S06WV019002	25	60	BE	0.23	1.65	0	0.23	1.65	1.33
S06WV019002	60	78	Btx1	0.08	1.64	0	0.08	1.64	0.24
S06WV019002	78	121	Btx2	0.08	1.57	0	0.08	1.57	0.54
S06WV019002	121	193	2Btg	0.11	1.57	0	0.11	1.57	1.24
S06WV019004	0	2	Oi	48.67		0	48.67	0.41	3.98
S06WV019004	2	9	Oa/A	5.72		10	5.72	1.00	3.61
S06WV019004	9	19	A/B	2.55		10	2.55	1.19	2.72
S06WV019004	19	35	Bt1	0.44	1.45	10	0.44	1.45	0.92
S06WV019004	35	80	Bt2	0.35	1.47	10	0.35	1.47	2.08
S06WV019004	80	112	Bt3	0.40	1.37	30	0.40	1.37	1.23
S06WV019004	112	122	2Bt4	0.21	1.57	30	0.21	1.57	0.23
S06WV019004	122	180	2Btx	0.15	1.68	40	0.15	1.68	0.88
S06WV019005	0	2	Oi	51.63		0	51.63	0.37	3.84
S06WV019005	2	4	Oe	43.63		0	43.63	0.52	4.49
S06WV019005	4	10	A	4.94		5	4.94	0.98	2.76
S06WV019005	10	17	B/A	2.19		5	2.19	1.22	1.78
S06WV019005	17	35	Bt1	0.70	1.45	10	0.70	1.45	1.64
S06WV019005	35	60	Bt2	0.47	1.44	40	0.47	1.44	1.02
S06WV019005	60	69	C	0.49		70	0.49	1.45	0.19
S06WV025001	0	2	Oi	50.48		0	50.48	0.36	3.67

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV025001	2	4	Oe	35.87		0	35.87	0.49	3.54
S06WV025001	4	7	Oa/A	21.53		0	21.53	0.55	3.57
S06WV025001	7	19	AE	1.46	1.35	0	1.46	1.35	2.37
S06WV025001	19	53	Bt1	0.39	1.60	0	0.39	1.60	2.12
S06WV025001	53	62	Bt2	0.15	1.69	0	0.15	1.69	0.23
S06WV025001	62	105	Btx	0.07	1.74	0	0.07	1.74	0.52
S06WV025001	105	130	C	0.08	1.72	0	0.08	1.72	0.34
S06WV067001	0	1	Oi			0	0.35	1.45	0.23
S06WV067001	1	6	A	3.81	1.03	5	46.49	0.39	1.82
S06WV067001	6	26	ABp	2.03	1.27	5	3.81	1.03	1.86
S06WV067001	26	38	BA	1.09	1.43	10	2.03	1.27	4.90
S06WV067001	38	60	Bt1	0.51	1.35	15	1.09	1.43	1.68
S06WV067001	60	80	Bt2	0.33	1.38	20	0.51	1.35	1.29
S06WV067001	80	89	BC	0.35	1.45	50	0.33	1.38	0.73
S06WV067002	0	3	Oi	51.58		0	51.58	0.43	6.66
S06WV067002	3	5	Oe	38.73		0	38.73	0.56	4.36
S06WV067002	5	7	Oa	41.74		0	41.74	0.62	5.20
S06WV067002	7	10	A	11.86		0	11.86	0.98	3.48
S06WV067002	10	25	BA	3.41	1.01	5	3.41	1.01	4.91
S06WV067002	25	44	Bt1	0.63	1.35	5	0.63	1.35	1.54
S06WV067002	44	66	Bt2	0.26	1.46	5	0.26	1.46	0.79
S06WV067002	66	79	Bt3	0.20	1.50	0	0.20	1.50	0.39
S06WV067002	79	100	Cr	0.20		17	0.20	1.51	0.53

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV067003	0	2	Oi	51.78		0	51.78	0.42	4.37
S06WV067003	2	13	A	6.59		17	6.59	1.02	6.13
S06WV067003	13	35	BA	2.53	0.96	45	2.53	0.96	2.94
S06WV067003	35	81	Bt1	0.15	1.64	45	0.15	1.64	0.62
S06WV067003	81	175	Bt2	0.13	1.45	70	0.13	1.45	0.53
S06WV067003	175	193	Btx	0.12	1.46	0	0.12	1.46	0.32
S06WV067003	193	194	C	0.10	1.45	0	0.10	1.45	0.10
S06WV067004	0	2	Oi	51.41		0	51.41	0.43	4.43
S06WV067004	2	3	Oe	46.27		0	46.27	0.59	2.73
S06WV067004	3	8	A	11.00	0.77	20	11.00	0.77	3.39
S06WV067004	8	16	BA	2.69	1.18	40	2.69	1.18	1.52
S06WV067004	16	34	Bt1	0.95	1.26	40	0.95	1.26	1.29
S06WV067004	34	60	Bt2	0.52	1.50	0	0.52	1.50	2.03
S06WV067004	60	87	Btg1	0.24	1.58	0	0.24	1.58	1.02
S06WV067004	87	108	Btg2	0.07	1.71	15	0.07	1.71	0.21
S06WV067005	0	2	Oi	50.27		0	50.27	0.46	4.61
S06WV067005	190	320	2Btx4	0.15		40	41.27	0.61	2.50
S06WV067005	320	400	3Btx5	0.11		40	6.20	1.04	1.46
S06WV067005	2	3	Oe	41.27		0	1.17	1.21	0.40
S06WV067005	3	8	A	6.20		55	0.30	1.51	0.90
S06WV067005	8	12	BA	1.17		30	0.19	1.52	1.54
S06WV067005	12	33	Bt1	0.30	1.51	5	0.12	1.76	0.71
S06WV067005	33	89	Bt2	0.19	1.52	5	0.15	1.54	0.17

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV067005	89	141	Btx1	0.12	1.76	35	0.15	1.56	0.58
S06WV067005	141	152	2Btx2	0.15	1.54	35	0.15	1.58	1.85
S06WV067005	152	190	2Btx3	0.15	1.56	35	0.11	1.58	0.83
S06WV067006	0	3	Oi	48.10		0	48.10	0.40	5.83
S06WV067006	3	4	Oe	36.05		0	36.05	0.54	1.93
S06WV067006	4	11	A	7.52		5	7.52	1.00	5.02
S06WV067006	11	28	BA	0.52	1.44	15	0.52	1.44	1.08
S06WV067006	28	50	Bt1	0.34	1.43	20	0.34	1.43	0.86
S06WV067006	50	63	Bt2	0.28	1.44	40	0.28	1.44	0.31
S06WV067006	63	84	BC	0.28	1.42	60	0.28	1.42	0.33
S06WV081001	0	2	Oi	49.63		0	49.63	0.41	4.10
S06WV081001	125	148	B/C	0.08		0	29.92	0.55	1.65
S06WV081001	2	3	Oe	29.92		0	12.74	1.04	5.31
S06WV081001	3	7	Oa/A	12.74		0	2.00	1.21	1.45
S06WV081001	7	13	AE	2.00	1.21	0	0.55	1.32	1.09
S06WV081001	13	28	BE	0.55	1.32	0	0.23	1.48	0.89
S06WV081001	28	54	Bt1	0.23	1.48	0	0.12	1.70	0.49
S06WV081001	54	78	Bt2	0.12	1.70	0	0.08	1.71	0.22
S06WV081001	78	94	Btx1	0.08	1.71	0	0.07	1.81	0.39
S06WV081001	94	125	Btx2	0.07	1.81	0	0.08	1.67	0.31
S06WV101001	0	2	Oi1	50.65		0	50.65	0.35	3.59
S06WV101001	2	3	Oi2	47.60		0	47.60	0.37	1.74
S06WV101001	3	9	A	4.55		0	4.55	0.93	2.55

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S06WV101001	9	15	BA	2.16	1.11	0	2.16	1.11	1.44
S06WV101001	15	47	Bt1	0.49	1.41	27	0.49	1.41	1.61
S06WV101001	47	64	Bt2	0.24	1.30	32	0.24	1.30	0.36
S06WV101001	64	82	Bt3	0.21	1.46	70	0.21	1.46	0.17
S06WV101001	82	91	BC	0.16	1.60	25	0.16	1.60	0.17
S06WV101001	91	135	C	0.20	1.25	70	0.20	1.25	0.33
S06WV101002	0	2	Oi	52.37		0	52.37	0.42	4.40
S06WV101002	2	4	Oe	46.00		0	46.00	0.56	5.18
S06WV101002	4	16	A	4.27	1.05	20	4.27	1.05	4.30
S06WV101002	16	25	BA	1.74		20	1.74	1.21	1.51
S06WV101002	25	40	Bt1	0.74		20	0.74	1.42	1.26
S06WV101002	40	56	Bt2	0.36	1.56	45	0.36	1.56	0.49
S06WV101002	56	72	Bt3	0.31		35	0.31	1.49	0.48
S09WV167500	0	3	Oi	36.88		0	36.88	0.49	5.47
S09WV167500	3	7	A	6.27		5	6.27	0.97	2.32
S09WV167500	7	15	AE	1.29	1.28	10	1.29	1.28	1.19
S09WV167500	15	47	Bt1	0.43	1.49	10	0.43	1.49	1.85
S09WV167500	47	66	Bt2	0.49	1.59	10	0.49	1.59	1.33
S09WV167500	66	102	Btx	0.62	1.85	10	0.62	1.85	3.72
S09WV167510	0	3	Oi	53.66		0	53.66	0.54	8.69
S09WV167510	3	6	Oe	47.77		0	47.77	0.60	8.58
S09WV167510	6	10	Oa/A	34.63		5	34.63	1.03	13.59
S09WV167510	10	24	BE	1.43	1.30	12	1.43	1.30	2.29

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S09WV167510	24	37	Bt1	0.46	1.51	12	0.46	1.51	0.79
S09WV167510	37	59	Bt2	0.33	1.49	12	0.33	1.49	0.95
S09WV167510	59	80	Btx1	0.16	1.78	12	0.16	1.78	0.53
S09WV167510	80	117	Btx2	0.08	1.84	12	0.08	1.84	0.48
S09WV167515	0	3	Oi	53.00		0	53.00	0.57	9.05
S09WV167515	3	6	Oe	51.94		0	51.94	0.62	9.72
S09WV167515	6	10	A	10.93		0	10.93	1.04	4.53
S09WV167515	10	17	BE	2.93	1.05	0	2.93	1.05	2.15
S09WV167515	17	25	Bt1	2.18	1.26	0	2.18	1.26	2.20
S09WV167515	25	52	Bt2	0.42	1.55	2	0.42	1.55	1.72
S09WV167515	52	72	Btx1	0.14	1.76	3	0.14	1.76	0.48
S09WV167515	72	116	Btx2	0.12	1.63	15	0.12	1.63	0.73
S09WV167515	116	150	Btx3	0.15	1.66	5	0.15	1.66	0.80
S09WV167530	0	3	Oi	30.84		0	30.84	0.49	4.50
S09WV167530	3	8	A	8.37		2	8.37	1.13	4.65
S09WV167530	8	17	BA	1.93	1.28	2	1.93	1.28	2.18
S09WV167530	17	33	Bt1	0.50	1.61	5	0.50	1.61	1.22
S09WV167530	33	58	Bt2	0.33	1.46	8	0.33	1.46	1.11
S09WV167530	58	72	Btx1	0.33	1.50	8	0.33	1.50	0.64
S09WV167530	72	96	Btx2	0.36	1.42	10	0.36	1.42	1.10
S09WV167530	96	123	Btx3	0.35	1.73	10	0.35	1.73	1.47
S09WV167530	123	150	Btx4	0.22	1.62	10	0.22	1.62	0.87
S09WV167540	0	6	Oi	31.12		0	31.12	0.41	7.69

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S09WV167540	6	14	A	8.17		2	8.17	1.15	7.37
S09WV167540	14	22	BA	2.23	1.19	2	2.23	1.19	2.08
S09WV167540	22	50	Bw1	0.49	1.47	5	0.49	1.47	1.92
S09WV167540	50	60	Bw2	0.35	1.41	15	0.35	1.41	0.42
S09WV167540	60	68	BC	0.28	1.58	15	0.28	1.58	0.30
S12WV071001	0	3	Oi	40.17	0.31		40.17	0.31	3.74
S12WV071001	3	7	A	12.81	1.20	20	12.81	1.20	4.92
S12WV071001	7	13	Bhs	5.52	1.53	20	5.52	1.53	4.05
S12WV071001	13	34	Bs1	1.43	1.15	40	1.43	1.15	2.07
S12WV071001	34	58	Bs2	1.30	1.12	32	1.30	1.12	2.38
S12WV071001	58	75	BC	0.70	0.16	55	0.70	0.16	0.09
S12WV075001	0	1	Oi	33.46	0.22		33.46	0.22	0.74
S12WV075001	1	2	Oe	30.67	0.93		30.67	0.93	2.85
S12WV075001	2	7	A1	15.25	1.06	5	15.25	1.06	7.68
S12WV075001	7	13	A2	8.93	1.19	10	8.93	1.19	5.74
S12WV075001	13	26	BE	1.96	1.07	12	1.96	1.07	2.40
S12WV075001	26	55	Bs	1.72		20	1.72	1.15	4.58
S12WV075001	55	92	BC	0.32		45	0.32	1.44	0.94
S12WV075001	92	113	C	0.25		65	0.25	1.43	0.26
S12WV075002	0	2	Oi	54.33	0.18		54.33	0.18	1.96
S12WV075002	2	5	Oe	54.52	0.43		54.52	0.43	7.03
S12WV075002	5	10	Oa	47.33	0.53		47.33	0.53	12.54
S12WV075002	10	18	E	1.67	1.02	50	1.67	1.02	0.68

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley-Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S12WV075002	18	26	Bhs	4.71	1.35	40	4.71	1.35	3.05
S12WV075002	26	46	Bs	2.15	1.17	25	2.15	1.17	3.77
S12WV075002	46	68	Bw	0.16	1.56	37	0.16	1.56	0.35
S12WV075002	68	91	2BC	0.09	1.89	10	0.09	1.89	0.35
S12WV075002	91	117	2CB	0.09	1.90	25	0.09	1.90	0.33
S12WV075003	0	1	Oi	53.97	0.14		53.97	0.14	0.76
S12WV075003	1	4	Oe	47.48	0.51		47.48	0.51	7.26
S12WV075003	4	9	A/Oa	45.32	0.74	12	45.32	0.74	14.76
S12WV075003	9	18	E	2.61	0.99	20	2.61	0.99	1.86
S12WV075003	18	27	Bhs	3.88	1.87	10	3.88	1.87	5.88
S12WV075003	27	37	Bs	3.79	1.06	10	3.79	1.06	3.62
S12WV075003	37	68	Bw	2.14	1.06	20	2.14	1.06	5.63
S12WV075003	68	88	BC	0.93	1.47	50	0.93	1.47	1.37
S12WV075004	0	1	Oi	44.04	0.14		44.04	0.14	0.62
S12WV075004	1	5	Oe	35.16	0.32		35.16	0.32	4.50
S12WV075004	5	8	Oa/A	27.02	0.78	5	27.02	0.78	6.01
S12WV075004	8	15	AE	12.76	1.06	20	12.76	1.06	7.57
S12WV075004	15	46	Bs/Bhs	2.58	1.27	35	2.58	1.27	6.60
S12WV075004	46	65	BC	0.42	1.42	50	0.42	1.42	0.57
S12WV075005	0	6	Oi	57.17	0.22		57.17	0.22	7.55
S12WV075005	6	13	Oe	53.98	0.04		53.98	0.04	1.51
S12WV075005	13	23	Oa/A	36.65	0.59	3	36.65	0.59	20.97
S12WV075005	23	29	E	2.52	1.29	3	2.52	1.29	1.89

PedonID	Top Depth (cm)	Bottom Depth (cm)	Horizon	Total Carbon% (Dry Combustion, Including Converted Walkley- Black)	33kPa Bulk Density (g cm⁻³)	Fragment % by Volume	Predicted OC%	Predicted 33kPa BD (g cm⁻³)	SOC Stock (kg m⁻²)
S12WV075005	29	37	Bhs	5.76		3	5.76	1.16	5.17
S12WV075005	37	50	Bs	4.72	0.82	5	4.72	0.82	4.78
S12WV075005	50	64	Bw	1.61	1.49	30	1.61	1.49	2.35
S12WV075005	64	77	BC	0.91	1.45	50	0.91	1.45	0.86
S12WV075005	77	98	C	0.60	1.40	75	0.60	1.40	0.44
S12WV083001	0	3	Oi	49.42	0.19		49.42	0.19	2.82
S12WV083001	3	10	A	14.79	1.13	10	14.79	1.13	10.53
S12WV083001	10	26	Bs1	2.41	0.97	10	2.41	0.97	3.37
S12WV083001	26	54	Bs2	1.01	1.02	15	1.01	1.02	2.45
S12WV083001	54	76	Bw	0.32	1.46	27	0.32	1.46	0.75
S12WV083001	76	120	BC	0.21		30	0.21	1.43	0.92

Appendix C: R Code Used for Outlier Detection and Normality Testing

```
### Soil organic carbon outliers###
```

```
outoc<-read.csv('C:/R/outoc.csv', header=TRUE)
```

```
attach(outoc)
```

```
outliers=boxplot(SOC~Horizon+Texture, plot=FALSE)$out
```

```
outlieroc<-outoc[outoc$SOC %in% outliers,]
```

```
write.csv(outlieroc, "C:/R/outlieroc.csv")
```

```
### To detect outliers in the bulk density dataset, use the above code and replace SOC with BD.
```

```
###
```

```
####Normality Testing Using D'Agostino###
```

```
oc<-read.csv('C:/R/outoc.csv', header=TRUE)
```

```
attach(oc)
```

```
library(fBasics)
```

```
dagoTest(oc)
```

```
dagoTest(log(oc)) ###
```

Appendix D: R Code Used for Random Forest Models

```
####Load randomForest package####
library(randomForest)

####Divide soil organic carbon data into training and testing sets####
oc<-read.csv('C:/R/oc.csv', header=TRUE)
set.seed(1789)

alpha<-0.7 ####Percentage of training set####
inTrain<-sample(1:nrow(oc), alpha*nrow(oc))
train<-oc[inTrain,]
test<-oc[-inTrain,]

####Random forest model####
rfoc<randomForest(SOC~median+desgn+sand+silt+clay+Texture+Value+Chroma+Epipedon+D
ePTH+LandCover+Order+Age+ROCKTYPE1+ROCKTYPE2+Group+Temp+Moist+Phase+Min
eralogy+CAC+SG+GG+PS, data=train, importance=TRUE, mtry=6, ntree=1000)

####Use random forest model to predict soil organic carbon for the test data####
predict<-predict(rfoc, test)
write.csv(predict, file ="predictoc.csv")
write.csv(test, file="testoc.csv")

####Variable importance plot####
varImpPlot(rfoc, main='Average Variable Importance for Soil Organic Carbon')

####Copy and paste predicted values into the test dataset and then bring the test dataset back into
R####
predictedoc<-read.csv('C:/R/testoc.csv', header=TRUE)
detach(oc)
attach(predictedoc)

####Plot observed versus predicted values from the test dataset and calculate the slope and
intercept of the line of best fit, coefficient of determination, and root mean square error.###
plot(Observed~Predicted)
fit<-lm(Observed~Predicted, data=predictedoc)
abline(fit)
rmse<-round(sqrt(mean(resid(fit)^2)), 2)
```

```

r2<-round(summary(fit)$r.squared, 2)
coefs<-coef(fit)
b0<-round(coefs[1],2)
b1<-round(coefs[2],2)
eqn<-bquote(italic(Observed) == .(b0)
+.(b1)*italic(Predicted)*", "~~r^2==.(r2)*", "~~RMSE==.(rmse))
### To create a random forest model for bulk density, use the above code and replace SOC with
BD. ###

```

Appendix E: Microsoft Excel Code for Calculating Mean and Median by Horizon and Texture

=MEDIAN(IF(C\$2:C\$1572=C2, IF(D\$2:D\$1572=D2, E\$2:E\$1572)))

=MEAN(IF(C\$2:C\$1572=C2, IF(D\$2:D\$1572=D2, E\$2:E\$1572)))

Where C represents the horizon column, D is the texture column, and E is soil organic carbon or bulk density. In order to extrapolate this function for every row in the dataset, type in the above formula in the first row and then hold down Ctrl+Shift+Enter.

Appendix F: Soil Organic Carbon Stock of Rapid Carbon Assessment Sites in MLRA 127

RaCA SiteID	SOC Stock % 1m	Soil Series	Particle-Size	Subgroup	Great Group	Order
C1303F01-2	22.25	Onoville	Fine-loamy	Aquic	Fragiudults	Ultisols
C1303F01-3	15.60	Onoville	Fine-loamy	Aquic	Fragiudults	Ultisols
C1303F01-4	32.98	Onoville	Fine-loamy	Aquic	Fragiudults	Ultisols
C1303F01-5	15.31	Onoville	Fine-loamy	Aquic	Fragiudults	Ultisols
C1304P01-2	18.30	Chavies	Coarse-loamy	Ultic	Hapludalfs	Alfisols
C1304P01-3	15.44	Chavies	Coarse-loamy	Ultic	Hapludalfs	Alfisols
C1304P01-4	18.42	Chavies	Coarse-loamy	Ultic	Hapludalfs	Alfisols
C1304P01-5	23.97	Chavies	Coarse-loamy	Ultic	Hapludalfs	Alfisols
C1305F07-2	32.09	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F07-3	30.18	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F07-4	26.49	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F07-5	44.60	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F08-2	13.30	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F08-3	11.42	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F08-4	10.74	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F08-5	11.58	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F11-2	21.04	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1305F11-3	34.58	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F11-4	32.33	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F11-5	32.24	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F14-2	17.92	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F14-3	13.98	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F14-4	12.53	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F16-2	20.59	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F16-3	53.39	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F16-4	36.07	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F16-5	40.22	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F20-2	33.72	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F20-3	31.55	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F20-4	27.10	Buchanan	Fine-loamy	Aquic	Fragiudults	Ultisols
C1305F20-5	25.80	Layland	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1305F29-2	12.06	Wharton	Fine-loamy	Aquic	Hapludults	Ultisols
C1305F29-3	15.17	Wharton	Fine-loamy	Aquic	Hapludults	Ultisols
C1305F29-4	19.66	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1305F29-5	23.10	Wharton	Fine-loamy	Aquic	Hapludults	Ultisols
C1307C06-2	8.91	Fairpoint	Loamy-skeletal	Typic	Udorthents	Entisols

RaCA SiteID	SOC Stock % 1m	Soil Series	Particle-Size	Subgroup	Great Group	Order
C1307C06-3	12.26	Fairpoint	Loamy-skeletal	Typic	Udorthents	Entisols
C1307C06-4	10.66	Fairpoint	Loamy-skeletal	Typic	Udorthents	Entisols
C1307C06-5	9.67	Fairpoint	Loamy-skeletal	Typic	Udorthents	Entisols
C1307F10-2	11.17	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F10-3	16.69	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F10-4	13.47	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F10-5	24.53	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F21-2	7.90	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F21-3	4.55	Dekalb	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1307F21-4	11.01	Dekalb	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1307F21-5	10.12	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F28-2	14.03	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F28-3	12.44	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F28-4	12.54	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F28-5	21.07	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F31-2	12.17	Laidig Taxadjunct	Fine-loamy	Typic	Fragiudults	Ultisols
C1307F31-3	21.04	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1307F31-4	7.25	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1307F31-5	18.44	Ernest	Fine-loamy	Aquic	Fragiudults	Ultisols
C1307F34-2	7.21	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F34-3	10.83	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F34-4	5.67	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F34-5	6.85	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307F37-2	11.90	Shouns	Fine-loamy	Typic	Hapludults	Ultisols
C1307F37-4	6.26	Shouns	Fine-loamy	Typic	Hapludults	Ultisols
C1307F37-5	6.06	Shouns	Fine-loamy	Typic	Hapludults	Ultisols
C1307F39-2	8.54	Culleoka	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F39-3	9.56	Culleoka	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F39-4	7.06	Culleoka	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F39-5	10.03	Culleoka	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F46-2	20.46	Leck Kill Taxadjunct	Loamy-skeletal	Typic	Hapludults	Ultisols
C1307F46-3	14.34	Clymer	Coarse-loamy	Typic	Hapludults	Ultisols
C1307F46-4	24.51	Clymer	Coarse-loamy	Typic	Hapludults	Ultisols
C1307F46-5	20.04	Leck Kill	Fine-loamy	Typic	Hapludults	Ultisols
C1307F53-2	8.65	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F53-3	9.71	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F53-4	14.77	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307F53-5	18.28	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols

RaCA SiteID	SOC Stock % 1m	Soil Series	Particle-Size	Subgroup	Great Group	Order
C1307P03-2	5.71	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307P03-3	4.36	Litz	Loamy-skeletal	Ruptic-Ultic	Dystrudepts	Inceptisols
C1307P03-4	7.77	Litz	Loamy-skeletal	Ruptic-Ultic	Dystrudepts	Inceptisols
C1307P03-5	5.32	Cateache	Fine-loamy	Ultic	Hapludalfs	Alfisols
C1307P13-2	12.51	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307P13-3	7.14	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307P13-4	8.86	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1307P13-5	8.66	Gilpin	Fine-loamy	Typic	Hapludults	Ultisols
C1309C03-2	18.94	Atkins	Fine-loamy	Fluvaquentic	Endoaquepts	Inceptisols
C1309C03-3	55.26	Atkins	Fine-loamy	Fluvaquentic	Endoaquepts	Inceptisols
C1309C03-4	30.45	Atkins	Fine-loamy	Fluvaquentic	Endoaquepts	Inceptisols
C1309C03-5	22.14	Atkins	Fine-loamy	Fluvaquentic	Endoaquepts	Inceptisols
C1309F03-2	22.05	Basher	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1309F03-3	29.42	Barbour	Coarse-loamy	Fluventic	Dystrudepts	Inceptisols
C1309F03-4	15.02	Basher	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1309F03-5	24.59	Basher	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1309F05-2	18.72	Philo	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1309F05-3	13.32	Philo	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1309F05-4	17.05	Philo	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1310F01-2	15.98	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1310F01-3	21.13	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1310F01-4	23.19	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1310F01-5	13.16	Rayne	Fine-loamy	Typic	Hapludults	Ultisols
C1310F03-2	21.65	Portville	Fine-loamy	Aeric	Fragiaqualfs	Alfisols
C1310F03-3	34.15	Portville	Fine-loamy	Aeric	Fragiaqualfs	Alfisols
C1310F03-4	24.61	Portville	Fine-loamy	Aeric	Fragiaqualfs	Alfisols
C1310F03-5	41.91	Portville	Fine-loamy	Aeric	Fragiaqualfs	Alfisols
C1310P02-2	21.36	Cavode	Fine	Aeric	Endoaquults	Ultisols
C1310P02-3	20.59	Cavode	Fine	Aeric	Endoaquults	Ultisols
C1310P02-4	15.18	Cavode	Fine	Aeric	Endoaquults	Ultisols
C1310P02-5	10.91	Cavode	Fine	Aeric	Endoaquults	Ultisols
C1311P04-2	11.66	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P04-3	10.00	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P04-4	10.57	Frederick	Fine	Typic	Paleudults	Ultisols
C1311P04-5	9.49	Frankstown	Fine-loamy	Typic	Hapludults	Ultisols
C1311P05-2	12.80	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P05-3	14.76	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P05-4	14.51	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P05-5	8.49	Caneyville	Fine	Typic	Hapludalfs	Alfisols

RaCA SiteID	SOC Stock % 1m	Soil Series	Particle-Size	Subgroup	Great Group	Order
C1311P10-2	10.79	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P10-3	12.16	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P10-4	9.18	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1311P10-5	8.90	Caneyville	Fine	Typic	Hapludalfs	Alfisols
C1313W05-2	36.76	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1313W05-3	24.26	Philo	Coarse-loamy	Fluvaquentic	Dystrudepts	Inceptisols
C1313W05-4	25.25	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1313W05-5	35.78	Brinkerton	Fine-silty	Typic	Fragiaqualfs	Alfisols
C1314F01-2	25.52	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F01-3	12.60	Muskingum	Fine-loamy	Typic	Dystrudepts	Inceptisols
C1314F01-4	14.29	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F01-5	5.84	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F02-2	10.03	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F02-3	7.41	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F02-4	7.94	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F02-5	17.69	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F07-2	13.54	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1314F07-3	13.40	Cookport	Fine-loamy	Aquic	Fragiudults	Ultisols
C1314F07-4	12.24	Clymer	Coarse-loamy	Typic	Hapludults	Ultisols
C1314F07-5	11.39	Clymer	Coarse-loamy	Typic	Hapludults	Ultisols
C1314F17-3	8.97	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F17-4	20.52	Ungers	Fine-loamy	Typic	Hapludults	Ultisols
C1314F17-5	12.26	Clymer	Coarse-loamy	Typic	Hapludults	Ultisols
C1314F29-2	17.84	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F29-3	15.36	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F29-4	17.68	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F29-5	7.27	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F32-2	15.84	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F32-3	20.87	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F32-4	26.60	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F32-5	21.79	Hazleton	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F33-2	17.09	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F33-3	21.16	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F33-4	28.93	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314F33-5	10.85	Berks	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314P03-2	10.13	Calvin	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314P03-3	7.78	Calvin	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314P03-4	8.21	Calvin	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
C1314P03-5	12.33	Calvin	Loamy-skeletal	Typic	Dystrudepts	Inceptisols

RaCA SiteID	SOC Stock % 1m	Soil Series	Particle-Size	Subgroup	Great Group	Order
F1303F03-2	23.08	Mandy	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
F1303F03-3	9.19	Mandy	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
F1303F03-4	11.95	Mandy	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
F1303F03-5	19.56	Mandy	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
F1314F03-2	8.52	Dekalb	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
F1314F03-3	14.56	Shouns	Fine-loamy	Typic	Hapludults	Ultisols
F1314F03-4	22.80	Shouns	Fine-loamy	Typic	Hapludults	Ultisols
F1314F03-5	13.30	Shouns	Fine-loamy	Typic	Hapludults	Ultisols

Appendix G: Soil Organic Carbon Stock of Pedons Described and Sampled by Sponaule (2005)

SiteID	SOC Stock % 1m	Particle- Size	Subgroup	Great Group	Order
FS04WV025001	17.15	Fine-loamy	Typic	Hapludults	Ultisols
FS04WV025002	10.81	Fine-loamy	Typic	Hapludults	Ultisols
FS04WV025003	18.44	Fine-loamy	Typic	Hapludults	Ultisols
FS04WV025004	15.39	Fine-loamy	Fragic	Hapludults	Ultisols
FS04WV025005	28.81	Coarse-loamy	Fragic	Hapludults	Ultisols
FS04WV025010	17.64	Loamy-skeletal	Typic	Fragiudults	Ultisols
FS04WV101001	20.33	Coarse-loamy	Typic	Hapludults	Ultisols
FS04WV067007	12.63	Fine-loamy	Typic	Hapludults	Ultisols
FS04WV067001	7.71	Loamy-skeletal	Psammentic	Hapludults	Ultisols
FS04WV067002	10.66	Loamy-skeletal	Typic	Dystrudepts	Inceptisols
FS04WV067003	11.24	Coarse-loamy	Typic	Hapludults	Ultisols
FS04WV067004	2.68	Loamy-skeletal	Aquic	Dystrudepts	Inceptisols
FS04WV067005	8.94	Loamy-skeletal	Typic	Fragiudults	Ultisols
FS04WV067006	8.25	Loamy-skeletal	Aquic	Dystrudepts	Inceptisols
FS04WV067017	10.30	Coarse-loamy	Typic	Dystrudepts	Inceptisols