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DEVELOPMENT OF A SOIL HEALTH CALCULATOR TOOL TO QUANTIFY IMPACTS OF AGRICULTURAL MANAGEMENT PRACTICES ON SOIL HEALTH IN THE LAKE CHAMPLAIN BASIN

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Soil Health Calculator

Development of a Soil Health Calculator Tool
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Multi-Objective Calibration of APEX

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Abbreviations

APEX	Agricultural Policy / Environmental Extender Model
C	Carbon
CASH	Comprehensive Assessment of Soil Health
CIG	Conservation Innovation Grant
Farm-PREP	The Farm-P Reduction Planner
LCBP	Lake Champlain Basin Program
MAE	Mean absolute error
N	Nitrogen
NEP	Net ecosystem production
NRCS	National Resources Conservation Service
P	Phosphorus
RMSE	Root mean square error
R^2	Coefficient of determination
SOC	Soil organic carbon
SSHVT	State of Soil Health Vermont
VAAFM	Vermont Agency of Agriculture, Food, and Markets

1. Introduction

The need to prioritize soil health in agricultural systems is more critical than ever before. Efforts have been conducted to characterize the state of soil health in Vermont, with one of the goals being to assess the impact of farming practices on soil health and evaluate ecosystem services that improved soil health would support. To understand, incentivize, and track improvements towards soil health goals, stakeholders need tools to systematically and quantitatively evaluate the impact of conservation practices and alternative agronomic management. This project developed and validated a web-based soil health calculator tool to quantify the impact of agricultural conservation practices at the field/farm scale on key soil health properties. The tool will provide farmers and state programs with actionable information that can enable informed decision making to increase regenerative agriculture and support healthy soils in Vermont. The tool was developed as a module of the existing Farm-P Reduction Planner (Farm-PREP) and tool outputs are based on the United States Department of Agriculture (USDA) Agricultural Policy Environmental eXtender model (APEX) (Steglich et al., 2016). This customized modeling-based approach was designed to align with the goals of the Vermont Agency of Agriculture, Food, and Markets (VAAFM) and ongoing research under a related National Resource Conservation Service (NRCS) Conservation Innovation Grant focused on enhancing Farm-PREP with predictions of greenhouse gas emissions, carbon sequestration, nitrogen loss, and the inclusion of non-agricultural working lands (e.g., forest and wetlands). The overall objective is to enhance the Farm-PREP system to that stakeholders can identify feasible field-specific practices that support sustainable and resilient agriculture in Vermont, within a framework that also demonstrates the impacts of those practices on water quality and a holistic suite of environmental outcomes.

An adjacent effort has also been underway to enhance Farm-PREP with greenhouse gas (GHG) outcomes, as well as predictions of nitrogen loss, and the ability to simulate working lands. Data compilation for this project (Section 2) was conducted prior to merging these two efforts, and subsequently datasets identified through both efforts were combined and used in a single, combined multi-objective calibration effort. This report documents data compilation, model evaluation, and tool enhancement specific to soil health outcomes in Vermont. To the extent that it was relevant to this project, this report also documents the model evaluation and associated approach that incorporates other aspects of model calibration (further described in Section 3). The presentation of results is specific to soil health outcomes.

The Soil Health Calculator tool supports the ability of state programs (such as administered by VAAFM and/or for future programs) to quantitatively evaluate the impact of agricultural conservation practices and provide a tool by which to quantify effectiveness for the purpose of incentivizing those practices. The tool enables stakeholders to evaluate the impact of simulated practices and alternative management scenarios on both soil health metrics as well as water quality metrics that have already been developed in Farm-PREP, allowing for a more holistic evaluation of impacts and the trade-offs that may result. The Soil Health Calculator is made available to public users, providing a broad range of stakeholders as an online resource that supports communication of scientifically defensible evaluation of the impact of conservation practices on soil health metrics, as well as water quality, agronomic, and GHG outcomes.

2. Data Compilation

The starting point for this effort was the parameterization/set-up of APEX that has been implemented in Farm-PREP for the last 5 years, through the pilot Pay for Performance program. However, the primary focus of prior APEX calibration efforts for Farm-PREP have been runoff, erosion, and phosphorus losses. Farm-PREP/APEX outputs had not previously been evaluated in the context of soil health and how relevant model simulated processes are affected by management practices aimed at maintaining and improving soil health. Therefore, the data compilation component of this project was intended to compile data that could be used to evaluate the APEX model in the context of predictions of key soil health metrics and the model response of those metrics to agronomic management. We aimed to identify measurements of soil health conditions at specific locations, measurements of the response of soil health metrics in response to agricultural management practices, and model simulation of soil health metrics. Soil health data used in the model calibration/validation ultimately came from only Vermont field sites (Table 3). After this initial data compilation effort, additional data on runoff, erosion, and associated nutrient losses were included for sites in Vermont and in New York, and GHG data for sites in Pennsylvania, Maine, New Hampshire, and Vermont (Table 3). The data compiled in this task was intended to be used to ensure the APEX model used in the Soil Health Calculator (and Farm-PREP) produced results consistent with known trends and observed data regarding soil health metrics specifically.

2.1. Summary of Compiled Data

A data compilation effort was the first task of this project (after establishing an approved Quality Assurance Project Plan [QAPP] and a project advisory committee [PAC]). The objective of Task 3 was to compile the data needed to evaluate APEX model performance both with respect to how well modeled outputs represent observed conditions in Vermont, and to how well the model represents known behaviors in soil health metrics in response to a suite of management practices. We conducted a targeted literature review focused on three separate sub-objectives: data representative of a range of conditions and locations in Vermont, data that could support a long-term model simulation, and data that established trends with respect to changes in management and/or implementation of specific practices. We also leveraged prior and ongoing work to develop a modeling approach that produces scientifically defensible results consistent with related efforts in the state and that produces outcomes that support a variety of stakeholders in assessing the impact of management on soil health indicators on agricultural lands in Vermont. The data found and compiled in this task supported the model evaluation and established the tool's initial conditions.

As the Soil Health Calculator tool was developed using the United States Department of Agriculture (USDA) Agricultural Policy Environmental eXtender model (APEX), an aspect of this data compilation was also to target data that could be readily simulated with this particular model. APEX is a physically based model that predicts the short- and long-term impacts of agronomic management decisions on environmental quality including nutrient cycling and transport (Gassman et al., 2010, 2005; Wang et al., 2012; Williams and Izaurralde, 2006). It was developed for field to small watershed scale simulations and has been used extensively including for the quantification of conservation practices including by the United States Department of Agriculture (USDA) in the Conservation Effects Assessment Project (CEAP) (Gassman et al., 2010). APEX simulates dynamic changes in soil organic matter, bulk density, changes in soil carbon pools, soil phosphorus and nitrogen, carbon emissions, nutrient losses associated with runoff and erosion processes, as well as crop growth and associated indicators including yields and biomass.

2.1.1. Observed Soil Health Data

We first sought observed or measured data from the state of Vermont or the Lake Champlain basin region of New York that included widespread and/or long-term indicators of soil health over a range of agricultural conditions in the region. We specifically looked for metrics that were potential candidates for being readily simulated using the APEX model, based on the processes simulated in APEX and currently available model outputs. We reviewed literature from peer reviewed journals for field studies in Vermont and New York, as well as contacted researchers involved in soil health data collection as part of efforts led by the Vermont Agency of Agriculture, Food and Markets (VAAFM) Payment for Ecosystem Services (PES) and Soil Health Working Group (White et al., 2022a) through the University of Vermont (UVM) Extension and the Vermont Land Trust Healthy Soils (VLTHS) project. Table 1 summarizes the relevant references we found pertaining to research data on soil health as well as indicates whether that data was selected for use in model evaluation/calibration. While we found many studies related to soil health indicators, there was considerable variability in the location, number of indicators, management practices included, and length of study. As a result, we proposed two components of model evaluation with respect to benchmarking the APEX model results for soil health indicators in Vermont. These components are further described in Section 4 below.

We primarily relied on data collected for and presented in the State of Soil Health report (SSHVT; White et al., 2022b) for evaluating the APEX model across a range of agricultural field conditions, as it contains statistical summaries of soil health metrics for 217 locations across the state of Vermont. This dataset was developed using the Comprehensive Assessment of Soil Health (CASH) framework (Moebius-Clune et al., 2016) and includes metrics such as soil organic matter, bulk density, soil carbon stocks, respiration, active carbon, and others. Most field sites were cropland, with a small subset of sites being pasture. Measurements were grouped by land use as well as soil texture, and statistics presented based on these categories. We also obtained data, also collected using the CASH framework, from the VLTHS program. The VLTHS data was collected on fields in use for rotational grazing, which was a beneficial compliment to the primarily cropland SSHVT data.

A small set of other studies were also identified that were suitable for long-term model simulation. For these, we set up site specific APEX models by parameterizing inputs to represent the sites described as closely as possible. We had originally planned to use all the sites noted in Table 1 to evaluate long term model performance with respect to the soil health metrics available in those studies. However, several of the non-Vermont sites lacked key data to replicate field-specific outcomes. After we identified these sites, we then also combined the model evaluation for this work with the VAAFM effort such that we brought in additional datasets from additional field sites (for metrics not specific to soil health, see Table 3).

Table 1: Regional soil health indicator data references

Title	Author	Publication Year	Study Location (s)	Reference #	Used in Model Calibration/Validation
Quantitative soil profile-scale assessment of the sustainability of long-term maize residue and tillage management	Kinoshita, Schindlebeck, van Es	2017	Chazy, NY	9	No
No-till and cropping system diversification improve soil health and crop yield	Nunes, van Es, Schindelbeck, Ristow, Ryan	2018	Willsboro and Aurora, NY	17	No
Effects of cover crops, rotation, and biological control products on soil properties and productivity in organic vegetable production in the Northeastern US	Larkin	2019	ME	10	No
Measuring the Supply of Ecosystem Services from Alternative Soil and Nutrient Management Practices: A Transdisciplinary, Field-Scale Approach	White, Faulkner, Conner, Barbieri, Adair, Niles, Mendez, Twombly	2021	Northeastern VT	25	Yes
The State of Soil Health in Vermont	White, Darby, Ruhl, Lane	2022	VT	22	Yes
Field Scale Soil Health Scenarios. Vermont Payment for Ecosystem Services Technical Report #2	White, Darby, Ruhl, Sands, Ziegler	2022	VT	23	Yes
Long term influence of alternative corn cropping practices and corn-hay rotations on soil health, yields and forage quality	White, Darby, Ruhl, Sands	2023	Alburgh, VT	24	Yes
Healthy Soils Land Grant Study	Vermont Land Trust	ongoing	VT	N/A	Yes

2.1.2. General soil health indicators' trends

We also looked for studies that included demonstration of the behavior of soil health indicators under different management practices and that could be used as evidence of expected trends. These studies did not need to include details of specific sites but instead included analyses/synthesis of multiple other datasets, review papers, and modeling studies that demonstrated or summarized generalized behavior in soil health metrics as a result of agronomic management. As these data was used to validate relative model behavior, as opposed to validate values of model output, we did not limit the search for these studies to being in Vermont or the Northeastern United States.

The Natural Resources Conservation Service (NRCS) performed a comprehensive review of existing research to assess the effects of several management practices on soil health (USDA, 2015). Crop rotation appears to have a small long-term effect on soil physical properties, mainly through indirectly increasing soil organic matter content. Some crop rotations did not affect aggregates, independently of soil or organic matter content. Planting of cover crops "had the greatest effect on physical soil properties" (USDA, 2015). Different studies have shown increases in organic matter content, nitrogen availability, improved soil aggregation and reduced bulk density. Moreover, the combination of cover crops and a no-till system “improved the stability of the aggregates, reduced the bulk density and penetration resistance of the surface layer, and increased the porosity and available water capacity of the soils” (USDA, 2015). No-till systems on their own had varied impacts on soil properties dependent on internal (specific crops/soils) and external (climate differences) factors to the systems. The effect of no tillage in bulk density is mixed. However, no till systems did have a positive effect on available water content and aggregate stability and showed increases in soil organic matter. These improvements to soil physical properties occur “regardless of the temperature and moisture region” (USDA, 2015).

Joshi et al. (2023) conducted a comprehensive meta-analysis on the effects of different types of conservation tillage on soil organic carbon. Their analysis found that no tillage significantly increased the topsoil organic carbon by 5%, and increased total and available nitrogen, phosphorus and potassium. Their evaluation results also showed an increase in the subsoil (15-40cm) organic carbon under no tillage compared to conventional tillage. They did not find a consistent effect of conservation tillage on pH.

A recent meta-analysis on the effects of cover crop on soil microbiome (Kim et al., 2020) found that cover cropping significantly increased microbial abundance and activity. Interestingly, they found that cover cropping under conservation tillage had a smaller impact on microbial biomass when compared to conventional tillage. A review of the impacts of cover crop on soil health more broadly found generally that cover crops increase soil organic carbon, aggregate stability and water infiltration (Sharma et al., 2018).

Mclelland et al. (2021) performed a meta-analysis on how the management of cover crops affects soil organic carbon (SOC). Their study of observations from 40 publications showed that cover crops led to a significant increase in soil organic carbon in the 0-30cm depth, with an average increase of 12% compared to a no cover crop control. The authors noted that the “strongest predictors of SOC response to cover cropping were planting and termination date (i.e., growing window), annual cover crop biomass production, and soil clay content” (Mclelland et al., 2021). Similarly, a recent review (Adetunji et al., 2020) also found that “management practices involving effective species selection, termination timing and termination method all contribute to successful cover cropping”, but that the effect of these options on nitrogen dynamics and soil organic carbon are not yet well understood. Qin and others (Qin et al., 2023) used a calibrated model to estimate cover crop impact on soil organic carbon at six sites in the US Midwest. They found that cover crop biomass increased soil organic carbon but also carbon oxidation, leading to higher heterotrophic respiration. Besides management options of cover crops already mentioned in other studies, such as planting and termination timing, they noted root to shoot ratio of the cover crop and the climate during the cover crop growing period as impact factors on the soil organic carbon benefits from cover cropping.

Several studies have looked at the complicated impacts of inorganic vs organic fertilizers (Liu et al., 2006; Mahmood et al., 2017; Singh Brar et al., 2015). Most generally show a higher increase in soil organic matter with applications of both chemical and organic fertilizer in comparison to either on their own. Study results vary with respect to the effect of inorganic fertilization alone on soil organic carbon or soil organic matter (Geisseler and Scow, 2014; Li et al. 2020). Inorganic fertilization does appear to increase soil organic carbon in grasslands (Eze, Palmer and Chapman, 2018). Geisseler and Scow’s literature review found that inorganic fertilization slightly increased microbial biomass in agricultural systems. A long-term inorganic and combined inorganic and organic fertilizer study in India showed no change in bulk density depending on fertilizer type but did show a significant decrease in pH for all fertilizer combinations compared to the control plots after 36 years of a maize-wheat rotation (Singh Brar et al., 2015). Similarly, a century-old fertilization experiment reported by Francioli et al. (2016) showed a marked decrease in pH under inorganic fertilization compared to the control or fertilization containing farmyard manure. Microbial biomass carbon was significantly higher in the combined inorganic and manure fertilization plots.

Table 2 is a simplified summary of long-term effects of these practices, based on the reviews mentioned above. It should be noted that climate, soil type, crop, and timing of management operations can all affect the magnitude and even direction of the effects.

Table 2: Summary of effect of agricultural practice on soil health indicators

Soil Health Indicator/ Practice	Organic Matter	Bulk Density	Microbial Biomass
Inorganic Fertilizer Application (IFA)	decrease to slight increase + OFA **increase**	mixed + OFA decrease	level to increase
Organic Fertilizer Application (OFA)	level to increase	Decrease	Increase
Cover Crops (CC)	increase + CT **increase**	Decrease	Increase
Crop Rotation (CR)	crop dependent + CC level to increase	Decrease	Increase
Conservation Tillage (CT)	increase + CC/CR **increase**	Mixed	Increase

3. Expansion of Model Evaluation Components

The overarching goal of this project, the Soil Health Calculator, was to develop a tool for evaluating soil health outcomes in response to agricultural management. An aligned scope of work with VAAFM, has concurrently focused on enhancing the Farm-PREP tool to evaluate greenhouse gas (GHG) emissions, carbon sequestration, and nitrogen losses on agricultural and working lands in Vermont. As both these projects included a calibration component to ensure the APEX model appropriately represents processes and outputs of interest for agricultural lands in Vermont and both projects aimed to incorporate these components into the existing Farm-PREP tool, we developed a calibration approach that incorporates data and metrics important for both projects. The combined objective was to develop a single global APEX parameterization that performs well with respect to driving hydrological processes (where key metrics include runoff and erosion), water quality (where key metrics include soluble/sediment-bound phosphorus [P] and nitrogen [N] losses), soil health (where key metrics include soil organic matter, active carbon, soil respiration, and plant available water capacity), and GHG/carbon processes (where key metrics include carbon/nitrogen emissions, carbon storage, and carbon sequestration).

To achieve a robust, reproducible and unbiased model calibration that appropriately simulates all these processes, we developed a multi-objective, auto-calibration approach to optimize performance of the APEX model across multiple outputs of interest. The first step of this approach included development of APEX file decks to represent several site-specific verification scenarios and then compiling the corresponding observed data on which to base a calibration. Parameters tested in the calibration were selected and ranges defined (Table 6). The next step of the calibration was then a comprehensive parameter sensitivity analysis to evaluate the level of influence on selected outputs and to exclude parameters that have minimal impact on key processes. Using a smaller set of parameters identified in the sensitivity analysis, tan auto-calibration process was implemented, which involved parameter sampling, model runs, performance evaluation, and the selection of best fitting parameter set/s. This workflow established a flexible and scalable framework that could be used for current and future model calibration efforts. The final step was to use the calibrated parameter set on a larger number of hypothetical fields that represent a range of field conditions across Vermont and with a set of management scenarios; these were used to further validate model results, identify outliers, and evaluate behavior with respect to known trends.

Two sets of simulations were used to conduct each of the two components in this calibration effort. The first set of simulations used to auto-calibrate the APEX model were representative of specific agronomic fields with corresponding observed data that was documented in either peer-reviewed literature, reports from University of Vermont (UVM) Extension projects, or previous Lake Champlain Basin Program (LCBP)-funded projects and associated reporting. The second set of field simulations - referred to as batch simulations – were set up using publicly available datasets and were designed to represent hypothetical fields with a range of physical and agronomic conditions representative of agricultural fields in Vermont.

Section 4 describes the model evaluation framework developed to address the needs of both projects. This includes a site-specific multi-objective calibration as well as batch simulations of hypothetical fields in Vermont.

4. Modeling Approach

The following sections describe the methodology implemented to meet *Task 4-1 Calibration/Parameterization/Evaluation of APEX With Respect to Soil Health Metrics* and *Task 4-2 Evaluation of APEX Response to Practice and Management Options* of the Soil Health Calculator Project.

4.1. Site-Specific Calibration

4.1.1. APEX Scenarios

Site-specific APEX simulations were developed for 32 fields where data could be compiled of a significant quality and/or quantity to inform model calibration. Sites selected for water quality and soil health data were located in Vermont and New York, while sites with GHG data were selected from the New England region due to data scarcity in Vermont alone. We prioritized long-term continuous data, such as results from continuous monitoring efforts (e.g., Braun and Meals, 2019, Braun et al., 2019) but also included multi-year measurements that corresponded with APEX outputs in the areas of greenhouse gas emissions, soil health metrics, runoff, erosion, and water quality. Sufficient descriptive data had to be available to accurately characterize site specific physical conditions (e.g., soils, slope, weather), as well as agronomic management (e.g., crop rotation, tillage and manure application practices) for years where environmental metrics were predicted. Sites with multiple types of data measurements were considered more useful than sites where only a single type of data was collected. Field sites that include 'SH' in the Field Site ID were one of the datasets identified in the data compilation task of this project (Table 1). Other sites were sources from data compilation efforts focused on not only soil health metrics but data that reflected runoff, erosion, nutrient loss, and GHG emission/carbon sequestration. Metadata and source information about these field scenarios are provided in Table 3. These site-specific scenarios and associated observed data were the basis of model parameter adjustments needed to determine a global parameter set to be applied in the Farm-PREP tool.

Table 3. Site-specific field scenarios.

Field Site ID	Observed Data Category	Location	Cropping System	Source Documentation
CHA_01	Flow, erosion, surface phosphorus/nitrogen losses	Charlotte, VT	Corn silage, cover crop	Stone Environmental, 2020; Braun and Meals 2019
FER_01	Flow, erosion, surface phosphorus/nitrogen losses	Ferrisburgh, VT	Cropland hay (clover)	Stone Environmental, 2020; Braun and Meals 2019
PAW_01	Flow, erosion, surface phosphorus/nitrogen losses	Pawlet, VT	Corn silage, cover crop	Stone Environmental, 2020; Braun and Meals 2019
SHE_01	Flow, erosion, surface phosphorus/nitrogen losses	Shelburne, VT	Cropland hay (grass hay)	Stone Environmental, 2020; Braun and Meals 2019
SHO_01	Flow, erosion, surface phosphorus/nitrogen losses	Shoreham, VT	Cropland hay (grass hay)	Stone Environmental, 2020; Braun and Meals 2019

GHG_01	NEP, NO^2 emissions	PA	Cropland grass/hay	Chianese et al. 2009
GHG_02	NEP, NO^2 emissions	PA	Cropland alfalfa	Chianese et al. 2009
GHG_03	NEP, NO^2 emissions	PA	Corn silage	Chianese et al. 2009
GHG_04	NEP, NO^2 emissions	PA	Corn grain	Chianese et al. 2009
GHG_05	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	VT	Pasture, grazing	Contosta et al. 2021
GHG_06	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	VT	Cropland hay	Contosta et al. 2021
GHG_07	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	ME	Grazing	Contosta et al. 2021
GHG_08	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	ME	Cropland hay	Contosta et al. 2021
GHG_09	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	NH	Pasture, grazing	Contosta et al. 2021
GHG_10	CO^2 emissions, NO^2 emissions, soil carbon, soil nitrogen	NH	Cropland hay	Contosta et al. 2021
GHG_11	CO^2 emissions, NO^2 emissions, yield, soil organic carbon	Alburgh, VT	Corn (control site)	(Twombly et al., 2021; White et al., 2021)
GHG_12	CO^2 emissions, NO^2 emissions, yield, soil organic carbon	Alburgh, VT	Cropland hay (control site)	White et al. 2021; Twombly et al. 2021
SH_01	Yield, soil respiration, soil organic carbon	Alburgh, VT	Corn, tilled	Darby et al., UVM Extension, 2012-2023
SH_02	Yield, soil respiration, soil organic carbon	Alburgh, VT	Corn-hay, rotation	Darby et al., UVM Extension, 2012-2023
SH_03	Yield, soil respiration, soil organic carbon	Alburgh, VT	Corn, no till	Darby et al., UVM Extension, 2012-2023
SH_04	Yield, soil respiration, soil organic carbon	Alburgh, VT	Corn, no till with winter cover crop	Darby et al., UVM Extension, 2012-2023
SH_05	Yield, soil respiration, soil organic carbon	Alburgh, VT	Winter cover crop, tilled	Darby et al., UVM Extension, 2012-2023
SH_06	Yield, soil respiration, soil organic carbon	Alburgh, VT	Perennial forage - corn, rotation	Darby et al., UVM Extension, 2012-2023
JBT_01	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Corn silage – soybean, rotation/tilled	Stone Environmental, 2020; Braun et al. 2019
JBT_04	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Corn silage, tilled	Stone Environmental, 2020; Braun et al. 2019
JBT_05	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Corn silage, tilled with winter cover crop	Stone Environmental, 2020; Braun et al. 2019
JBT_07	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Corn silage, tilled	Stone Environmental, 2020; Braun et al. 2019
JBT_11	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Cropland hay (alfalfa)	Stone Environmental, 2020; Braun et al. 2019
JBT_18	Tile flow, tile phosphorus and nitrogen losses	Jewett Brook, VT	Hay – Corn silage, rotation	Stone Environmental, 2020; Braun et al. 2019
KV_01	Runoff, erosion, surface phosphorus and nitrogen losses, yield	Keeseville, NY	Corn silage	Thalmann 2021
KV_02	Runoff, erosion, surface phosphorus and nitrogen losses, tile flow, tile phosphorus and nitrogen losses, yield	Keeseville, NY	Corn silage	Thalmann 2021
M_01	Runoff, erosion, tile loss, surface	Chazy, NY	Corn silage	Correspondence with Laura

	phosphorus loss, tile phosphorus loss	Klaiber, 2019

APEX models were set up for each of the field scenarios in Table 3 using measured data (e.g. site-specific soil test phosphorus) and/or documented source data (e.g. management/practices) wherever possible. The Vermont edge of field and tile drain monitoring sites were described in Braun and Meals (2019) and Braun et al. (2019), respectively. APEX models had been previously set up for a calibration effort focused on runoff and phosphorus losses (Stone Environmental, 2020a); these models were largely unchanged for this effort. Inputs were reviewed for accuracy and consistency with current parameter settings in Farm-PREP. The remainder of the sites were set up for this work. Key components of setting up APEX models included physical field attributes (soils, slope, slope length), weather, and agronomic management. The development of APEX models for the GHG scenarios identified in Table 3 are summarized in the following sections.

4.1.1.1. Soil Attributes

APEX requires a set of key soil inputs for each field simulated (Table 4). These were obtained from the National Resource Conservation Services (NRCS) National Soil Survey Geographic Database (gNATSGO) database (Soil Survey Staff, 2021) based on the representative soil map unit for a field. The soil map unit was obtained either from source documentation (Table 3) or based on field delineation and the dominant soil from NRCS soil maps - this was the case for the Vermont (VT) edge of field and tile monitoring sites used in the previous APEX phosphorus calibration (Stone Environmental, 2020a; JBT sites and CHA_01, FER_01, PAW_01, SHE_01, and SHO_01).

The dominant soil component associated with the identified soil map unit representative of the field was used to query the gNATSGO database and select specific APEX soil input values for each field. The gNATSGO database contains a national 30-meter resolution raster of soil map units and 70 related tables of soil properties and interpretations. It was created by combining data from the Soil Survey Geographic Database (SSURGO), State Soil Geographic Database (STATSGO2), and Raster Soil Survey Databases (RSS) into a single seamless Esri file geodatabase. The gNATSGO version used for this study was released in November, 2021. To facilitate national applications of the APEX model, Stone gap-filled missing soil attributes required by APEX in the gNATSGO database using a soil similarity-based parameter substitution approach. The method starts from the data gap filling procedure described for the development of the US-ModSoilParms-TEMPLE database (Di Luzio, 2017; Texas A&M AgriLife Research, 2016) and was modified to address missing data issues more thoroughly (documentation on developing this database is included as Appendix A).

Table 4. APEX soil attributes extracted from gNATSGO database.

Soil Attribute	gNATSGO Data Source[1]
Hydrologic soil group (HSG)	hsydgrpdcd from muaggatt table
Slope	slopegradwta from muaggatt table
Albedo	albedodry_r from component table
Number of soil horizons	nhorizons _r from component table
Soil layer depth/thickness	hzthk_r/hzdepb_r from chorizon table
Moist bulk density	dbthirdbar_r from chorizon table
Soil water content at wilting point	wfifteenbar_r from chorizon table

Soil water content at field capacity	wthirdbar_r from chorizon table
Sand content	sandtotal_r from chorizon table
Silt content	silttotal_r from chorizon table
pH	ph1to1h3o_r from chorizon table
Organic carbon	om_r/1.72 from chorizon table
Cation exchange capacity	cec7_r from chorizon table
Coarse fragment content	rock_r from chorizon table
Dry bulk density	dbovendry_r from chorizon table
Saturated conductivity	ksat_r from chorizon table
[1]Component and horizon attributes were selected from the dominant component of the map unit with highest area in a field	

4.1.1.2. Initial Soil Phosphorus

The edge of field and tile drain monitoring sites had associated soil samples which were used to inform soil texture, organic matter, and initial soil phosphorus concentrations. Soil test phosphorus (P) was also available for additional sites with observed data related to soil health and/or water quality (M_01, SH sites, KV sites). Soil tests were conducted at the University of Vermont (UVM) and soil phosphorus reported in terms of Modified Morgan's soil phosphorus concentration. This was converted to a Mehlich 3 soil phosphorus concentration using an equation developed by Winchell et al. (2011), which is consistent with how Farm-PREP converts user-entered soil test phosphorus to an initial soil phosphorus concentration (Stone Environmental, 2020a). The initial soluble mineral phosphorus (SSF parameter) value in APEX was set to 50% of the Mehlich 3 concentration as recommended by Vadas and White (2010) for initializing soluble, active, and stable soil phosphorus pools. The phosphorus sorption ratio (PSP parameter) is then set based on this initial soluble mineral phosphorus value. The PSP value was calculated for each soil layer using the equation proposed (Vadas and White, 2010) where PSP is a function of clay content and organic carbon. The report submitted by Stone Environmental (2020a) on the initial phosphorus calibration of APEX for Farm-PREP presents these equations as well as key soil input values used in these APEX models (see Section 3.2.1.1 and Table 4 of that report).

4.1.1.3. Physical Characteristics

Important field characteristics that need to be input to APEX include area, slope, and slope length. Area and slope were found in source documents (Table 3) for each of the fields. Slope length is an important field attribute used in APEX erosion equations. For the edge of field and tile drain monitoring sites used in the previous APEX phosphorus calibration (JBT sites and CHA_01, FER_01, PAW_01, SHE_01, and SHO_01), slope length was determined via a GIS analysis based on a 10- m resolution digital elevation model (DEM), where flow accumulation and flow paths were determined, and slope length calculated for each delineated field. Where field boundaries were not available (the remainder of sites) slope length was calculated using an equation fit to gNATSGO slope and slope length data from the component table. This regression equation was developed to smooth the transition of slope length inputs across slope changes because slope length values are not available for many soil components. The gNATSGO component data was filtered to include integer slope values and slopes of less than or equal to 50%, then grouped by slope value to determine the average slope length for each slope group (each integer slope value). The following equation was then fit to the data and was used to calculate slope length in feet. This value was subsequently converted to meters for use in APEX:

$$\text{Slope length (ft)} = -49.39\ln(\text{slope}) + 251.59.$$

Figure 1 shows the average slope/slope length pairs (grouped by slope value) used to develop the slope length equation.

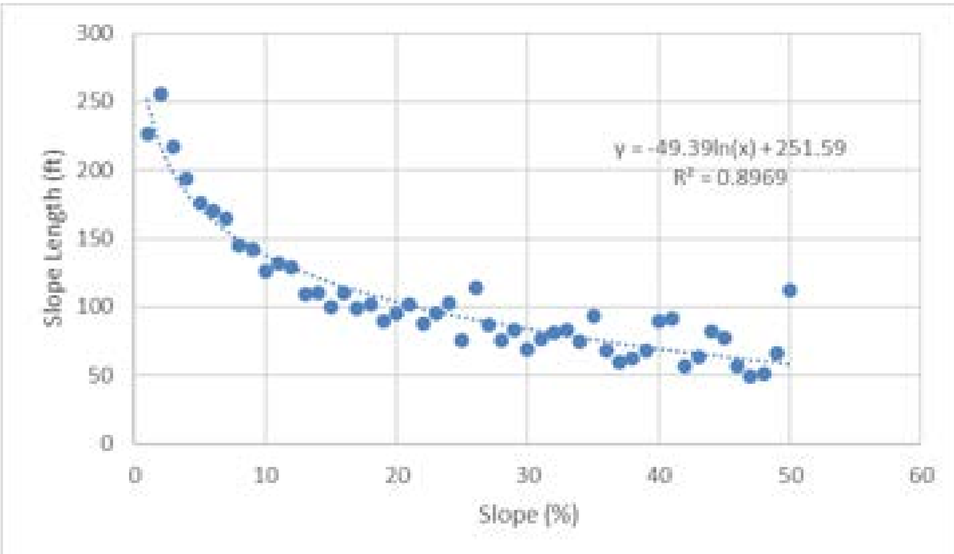

Figure 1. Slope vs. slope length relationship and empirical model fit.

4.1.1.4. Weather

Daily time series of weather inputs were generated for the field scenarios. APEX weather inputs include (**bold** indicates required data):

- **Daily precipitation total (mm)**
- **Max daily temperature (C)**
- **Min daily temperature (C)**
- Average daily humidity (fraction)
- Average daily wind speed (m/s)
- Total daily solar radiation reaching the Earth (MJ/m^2)

APEX also requires monthly weather inputs which are used to generate daily inputs if there are gaps in the daily data. There were no gaps in daily data used for the sites in this modeling, and therefore monthly inputs were not used in any calculations, but they are still a required model input and were therefore generated from the daily data such that for each daily weather input file, a corresponding monthly file was created. Statistics were calculated from the daily files described above, including the following:

- Average monthly maximum and minimum air temperature
- Monthly average standard deviation of the daily maximum and minimum temperatures
- Average monthly precipitation

- Monthly standard deviation of daily precipitation
- Monthly skew coefficient for daily precipitation
- Monthly probability of wet day after dry day
- Monthly probability of wet day after wet day
- Average number days of rain per month
- Monthly maximum 0.5h rainfall
- Average monthly solar radiation
- Average monthly wind speed

Timeseries of precipitation and maximum and minimum daily temperatures were generated from Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate data (PRISM Climate Group) for the GHG sites. PRISM was selected for these scenarios because it was also used to compare model performance between APEX, DNDC, and COMET-Farm and since COMET-Farm requires PRISM data. To enable a meaningful comparison, we obtained PRISM data associated with the location of these GHG field sites, converted it into APEX format, and used that to drive the APEX simulations.

In the initial phosphorus calibration of the edge of field and tile monitoring sites (JBT sites and CHA_01, FER_01, PAW_01, SHE_01, and SHO_01), time series weather inputs for APEX simulations were prepared from local precipitation and temperature monitoring. Data gaps were then filled by the closest land weather station. Data collection is described in Braun and Meals (2019) and Braun et al. (2019) and gap filling in the development of the APEX inputs is described in Stone Environmental (2020a). We initially ran these sites with the previously developed weather but noted that for some sites and events, the precipitation and runoff or tile drainage did not align well. We then tried simulating these sites using inputs prepared from a high-resolution gridded dataset (Fry et al., 2016; US EPA, 2020), made available by US EPA. This dataset was developed using Unified Gauge-Based Analysis of Daily Precipitation from the NOAA Climate Prediction Center (CPC) and Reanalysis Data (NOAA Physical Sciences Library, formerly the National Centers for Environmental Prediction [NCEP]). A total of 13,623 time series were generated, spanning the continental United States at a spatial resolution of 0.25° x of 0.25° (approximately 25 km X 25 km). Fry et al (2016) describe the source data, processing, and the quality assurance analysis they conducted on the data. US EPA (2020) also provides an overview of individual weather inputs included in the dataset. Inputs in this dataset included in the corresponding APEX input files were daily precipitation, temperature, wind speed, and solar radiation. This dataset included daily weather inputs from Jan 1, 1961 to Dec 31, 2021.

For consistency, we also used the gridded time series product described above to drive the remainder of the sites (except the GH sites).

4.1.1.5. Tile Drainage

Sites with tile drainage required additional APEX parameters to be defined, including depth to drainage system and time to drain the soil to field capacity. Based on recommended APEX default values, observed trends in the monitoring data, and our experience in parameterizing APEX, we estimated this value to be 2 days for a tile spacing of <= 30 ft, 3 days for a tile spacing of between 30 ft and 60 ft, and 4 days for a tile spacing of greater than 60 ft. Currently this parameterization is static in Farm-PREP, not adjusted for rainfall characteristics or soil type. However, water storage routing and movement between soil layers is still governed by specific soil characteristics and conditions driven by precipitation such that the response to tile drainage is field specific. These values for the original calibration sites are also shown in Table 4 of Stone Environmental (2020a). The newly set up Keeseville site with tile drainage (KV_02) was set to a depth of 1 m and assigned a time to drain value of 3 based on the documented spacing of approximately 10 m (32 ft) (Thalmann, 2021).

4.1.1.6. Agronomic Management

Agronomic management is a critical component of APEX field models. Management for the VT edge of field and tile drain sites is described in Stone Environmental (2020a). For the remaining sites, management details such as the date and other key information for each specific operation were similarly obtained from source documentation and converted to APEX format. Basic rotation information and practices specified in source documentation are provided in Table 3.

4.1.2. Observed Data for Site-Specific Sensitivity Analysis and Parameter Optimization

Observed data from the field sites and associated documentation (Table 3) consisted of multiple data types (e.g. soil respiration, carbon emissions, soluble phosphorus in runoff, etc.), time periods, and units across the sites used in the site specific simulations (described in Section 4.1.1). Table 5 shows each data type for which we had some data across sites, the corresponding APEX output, and a description based on APEX documentation. We first compiled data and associated time periods from source documentation into a single table for use in the auto-calibration process. This data table is used to automate the extraction of model outputs and aggregation to match observed data for comparison and performance evaluation. This single data table was split into three tables for reporting and is provided in Appendix B. Data were generally aggregated to an annual value, though in some cases was represented slightly differently (for example soil carbon on a particular day or monitoring data only for non-winter months). The time period column of tables in Appendix B (Table 18, Table 19, Table 20) shows the start and end dates corresponding to the observed data collection period and over which model results were aggregated and compared to this value. 'Site ID' indicated the site from which that data were obtained, and the remaining columns show the aggregated data point for each data type/output variable. Observed data were also converted from source documentation units to APEX output units, to streamline post-processing and reduce computing time as we are running large numbers of simulations.

For event-based data (the JBT sites and CHA_01, FER_01, PAW_01, SHE_01, SHO_01, and M_01 sites), we aggregated event data to annual values but also specified event dates including a one-day lag after the event end date to account for model lag. That enables the model outputs to be extracted for those specific events and to exclude any time periods where monitoring equipment may have been not operational (e.g. winter months). As there were many events per year that were extracted and aggregated, we did not provide the dates for each event in Table 19 of Appendix B, but instead we provided the year and number of events used. Event dates are provided in a full table in Excel format as supplemental material to the final report. Note that in this multi-objective calibration approach, we consider each of the values shown in Table 19 and Table 20 as an independent data point. Therefore, we included monitored flow events even if for various reasons, no phosphorus or nitrogen sample was obtained. That means that event dates extracted for each data type are not necessarily the same even for the same site. We took this approach to maximize the number of data points on which to compare the model results to observed, without going to the extent of calibrating on an event basis.

Custom Python scripts were developed to read and parse the necessary APEX output files, read the observed data table, and compute performance statistics for each data type/model output across all sites where that data was available.

Table 5. Summary of APEX outputs evaluated.

Observed Data	APEX Output Variable	APEX Output Description	Number of Data Points	Number of Sites with Data
Runoff	Q	Surface Runoff (mm)	34	9
Erosion	MUSS	Soil erosion (sediment) by water (T/ha)	32	8
Tile Drainage	QDR	Tile drainage (mm)	24	8
Sediment-bound P Loss	YP	Sediment P transported from field in surface runoff (kg/ha)	25	6
Soluble P Loss	QP	Soluble P transported from field in surface runoff (kg/ha)	30	7
Soluble P in Tile Drainage	QDRP	Soluble P transported from field in tile drainage (kg/ha)	14	7
Total P Loss	TP	Sum of soluble, sediment, and tile P losses (kg/ha)	29	8
Sediment-bound N Loss	YN	Sediment N transported from field in surface runoff (kg/ha)	22	5
Soluble N Loss	QN	Soluble N transported from field in surface runoff (kg/ha)	22	5
Soluble N in Tile Drainage Loss	QDRN	Soluble N transported from field in tile drainage (kg/ha)	14	7
Total N Loss	TN	Sum of soluble, sediment, and tile N losses (kg/ha)	25	6
Yield	YLDF	Forage yield (dry matter, T/ha)	51	7
CO_2 emissions	DFCO2T	Total CO_2 flux (kg/ha)	18	8
N_2O emissions	DFNO2T	Total N_2O flux (kg/ha)	22	12
Carbon in soil	WOC	Total organic carbon in soil (kg/ha)	6	6
Nitrogen in soil	WON	Total nitrogen in soil (kg/ha)	6	6
Soil respiration	RSPC	Carbon respiration from residue (T/ha)	52	8
Organic carbon in the plow layer	OCPD	Organic carbon in plow depth (%)	52	8
Net Ecosystem Production[1]	-	Kg C/ha	4	4
Total Data Points			**482**	**135**

[1]Net ecosystem production was calculated using multiple APEX outputs as it represents a measure of carbon accumulation (existing and created carbon – respiration and carbon removed).

4.1.3. Parameter Definition and Sampling for the Sensitivity Analysis

An iterative approach was applied where initially, a larger set of 38 key parameters affecting all relevant APEX outputs of interest was identified from the APEX parameter (parm.dat) file and the soil input files. These parameters influence hydrology, nutrient transport, erosion, greenhouse gas emissions, soil carbon cycling and crop yields in the model to differing degrees. Each parameter was assigned a physically plausible range based on expert knowledge and previous studies conducted at Stone. To sample the parameter space most effectively for the sensitivity analysis, Latin Hypercube Sampling (LHS, Mckay et al. 2000) was used to generate 30,000 evenly distributed parameter combinations. Table 6 shows the initial set of parameters selected to be included in a sensitivity analysis. Based on the results of the sensitivity analysis, most sensitive parameters are selected for the actual calibration, which is a refined round of model runs used to identify the best-performing parameter values (Section 4.1.4).

Table 6. 38 parameters included in parameter sensitivity analysis with 30,000 LHS runs.

Parameter	File	Description	Minimum Value	Maximum Value	Showed > 20% Importance on at Least 1 Output
ICP	APEXCONT.dat	ICP	0	1	Yes
FHP	.sol	Fraction of Humus in Passive Pool	0.3	0.7	Yes
HE	tillcom.dat	Harvest efficiency for grazing - important for N_2O emissions	0.1	0.25	No
PARM(2)	Parm1501.dat	Root-growth-soil strength	1.15	2	Yes
PARM(4)	Parm1501.dat	Water storage N leaching	0.2	0.9	Yes
PARM(7)	Parm1501.dat	N fixation	0.2	0.99	No
PARM(8)	Parm1501.dat	Soluble phosphorus runoff coefficient	10	18	No
PARM(12)	Parm1501.dat	Soil evaporation coefficient	1.5	2.5	No
PARM(14)	Parm1501.dat	Nitrate leaching ratio	0.6	1	No
PARM(15)	Parm1501.dat	Runoff CN adjustment	0	0.3	Yes
PARM(17)	Parm1501.dat	Soil evaporation plant cover	0.1	0.3	No
PARM(19)	Parm1501.dat	Sediment routing coefficient	0.001	0.05	No
PARM(21)	Parm1501.dat	Soluble Carbon adsorption Coefficient	10	18	No
PARM(23)	Parm1501.dat	Hargreaves PET equation coefficient	0.0022	0.0032	Yes
PARM(28)	Parm1501.dat	Upper Nitrogen Fixation limit	0.1	20	No
PARM(29)	Parm1501.dat	Biological mixing efficiency	0.001	0.01	No
PARM(46)	Parm1501.dat	RUSLE-C factor coefficient	0.5	1.5	No
PARM(59)	Parm1501.dat	P upward movement by evaporation coefficient	1	18	Yes
PARM(62)	Parm1501.dat	Manure erosion coefficient	0.2	0.45	No
PARM(72)	Parm1501.dat	Volatilization/nitrification partitioning	0.08	0.4	No
PARM(74)	Parm1501.dat	Partitions N flow from groundwater	5	15	No
PARM(68)	Parm1501.dat	Manure erosion exponent	0.3	0.8	No
PARM(69)	Parm1501.dat	Coefficient adjusts microbial activity in top layer	0.1	1	No
PARM(70)	Parm1501.dat	Microbial decay	0.6	1.4	Yes
PARM(85)	Parm1501.dat	P partitioning between stable/active	0.0001	0.001	No
PARM(76)	Parm1501.dat	Conversion of residue	0.001	0.1	Yes
PARM(86)	Parm1501.dat	N upward movement	0.005	3	No
PARM(83)	Parm1501.dat	Estimates drainage system lateral hydraulic conductivity	0.5	5	Yes
PARM(84)	Parm1501.dat	Coefficient regulating P flux between labile and active pool	0.0001	0.001	No
PARM(92)	Parm1501.dat	Runoff Volume Adjustment	0.8	1.2	Yes
PARM(96)	Parm1501.dat	soluble p leaching	1	15	Yes
PARM(107)	Parm1501.dat	Maximum rate of uptake of nitrogen during immobilization	0.2	0.5	No
PARM(108)	Parm1501.dat	Half Saturation constant for ammonia immobilization	10	20	No

PARM(109)	Parm1501.dat	Half Saturation constant for nitrite immobilization	5	15	No
PARM(110)	Parm1501.dat	Half Saturation constant for nitrate immobilization	10	20	No
XKN3	Parm1501.dat	Michaelis Menten constant	5	30	No
XKN1	Parm1501.dat	Michaelis Menten constant	0.1	1	No
PARM(71)	Parm1501.dat	Manure erosion exponent -adjusts based on plant material	1	1.5	No

4.1.4. Sensitivity Analysis and Parameter Refinement

The reduction of the initially defined, large parameter space of 38 parameters is an important step in the calibration process as it allows for a more computationally efficient way to find the optimum parameter set. Key steps included:

- Identifying influential parameters: Parameters that showed a strong influence on performance metrics are prioritized for further analysis.
- Refining parameter ranges: Based on the observed sensitivity trends, parameter ranges were adjusted to focus on the most influential values and to reduce uncertainty.
- Eliminating redundant parameters: Parameters with minimal influence on all outputs were deprioritized or excluded from the subsequent calibration step.

The sensitivity analysis was initially based on inspection of scatter plots of RMSE against parameter value, which allowed for the identification of parameters that significantly influenced model outputs. We created and reviewed these plots for each parameter and output pair. Initially we looked at multiple metrics (including mean and median, as well as unaggregated absolute error and RMSE) but determined to primarily evaluate sensitivity based on mean RMSE.

As an example, Figure 2 shows scatter plots of the mean RMSE for total phosphorus loss (TP) and total nitrogen loss (TN) in response to changes in two parameters (Parm(59): phosphorus upward movement by evaporation and Parm(70): microbial decay rate coefficient). The model response (in terms of mean RMSE across sites) of total phosphorus is shown in the top two subplots and the model response in total nitrogen in the bottom two subplots. This demonstrates that total phosphorus was sensitive to changes in the coefficient governing upward phosphorus movement by evaporation but was only minimally sensitive to changes in the microbial decay rate coefficient. Total nitrogen shows no sensitivity to the evaporation coefficient but shows significant sensitivity to the microbial decay rate coefficient.

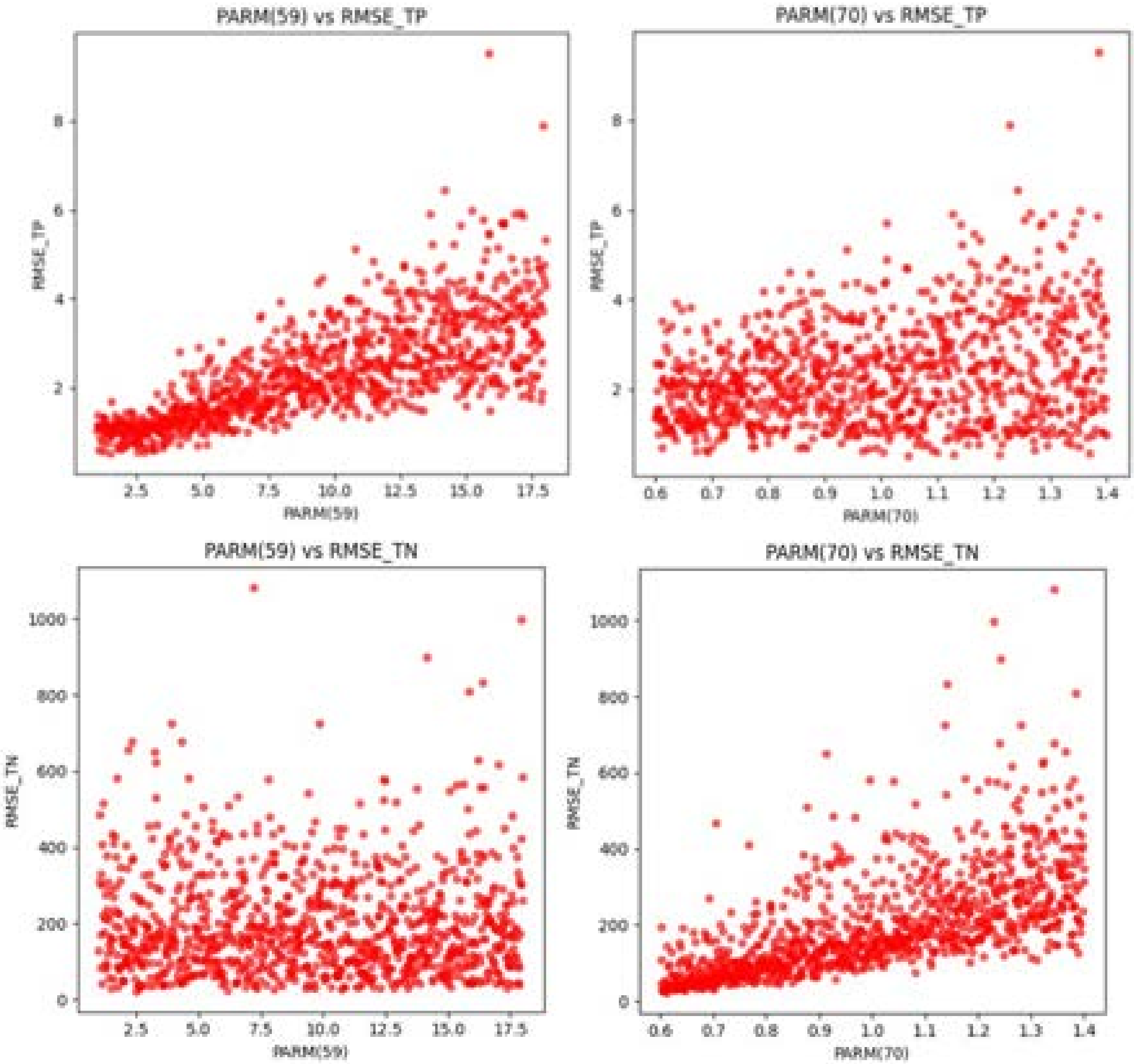

Figure 2. Mean RMSE of total phosphorus (top subplots) and total nitrogen (bottom plots) in response to changes in parm(59) (left) and parm(70) (right), across all sites.

On further evaluation of these plots, we were concerned that using this approach, we could underestimate the sensitivity of parameters on outputs due to the interactions between parameters and/or because we only had certain types of observed data for particular sites and not all processes were simulated at all sites (e.g. tile drainage). In addition, the large number of plots and varying patterns of parameter value vs performance value made it difficult to draw objective conclusions regarding in/sensitive parameters.

Therefore, we additionally used a random forest algorithm to evaluate parameter importance on the RMSE of all output variables per site. This allowed us to see which parameter impacts which output variable relative to others in an objective manner. The boxplots in Figure 3 show an example of the sensitivity boxplots, where the y axis is the relative importance of the specified parameter across all the sites for which there was observed data matching the output on the x axis. These plots also show the 20% 'importance' threshold as a dotted horizontal line, and parameters that had a larger than 20% importance of the upper 75th percentile (the upper boundary of each boxplot) across all sites are indicated in Table 6. While we examined several threshold values, the 20% threshold gave us the best result in terms of a resulting parameter set that excluded parameters that made sense to exclude, identified interactions we expected based on our experience with APEX, and resulted in a reasonable parameter set to continue with. As some parameters are only sensitive at certain sites where the respective process is modelled or where we had observed data for that particular output variable, this approach allowed us to isolate what parameters were sensitive at which sites and for what output variables. Furthermore, the identification of sensitive and insensitive output variables for a certain model parameter allows for a more targeted selection of the best set of parameters (see Section 5.1).

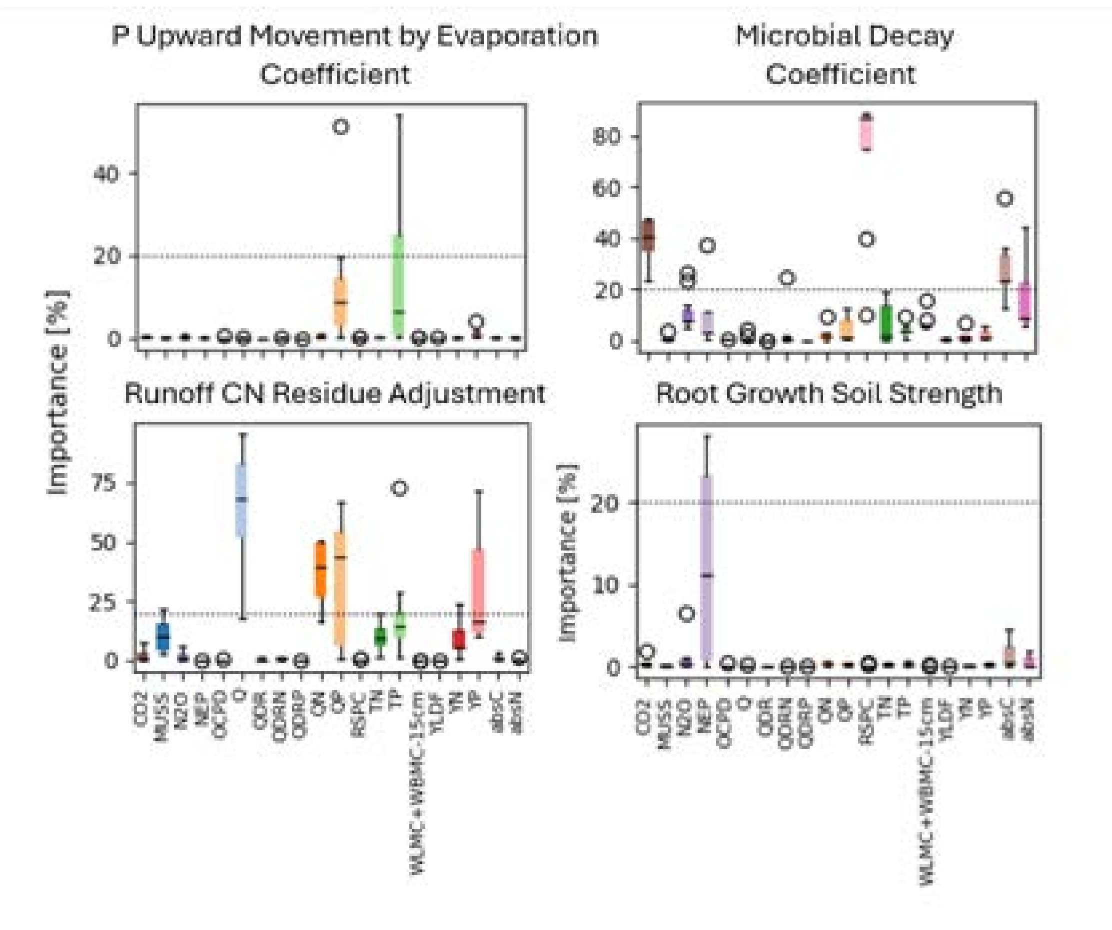

Figure 3. Sensitivity boxplots showing percent importance across sites for each APEX parameter tested.

Relying primarily on the boxplots of relative parameter uncertainty, we were able to objectively and reproducibly determine which parameters had complex impacts on multiple outputs (e.g. the microbial decay coefficient, where the relative importance of this parameter across sites was above 20% for CO_2 emissions, soil carbon, soil nitrogen, and soil respiration). This is in agreement with sensitivity scatter plots (examples shown in Figure 2) but provides additional information that was helpful in determining the best approach for selecting best fit parameters. We were also able to isolate parameters that had minimal impact on any outputs of interest. The set of 23 calibration parameters is shown in Table 7.

Table 7. Parameters and ranges selected for the calibration runs with 50,000 LHS runs.

Parameter	File	Description	Min Value	Max Value
ICP	APEXCONT.dat	ICP	0	1
FHP	.sol	Fraction of Humus in Passive Pool	0.3	0.7
HE	tillcom.dat	Harvest efficiency for grazing - important for N_2O emissions	0.1	0.25
PARM (2)	Parm1501.dat	Root-growth-soil strength	1.15	2
PARM (4)	Parm1501.dat	Water storage N leaching	0.2	0.9
PARM (7)	Parm1501.dat	N fixation	0.2	0.99
PARM (8)	Parm1501.dat	Soluble phosphorus runoff coefficient	10	18
PARM (14)	Parm1501.dat	Nitrate leaching ratio	0.6	1
PARM (15)	Parm1501.dat	Runoff CN adjustment	0	0.3
PARM (17)	Parm1501.dat	Soil evaporation plant cover	0.1	0.3
PARM (23)	Parm1501.dat	Hargreaves PET equation coefficient	0.0022	0.0032
PARM (29)	Parm1501.dat	Biological mixing efficiency	0.001	0.01
PARM (46)	Parm1501.dat	RUSLE-C factor coefficient	0.5	1.5
PARM (59)	Parm1501.dat	P upward movement by evaporation coefficient	1	18
PARM (72)	Parm1501.dat	Volatilization/nitrification partitioning	0.08	0.4
PARM (69)	Parm1501.dat	Coefficient adjusts microbial activity in top layer	0.1	1
PARM (70)	Parm1501.dat	Microbial decay	0.6	1.4
PARM (76)	Parm1501.dat	conversion of residue	0.001	0.1
PARM (83)	Parm1501.dat	Estimates drainage system lateral hydraulic conductivity	0.5	5
PARM (92)	Parm1501.dat	Runoff Volume Adjustment	0.8	1.2
PARM (96)	Parm1501.dat	soluble p leaching	1	15
XKN3	Parm1501.dat	Michaelis Menten constant	5	30
XKN1	Parm1501.dat	Michaelis Menten constant	0.1	1

4.1.5. Validation

Based on the number of metrics included in the multi-objective calibration and the limited time series of the observed datasets, validation of APEX model performance was largely conducted through the second component of this effort. Batch simulations were conducted to represent all possible soil and weather conditions in Vermont and results compared to larger datasets and/or established expectations (described in Sections 4.2 and Section 5.2).

4.1.6. Approaches for Selection of a Global Parameter Set

The last step in the site-specific calibration process was to identify a best fit set of parameter values that provide a robust model performance for all processes and associated outputs of interest. Selection of 'best' parameter values were done using two different approaches: (1) a multi-objective function created by assigning weights to each of the outputs for which observed data was available (Section **Error! Reference source not found.**, Table 3), and (2) a sensitivity-based approach, where each parameter was evaluated independently across all runs conducted against the output variables for which the parameter was sensitive (Section 4.1.4). While this allowed a more targeted optimization for the different outputs and across the different sites available, the assumption was, that parameter interaction is negligible for insensitive output variables.

4.1.6.1. Weighting Approach for Multi-Objective Function

The premise of the weighting approach is that some outputs may be considered higher priority for reducing error than other outputs. For example, hydrology and erosion are drivers of soluble and sediment phosphorus and nitrogen losses and therefore achieving minimal errors in these processes should result in more accurate representation of other modeled processes. Different weighting options that were evaluated are shown Table 8. Weights were applied to the specified data types as shown in Table 8. For each data type, we applied the specified weight to the mean RMSE across sites where that particular data type was available. We selected RMSE as the sole performance metric for the selection process to simplify the procedure of determining and applying weights to both different data types and different performance metrics. RMSE was used here as it highly correlates to other absolute metrics as well also inherently incorporates the variability between all data points of a specific type (e.g., where we have multiple annual values of runoff per site). As the RMSE retains the units of the data, this results in higher RMSE values for large outputs (such as soil organic carbon in kg/ha) and lower RMSE values for small variables (such as N_2O emissions in kg or sediment nitrogen loss in kg). We therefore scaled the RMSE to make it comparable between large and small variables. Different scaling methods were also tested, but ultimately, we used a min-max normalization approach, where values were rescaled to a range of 0 – 1 and 0 value represented the 'best' value (minimum error).

We first designed 'extreme' weighting options to evaluate that the selection process worked as expected (identified as 'plausibility' weightings in Table 8). These plausibility weightings were designed to optimize for ONLY hydrology outputs, GHG outputs, phosphorus outputs, and nitrogen outputs, respectively. Again, these were not proposed for use in selecting a final parameter set but as a way of ensuring the use of weights would appropriately prioritize identified metrics. The results of this plausibility analysis are presented in Figure 4, and show the optimization results are consistent with expectations. The GHG-only weighting results in the lowest errors for CO_2 emissions, N_2O emission, and NEP. Similarly, the P-only weighting results in the lowest errors for most phosphorus outputs, and the N-only weighting results in the lowest errors for nitrogen outputs, etc. We also see in Figure 4 that these weighting functions can result in significantly different outcomes and model performance. For example, the GHG-only weighting results in high errors for soluble nitrogen and phosphorus losses, as well as other metrics.

Based on these initial results, we considered this a viable approach for applying the multi-objective function to select a parameter set for use in Farm-PREP and the Soil Health Calculator Tool. We next determined a set of weighting scenarios for further evaluation, where this time we assigned some weight on all of the output variables. The following weighting scenarios were considered:

- Balanced: all data types/outputs weighted equally
- GHG-focused: NEP, CO_2 and N_2O emissions are weighed 2.5 times higher and soil respiration 1.5 times higher than other outputs
- P-focused: phosphorus outputs (soluble P, sediment P, total P) are weighed 2.5 times higher and tile drain phosphorus 1.5 times higher than other outputs
- N-focused: nitrogen outputs (soluble N, sediment N, total P, and N_2O emissions) are weighed approximately 2.8 times higher and tile drain nitrogen 1.7 times higher than other outputs
- SH-focused: Total soil organic carbon, total soil nitrogen, soil organic matter in top 30 cm, and soil respiration were weighed approximately 2.9 times higher and yield approximately 1.8 times higher than other outputs
- Process-focused: Hydrology processes (runoff and erosion outputs) were weighed most heavily as these processes drive the response of other outputs, these processes are well-established in APEX, and data representing these processes in the site-specific calibration were relatively robust, coming from multiple sites and covering time periods and where data collection processes are also well-established for runoff and erosion monitoring. Phosphorus outputs were weighed next heaviest as phosphorus is the primary focus of total maximum daily load (TMDL) objectives and associated accounting, and similar to hydrology, the model components representing phosphorus cycling and transport are well established and observed data for this calibration was considered relatively robust. Nitrogen results were weighed just slightly less than phosphorus outputs based on lower concern around surface nitrogen losses in the state. Soil carbon was weighed similarly to nitrogen because soil carbon is closely related to soil N. Tile outputs were weighed lower than these processes because we expect model representation of tile drainage is less robust than some other processes (e.g. APEX only simulates dissolved nutrients in tile) and we expect higher uncertainty in monitoring data from tile drained systems. Yield, soil respiration, and GHG emissions were weighed second lowest due primarily to the uncertainty in associated observed data and whether reported measurements were representative of exactly the same outputs as simulated in APEX. Soil carbon and soil organic nitrogen (representative of kg carbon or kg organic nitrogen in the entire soil column) were weighed lowest, again based on uncertainty in the correlation between observed data and model simulated processes for these outputs and early indications these observed and modeled values may not align well. One reason for this could be assumptions around depth of the soil column and how carbon and nitrogen may vary with depth.

Table 8. Objective Function Weights.

Output Variable	Output Abbreviation	Plausibility Weightings				Considered Weightings for Final Selection					
		GHG-Only	P-Only	N-Only	Hydrology - Only	Balanced	GHG-Focused	P-Focused	N-Focused	SH-Focused	Process-Focused[1]
Runoff	Q	0	0	0	0.33	0.05	0.04	0.04	0.036	0.034	0.1
Erosion	MUSS	0	0	0	0.33	0.05	0.04	0.04	0.036	0.034	0.1
Soluble Phosphorus	QP	0	0.25	0	0	0.05	0.04	0.1	0.036	0.034	0.08
Sediment Phosphorus	YP	0	0.25	0	0	0.05	0.04	0.1	0.036	0.034	0.08
Total Phosphorus	TP	0	0.25	0	0	0.05	0.04	0.1	0.036	0.034	0.08
Soluble Nitrogen	QN	0	0	0.2	0	0.05	0.04	0.04	0.1	0.034	0.06
Sediment Nitrogen	YN	0	0	0.2	0	0.05	0.04	0.04	0.1	0.034	0.06
Total Nitrogen	TN	0	0	0.2	0	0.05	0.04	0.04	0.1	0.034	0.06
Tile Drain Flow	QDR	0	0	0	0.33	0.05	0.04	0.04	0.036	0.034	0.04
Tile Drain Phosphorus	QDRP	0	0.25	0	0	0.05	0.04	0.06	0.036	0.034	0.04
Tile Drain Nitrogen	QDRN	0	0	0.2	0	0.05	0.04	0.04	0.06	0.034	0.04
Forage Yield	YLDF	0	0	0	0	0.05	0.04	0.04	0.036	0.06	0.03
Net Ecosystem Production	NEP	0.25	0	0	0	0.05	0.1	0.04	0.036	0.034	0.03
Carbon Dioxide Emissions	CO_2	0.25	0	0	0	0.05	0.1	0.04	0.036	0.034	0.03
Nitrous Oxide Emissions	N_2O	0.25	0	0	0	0.05	0.1	0.04	0.1	0.034	0.03
Soil Organic Carbon	absC	0	0	0	0	0.05	0.04	0.04	0.036	0.1	0.01
Soil Nitrogen	absN	0	0	0.2	0	0.05	0.04	0.04	0.036	0.1	0.01
Soil Respiration	RSPC	0.25	0	0	0	0.05	0.06	0.04	0.036	0.1	0.03
Organic carbon (top 30 cm)	OCPD	0	0	0	0	0.05	0.04	0.04	0.036	0.1	0.06

[1]Used to select 'final' parameter set

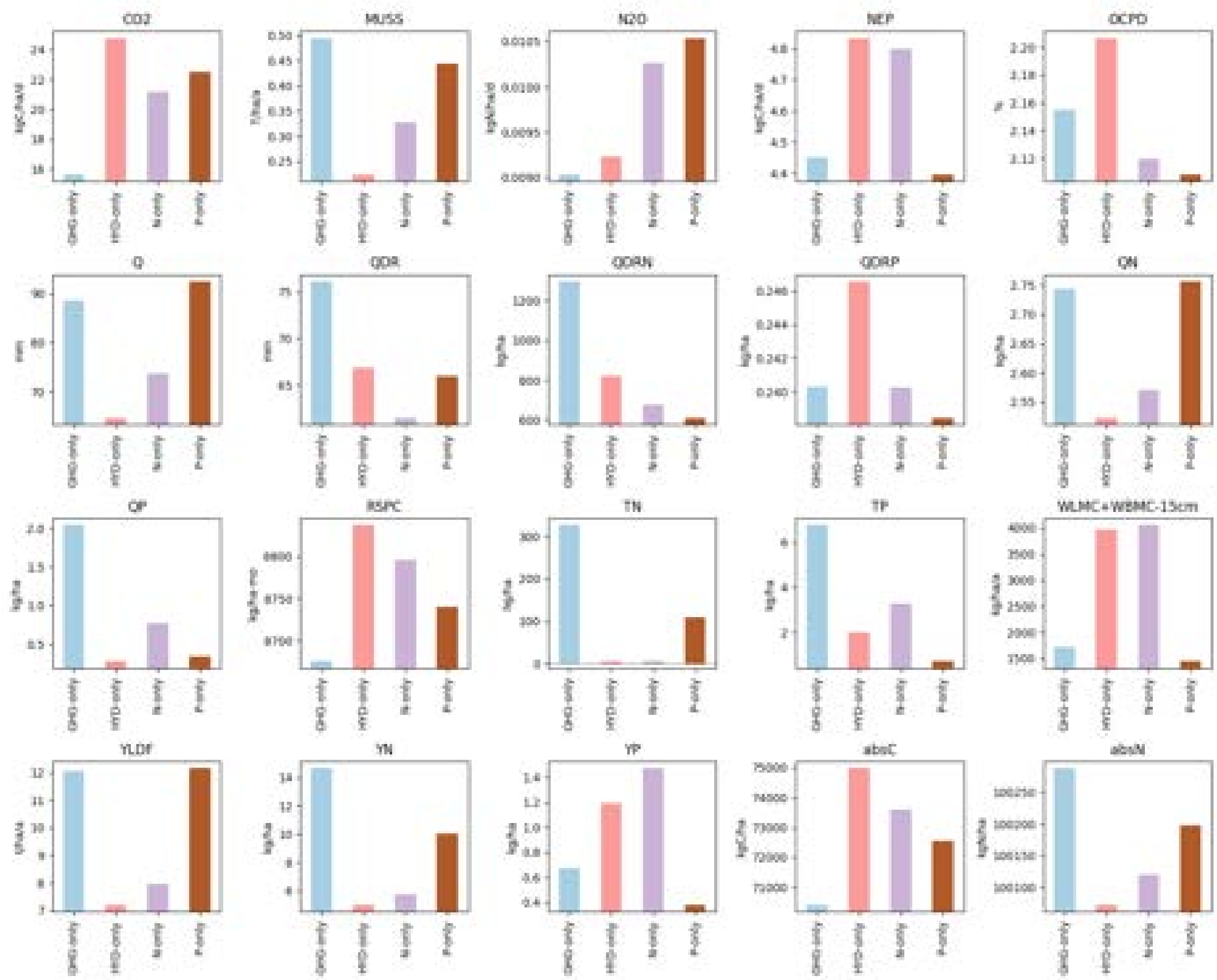

Figure 4. Plausibility weighting of objective function.

Using this approach, a single parameter set would be selected based on its performance across all outputs/observed data types.

4.1.6.2. Sensitivity-Based Approach

In the sensitivity-based approach, we first identified output variables for each of the 23 APEX calibration parameters that are impacted significantly by changing that parameter value (based on sensitivity boxplots as shown in Figure 3). We tested different thresholds (2, 5, 10 and 20%) on the Random-Forest-based sensitivity evaluation and assigned sensitive parameter if their 75th percentile (upper boundary of the sensitivity boxplot) was located above the threshold (see Figure 3, dashed line for 20%). Note Figure 5 shows all parameters tested in the sensitivity analysis, where Figure 3 shows a subset of these for closer examination. All output variables that have their upper end of the box above the dashed line were selected for the parameter value identification (also indicated in Table 7). We then used the method of applying a multi-objective function to select the parameter value that led to the lowest RMSE for the sensitive output variables. The primary difference in this approach is that we did not select a single run/parameter set with multiple fixed parameter values, but ideal parameter values were selected independently from runs where sensitivity was observed.

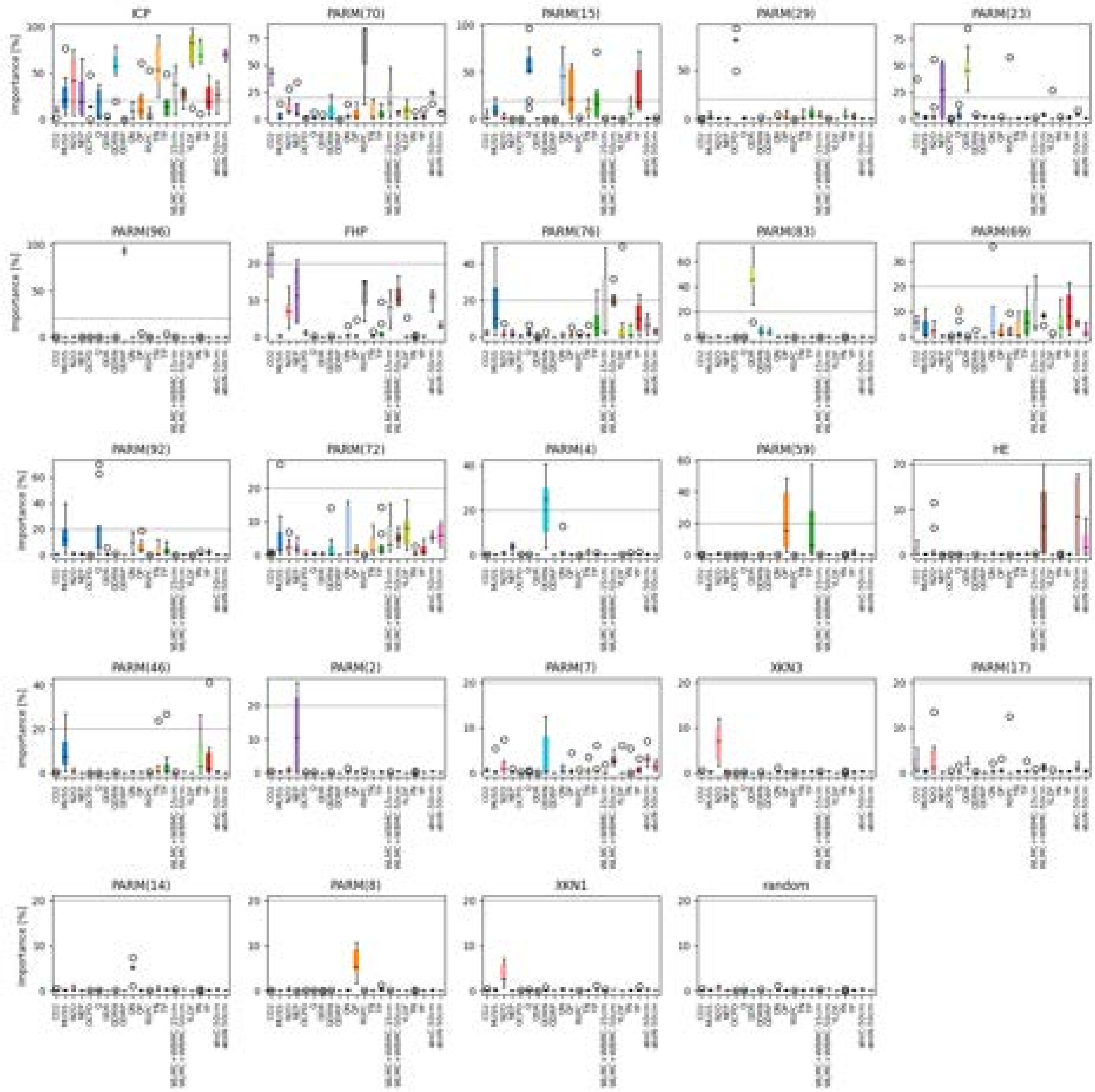

Figure 5. Sensitivity boxplots for all 23 calibration parameters evaluated (plus the random variable) with the 20% importance threshold.

4.1.7. Workflow Summary

A parallelized Python workflow was developed to automate the previously described sensitivity analysis and calibration process, enabling reproducible parameter sampling, computationally efficient model execution, and evaluation of the parameter set across the 32 APEX field model setups. The workflow included the following steps:

1. Input File Preparation: The LHS-sampled parameter values were dynamically written into the APEX input files (parm.dat and soil files) for each of the LHS parameter combinations, resulting in 30,000 runs per model setup (site).
2. Model Execution (sensitivity sampling): For each parameter combination, the Python script executed all 32 APEX models.
3. Output Extraction: Relevant model output variables were extracted from the respective APEX output file for the specified time periods for which the observed variables were available.
4. Performance Evaluation: Six performance criteria were calculated from the simulated and observed data value for each output variable and model run: Root Mean Square Error (RMSE), Absolute Error (AbsErr), Relative Error (RelErr), Bias, Ratio, Percent Difference (PctDif). This resulted in six performance criteria values for each output variable, model setup and LHS parameter combination (this is combination is referred to as a 'model run'). To aggregate the performance criteria for each model run, the mean and median value of the performance criteria were calculated across all 32 models (the sites) for each output variable. This resulted in 156 performance values (21 output variables x 6 performance metrics) for each of the 30,000 parameter combinations.
5. Sensitivity Visualization: Scatter plots of parameter values versus performance metric were generated for each output variable. These plots provided an initial visual representation of parameter sensitivities. For the selection of parameters for the calibration, box plots were generated based on a random forest model that objectively evaluated parameter importance on the RMSE performance criterion. This led to the definition of the final set of 23 calibration parameters (Table 6).
6. Model execution (full sampling): 50,000 parameter sets developed using LHS-sampling were run post-sensitivity analysis as the basis for applying the multi-objective function and selecting optimum parameter values.
7. Application of multi-objective function: We developed weighting scenarios to represent relative importance of, or confidence in, some observed data/model outputs. For example, we generally felt more confident in edge of field monitoring data than field-scale measurements of GHG emissions. These were used in tandem with the sensitivity-based approach (4.1.6.2) to determine the 'best fit' parameter values to be used as a global parameterization of APEX in subsequent tasks.
8. Validation of the optimum parameter set using batch runs for hypothetical Vermont fields described in Section 4.2, and comparison against additional observed data and against expected trends in model outputs.

4.2. Batch Simulations for Trend and Management Evaluation

Batch simulations were conducted as a second component of model calibration and to meet multiple objectives of this effort. This was determined as the best approach to a) validate model performance in association with the site-specific multi-objective calibration that established a global parameters set, b) compare relative performance of APEX to DNDC and Comet-Farm with respect to the impact of management, c) ensure simulated values of runoff, erosion, nutrient losses, GHG emissions, and key soil health indicators are within expected ranges across a range of field conditions and crop rotations that could be simulated in Farm-PREP and are representative of agricultural fields across the state, and d) evaluate the impact of practices and management as there is not enough data to do a true calibration that would specifically incorporate agronomic management. This section of the report describes the setup of batch simulations, the approach for evaluating impacts of management and practices, as well as how we incorporated additional datasets to further validate model performance.

4.2.1. APEX Scenarios

Batch simulations were designed to represent hypothetical fields across a range of soil, weather, and slope conditions in Vermont. As much as possible, we relied on source datasets (publicly available) and parameterization approaches already vetted and used in Farm-PREP. The primary components of setting up field simulations in APEX include defining the field/s boundaries and associated physical characteristics, weather inputs, and agronomic management. Determination of these inputs are described below.

4.2.1.1. Spatial Sampling

Representative field sites for cropland, pasture/hay, as well as non-agricultural land use types were obtained based on a spatial sampling approach. While the particular location of the field is not significant in the modeling, the location was used to determine the associated physical characteristics (soils, slope, weather). Locations for hypothetical fields and associated conditions were identified by creating a square grid covering the state of Vermont and sampling a set of underlying spatial datasets at those grid points. Datasets sampled are shown in Table 9.

Table 9. Datasets sampled for creating batch simulation.

Dataset	Source	Resolution	Attribute Sampled
Digital elevation model (DEM)	USGS National Elevation Dataset (NED)	10 m	Elevation
Soils	National Soil Survey Geographic Database (gNATSGO) 2021	NA	Soil map unit (mukey)
Land use	National Land Cover Database (NLCD) 2021	30 m	Forest, cropland, or pasture/hay
Grid	Created using ArcPRO tools (tessellation)	5 km^2, 1 km^2, 0.2 km^2	Latitude/longitude

Field elevation was obtained from the DEM, soil map unit was obtained from the gNATSGO (SSURGO) data, land use from the NLCD dataset, and latitude/longitude from the grid point locations. Land use categories were obtained from the NLCD dataset. Deciduous forest, evergreen forest, and mixed forest (41,42, and 43, respectively) were considered forest locations; grassland/herbaceous (71) and pasture/hay (81) were considered pasture/hay locations; and cultivated crops (82) were considered cropland. Initially, a grid with spatial resolution of 5 km was used. As only approximately 1.6% and 11.4% of the state is classified as cropland and pasture/hay, respectively (Figure 6), three grid sizes were used to sample the three land use classes of interest, with the end results being 5 km^2 for forest, 1 km^2 for pasture/hay, and 0.2 km^2 for cropland (Figure 7). This resulted in 3527 forest sites, 2814 pasture/hay sites, and 2009 cropland sites. We thinned the grid points based on repeating soil map units such that if the same soil/weather combination was associated with multiple grid points, we simulated only one point (as this would result in the same conditions and duplicate results). Figure 8 shows the distribution of sampled elevation and hydrologic soil types for the cropland sampling points and Figure 9 shows the distribution of hydrologic soil group and elevation for sampled pasture/hay sites.

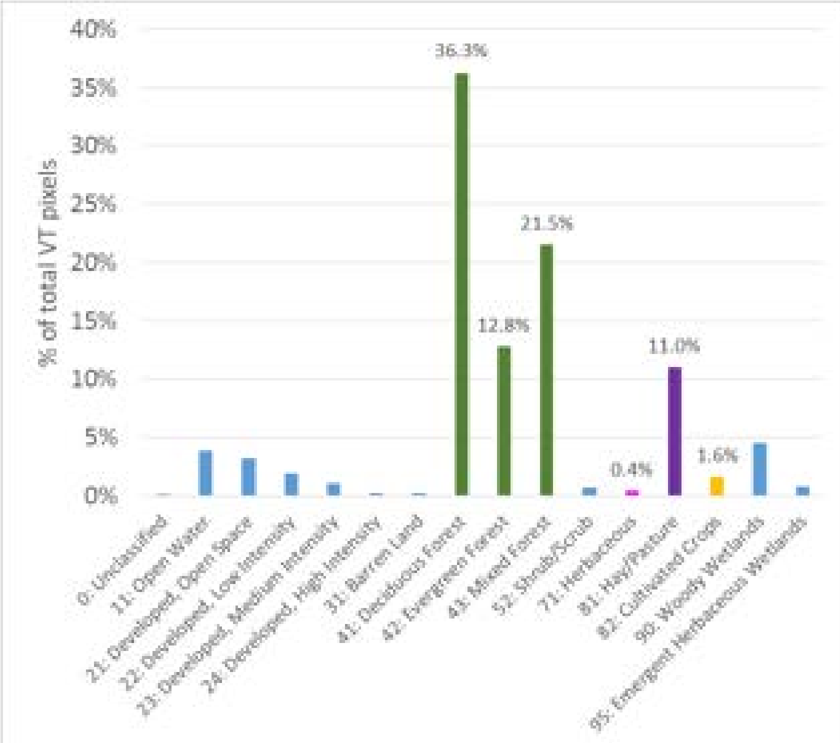

Figure 6. Land use percentages for Vermont based on NLCD classification.

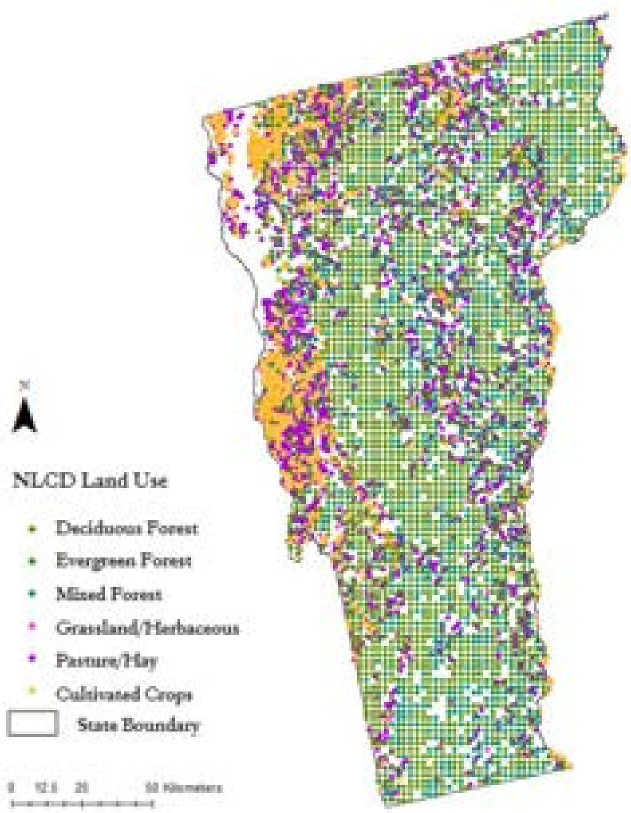

Figure 7. Grid sampling for creation of hypothetical fields.

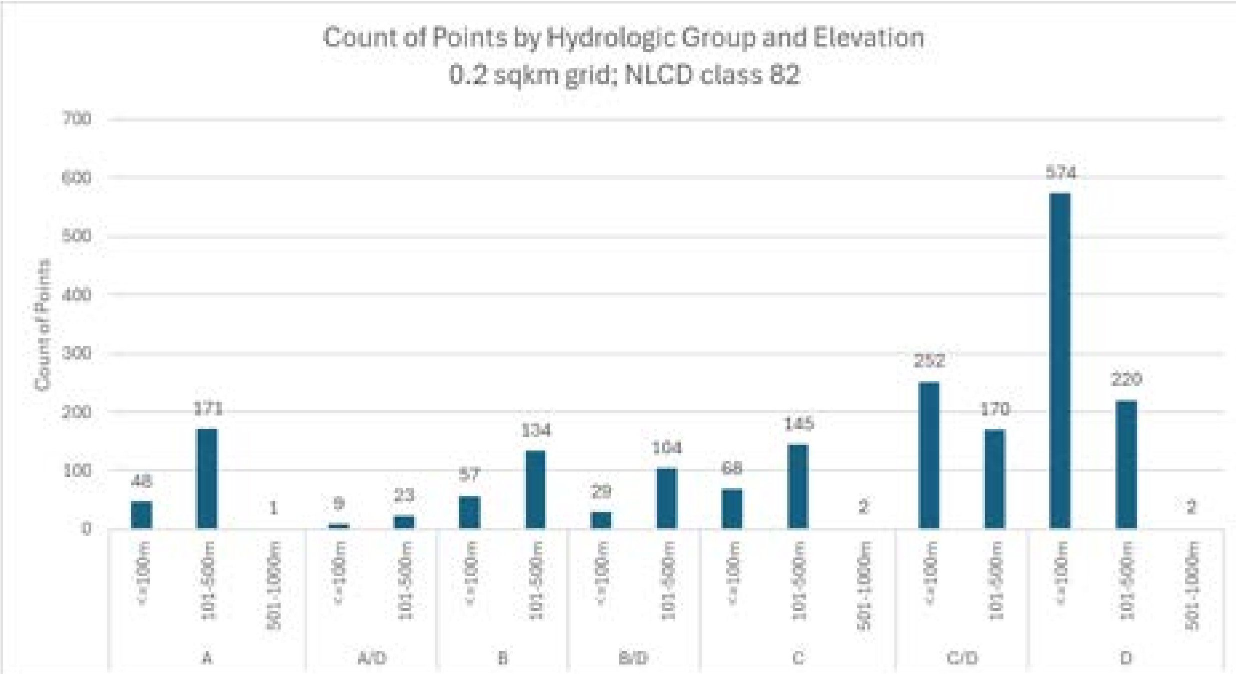

Figure 8. Distribution of hydrologic soil group and elevation across sampled cropland sites.

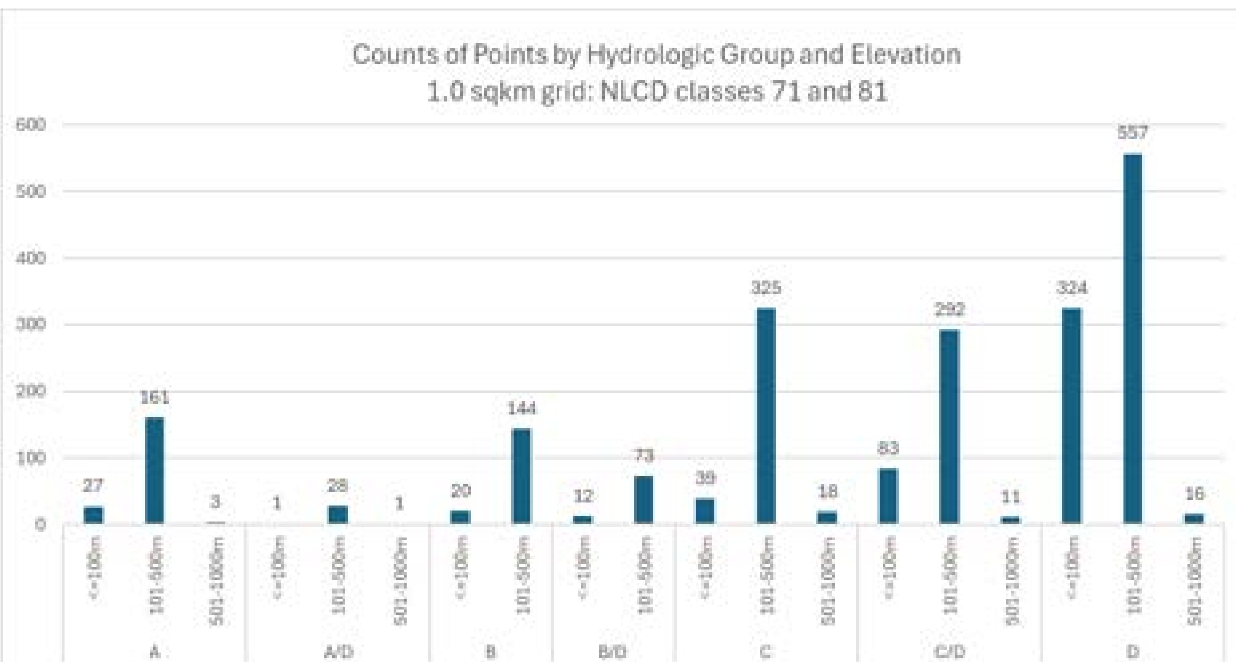

Figure 9. Distribution of hydrologic soil group and elevation across sampled pasture/hay sites.

While we expect many soils are not suitable for farming in Vermont and are not likely to be simulated in the context of Farm-PREP, we do not constrain users to specific soils and therefore we additionally set up simulations for dominant soil map units that were not identified in the grid sampling (a total of 400 additional soils). These were run with time series data from a single weather station (USC00430942, located near Greensboro, VT at an elevation of 549 m). We also later incorporated woody and herbaceous wetlands (CDL classes 190 and 195), and shrubland (CDL class 152) from the same grid sampling approach (weather assigned based on closest to grid point). Note that land uses other than cropland and pasture were not used in the Soil Health Calculator model evaluation, but were sampled and set up similarly as part of ongoing work with VAAFM.

A total of 5169 sites were set up for these batch simulations. The number associated with each of the identified land uses was: 779 cropland, 1623 pasture, 2120 forest, 214 wetland, 33 shrubland, and 400 not identified through grid sampling and associated with a particular land use. Note that while we considered it important to know what the 'real' land use for these sites (based on NLCD data), we ran all management on all sites. We then looked at whether there were differences in model results based on whether management scenarios matched land uses. Most of the results presented in subsequent sections are filtered so that management matched assigned land uses (for example, we used model results from cropland management scenarios and only locations identified as cropland to compare to SSHVT data and results from pasture management scenarios on only locations identified as pasture to compare to VLTHS data). We expect that areas identified as wetlands or fores likely have particular soils that might not be well suited for cropland or pasture and would therefore give results that may not align with expectations for cropland or pasture fields. For example, some forest soils are defined in the gNATSGO database as having an Oi horizon layer at the surface comprised of 3 cm of fibric material characteristic of the topmost organic layer found in forest soils or wet areas. These soils could produce outlier results in APEX due to unique properties not representative of cropland soils.

Again, for this effort, we primarily focused on fields (soil-weather combinations), that were classified as pasture or cropland land uses. Forest, wetland, and shrub simulations are being evaluated in a related effort with VAAFM. Filtering of results based on management schedules for specific comparisons to observed data and/or evaluation of practices and trends is described in Section 5.2.

4.2.1.2. Physical Characteristics and Soils

These hypothetical field sites (or APEX subareas) were set to be 10 ha in area. Subareas in APEX have homogeneous climate inputs, soils, slope, and management practices. For all land use types, slope and soil parameters for APEX (Table 4) were determined based on the soil map unit identified in the point sampling and the associated gNATSGO data and slope length was calculated using equation 1 presented in Section 4.1.1.3.

A soil test phosphorus of 5 ppm Modified Morgan's phosphorus was assumed for these simulations. No tile drainage was simulated in these batch simulations.

4.2.1.3. Weather

As with the SH field sites, the same Vermont weather stations as are currently implemented in Farm-PREP were used for these sites (based on gap-filled NOAA Coop Station data), where the time series were updated using USDA-ARS to extend through the end of 2020. Batch model simulations were run for 30 years from 1990 through 2020. The closest Vermont weather station to the sampled location was found based on the latitude and longitude of the field centroid and the latitude and longitude associated with the weather station location, and the associated time series used for each hypothetical field site.

4.2.1.4. Agronomic Management

Agronomic management schedules were developed for 9 'crop groups' reflective of cropping systems implemented in Farm-PREP including corn, grass hay, alfalfa hay, legume hay, corn-grass hay rotation, corn-alfalfa rotation, soybean, potatoes, and lettuce. These are summarized in Table 10. The current implementation of Farm-PREP uses lettuce as a representative vegetable crop, however because of the short amount of time it provides ground cover we also selected to simulate potatoes. Based on analysis of a 5-year (2018-2022) composite cropland data layer (USDA National Agricultural Statistics Service, 2018), potatoes were the most dominant fresh vegetable crop grown in Vermont. For each of these crop groups, we established a baseline agronomic management schedule reflective of conventional practices (conventional spring and fall tillage, incorporated surface manure applications, no conservation practices). We then developed agronomic management schedules for each crop group that differed from the baseline by incorporating the practices identified in Table 10 for applicable crop groups. Timing of planting, manure applications, and tillage were selected based on current implementation of management in Farm-PREP, described in Stone Environmental (2018; 2020b). All scenarios were used to evaluate the overall behavior of APEX with respect to soil health metrics, while the baseline scenarios have the additional purpose of serving as a basis for evaluating the impact of practices on simulated outcomes.

All of management scenarios summarized in Table 10 were run on each of the hypothetical fields, representative of unique soil-weather combinations as described above, regardless of their original CDL land use classification. Farm-PREP allows users to create fields anywhere in the state of Vermont, and while we expect users to typically delineate fields on areas identified primarily as cropland or pasture, this was also a way to identify outliers or key attributes of soil that may produce anomalous results in APEX. Section 5.2 described results of this analysis, including how fields and management scenarios were filtered to support specific evaluations.

Table 10. Agronomic management schedules for batch simulations.

Crop Group	Practice	Notes	Nutrients Applied	Category for Comparison to Observed Datasets by Texture
Continuous Corn, Continuous Soy, Continuous Vegetable, Continuous Potato	None (conventional assumptions)	continuous corn; spring and fall manure applications, spring commercial P and N applications, conventional tillage	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lb/ac; commercial N: 180 lb/ac	Cropland
	Low nutrient applications	continuous corn with low nutrient inputs - halved manure and commercial P and N from baseline	spring and fall manure: 18 lb P2O5, 45 lb/ac N; commercial P: 20 lbs/ac; commercial N: 90 lbs/ac	Cropland
	High nutrient applications	continuous corn with high nutrient inputs - doubled manure and commercial P and N from baseline	spring and fall manure: 72 lb P2O5, 180 lb/ac N; commercial P: 80 lbs/ac; commercial N: 360 lbs/ac	Cropland

	Cover crop	winter hardy, mid planting date	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
	No till	no-till and surface manure application	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
	Manure injection	baseline nutrients amounts, injected	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
	Reduced till	reduced soil disruption in spring, no fall tillage	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
	No till and manure injection	no-till and injection	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
	Mulching	apply high carbon, low nutrient matter in spring post nutrient applications	spring and fall manure: 36 lb P2O5, 90 lb/ac N; commercial P: 40 lbs/ac; commercial N: 180 lbs/ac	Cropland
Continuous Grass Hay, Continuous Alfalfa, Continuous Legume Hay	None (conventional assumptions)	3 cuttings	spring commercial N: 180 lbs/ac; manure after cuttings: 64 lb P2O5/ac-yr, 160 lb N/ac-yr	Cropland
	Low nutrient applications	halved manure and commercial N and P from baseline	spring commercial N: 90 lbs/ac; manure after cuttings: 32 lb P2O5/ac-yr, 80 lb N/ac-yr	Cropland
	High nutrient applications	doubled manure and commercial N and P from baseline	spring commercial N: 360 lbs/ac; manure after cuttings:128 lb P2O5/ac-yr, 320 lb N/ac-yr	Cropland
	Manure injection	use baseline nutrients + injection, 3 cuttings	spring commercial N: 180 lb/ac; manure after cuttings: 64 lb P2O5/ac-yr, 160 lb N/ac-yr	Cropland
Corn-Alfalfa, Corn-Grass Hay	None (conventional assumptions)	combined corn and hay baselines; 4 yr rotation, surface manure application, 3 cuttings	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
	Low nutrient applications	halved manure and commercial N and P from baseline	same as Low Nutrient Continuous Corn for corn years, same as Low Nutrient Continuous Hay for hay years	Cropland
	High nutrient applications	doubled manure and commercial N and P from baseline	same as High Nutrient Continuous Corn for corn years, same as High Nutrient Continuous Hay for hay years	Cropland
	Cover crop	winter hardy cover crop, mid planting date applied to corn years	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
	No till	tillage removed, no till planter	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
	Manure injection	manure injected	same as baseline Continuous Corn for corn years, baseline	Cropland

			Continuous Hay for hay years	
	Reduced till	reduced tillage in corn years	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
	No till and manure injection	no till and manure injection	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
	Mulching	applied in corn years	same as baseline Continuous Corn for corn years, baseline Continuous Hay for hay years	Cropland
Pasture (Grazing)	None (baseline)	1 animal per acre (~.4 ha/hd); 14 hrs per day on the field; grass hay; no cuts or additional p inputs		Pasture
	Low stocking	lower stocking than 'baseline', 2.5 ha/hd		Pasture
	High stocking	higher than 'baseline', 0.25 ha/hd		Pasture
	Rotations: 3 days, 3 rotations			Pasture
	Rotations: 7 days, 3 rotations			Pasture
	Rotations: 1 day, 3 rotations	Similar to average rotation from VLTHS data		Pasture
	Rotations: 3 days, 7 rotations			Pasture
	Rotations: 7 days, 7 rotations			Pasture
	Rotations: 1day, 7 rotations			Pasture
	Additional nutrients	not to be compared to cropland low/high nutrients	commercial N: 200 lb/ac-yr; commercial P: 100 lb/ac-yr	Pasture
	Fewer cuts			Pasture
	Rotations: 1 day, 3 rotations, high stocking rate	Pasture_rotations1day3rotations, higher stocking rate (0.25 ha/hd)		Pasture
	Rotations: 1 day, 3 rotations, legume grass	same as Pasture_rotations1day3rotations with legume grass		Pasture

4.2.2. Observed Data and Model Post Processing

The batch simulations described in Section 4.2.1 are used in two ways:

1) To further validate a larger number of simulations to ensure conditions not represented by the field sites used in the calibration are also within expected ranges for key model outputs, particularly where less data or lower temporal resolution data was available.

2) To evaluate model performance with respect to expected trends when practices are implemented and/or management changed.

These batch simulations were also designed in part to make use of additional data sets described in this section. These data are not sufficient for site specific evaluation as locations and other site-specific information was not available. However, by simulating them in batch and comparing statistical summaries of outputs in comparison to statistical summaries of observed data, and looking at trends across all simulations, we can leverage these data to validate the parameter set derived from site-specific calibration and ensure simulations across the state are reasonable.

4.2.2.1. Model Validation

We have compiled a dataset comprised of point measurements with information on soil health and soil nutrient contents. These datasets include data collected for and presented in the State of Soil Health (SSHVT) report (White et al., 2022b), datasets collected through the Vermont Land Trust Healthy Soils (VLTHS) project, as well as Vermont portions of several larger data sets (Table 11).

Table 11. Point data of carbon, nitrogen, and/or phosphorus in soils.

Dataset	Author	Source	Variable name	Variables Description	Location	Measurements in VT	Years
RACA	NRCS/USDA	https://www.nrcs.usda.gov/resources/data-and-reports/rapid-carbon-assessment-raca	n_tot_ncs, c_tot_ncs, SOC_pred1	total combustion nitrogen, total_combustion_carbon, % Soil Organic Carbon predicted from VNIR scan	CONUS	265 profiles with 1282 horizons	2010-2011
WOSIS 1	ISRIC	https://www.isric.org/explore/wosis	Total_C, Total_N	total carbon, total nitrogen	Global	395 profiles with 2340 horizons	1970-2015
SoDaH	Wieder et al.	https://essd.copernicus.org/articles/13/1843/2021/#section3	layer_n_tot, layer_c_tot, p_ex_1	Bulk Layer Total Nitrogen concentration, Bulk Layer Total Carbon concentration, Extractable Phosphorus methods 1-4	CONUS	1 profile with 31 horizons	2018
ISCN 1	ISCN	https://iscn.fluxdata.org/data/access-data/	soc (g cm-2)	soil organic carbon in g/cm2	Global	310 profiles with 485 horizons	1952-2011
ISCN 2	ISCN	https://iscn.fluxdata.org/data/access-data/	n_tot_percent_by_weight, c_tot_percent_by_weight	nitrogen total percent by weight, carbon total percent by weight	Global	1910 observations	1952-2012
ISRIC	McDowell et al.	https://www.nature.com/articles/s41597-023-02022-4	p_olsn	Olsen phosphorus	Global	35 observations	2007-2014
WOSIS 2	McDowell et al.	https://www.nature.com/arti	P_avg	average phosphorus	Global	125 observations	2007-2014

		cles/s41597-023-02022-5					
Zinke	Zinke et al.	https://daac.ornl.gov/SOILS/guides/ZinkeSoil.html	Carbon_kg_m2	Carbon (kg/m2)	Global	5 observations	1965-1984

The SSHVT dataset contains statistical summaries of soil health metrics for 217 locations (single measurements) across the state of Vermont. This dataset was developed using CASH framework (Moebius-Clune, 2016) and includes metrics such as soil organic matter, bulk density, soil carbon stocks, respiration, and active carbon. Measurements were grouped by land use category and soil texture, and statistics are presented based on these categories. Our goal was to compare statistics calculated from APEX runs developed to represent Vermont agricultural soils to the statistics of measured values for soil health indicators included in the SSHVT. We also included 49 location/data points collected on pasture lands in 2022 from a CIG project managed by the VLTHS that were also analyzed using the CASH framework.

Analytical methods varied for the datasets shown in Table 11, but these were harmonized to represent soil carbon, nitrogen, and phosphorus concentrations and/or loads. This dataset does not have the additional metrics that are available through the CASH framework but still represents additional data that can inform plausible ranges of soil nutrients. The locations, numbers, and type of measurement from national datasets are shown in Figure 10. We acknowledge there were few phosphorus measurements in these national datasets for many parts of the state. SSHVT and VLTHS datasets did also include similar measurements and could not be mapped because of privacy requirements. We know soil phosphorus levels are highly sensitive to timing and rates of nutrient inputs and we did not have management data associated with these values, this data was used primarily to bracket model predictions.

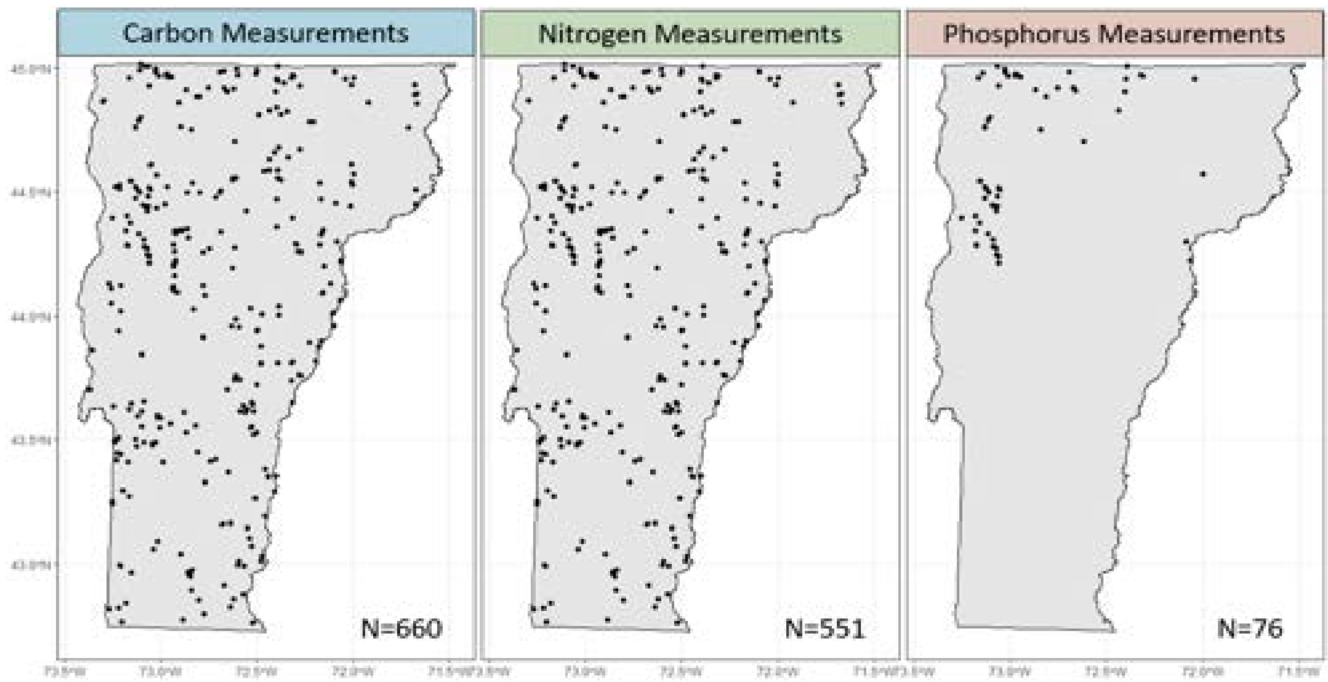

Figure 10. Carbon, nitrogen, and phosphorus measurements from national and global datasets within Vermont.

Statistical summaries of model outputs that can be mapped to metrics in these data sets (soil nutrient contents, bulk density, soil organic carbon, etc.) are compared to statistical summaries of these point datasets. We aggregated these points spatially as well as temporally to compare with model-predicted values. The goal in using this data was primarily to bracket in soil data across multiple management scenarios (including high and low nutrient input scenarios). As agronomic management is unknown for these data points, and location was also unknown for SSHVT and VLTHS datasets, we did not expect to replicate particular values in particular locations but aggregated these data to compare more generally.

4.2.2.2. Trend Evaluation

We reviewed literature to compile information on the expected behavior of key model outputs in response to certain management/practices. These are incorporated in an automated validation process similar to the field specific calibration to determine what portion of hypothetical fields show agreement vs disagreement with these trends. Table 12 shows an initial compilation of expected trends in model outputs.

Table 12. Table of expected behavior for model outputs in response to agronomic management changes.

	Management Practice							
	Buffer	**Cover Crop**	**High Nutrients**	**Low Nutrients**	**Manure Injection**	**No Till/ Reduced Till**	**Low Stocking**	**High Stocking**
Bulk Density	No change	Decrease	Mixed	Mixed	No change	Mixed		
CO_2 Emissions	No change	Decrease	Mixed	Mixed	Increase	Decrease		

Erosion	Decrease	Decrease	No change	No change	No change	Decrease	Decrease	Increase
Microbial Biomass	No change	Increase	Increase	Decrease	Increase	Increase		
N Stress Days	No change	Increase	Decrease	Increase	No change	Decrease		
N_2O Emissions	No change	Decrease	Increase	Decrease	Increase	Mixed		
P Stress Days	No change	Mixed	Decrease	Increase	No change	No change	Increase	Decrease
Runoff	Decrease	Decrease	No change	No change	No change	Decrease	Decrease	Increase
Sediment N Loss	No change	Decrease	Increase	Decrease	Decrease	Increase		
Sediment P Loss	No change	Mixed	Increase	Decrease	Decrease	Decrease	Decrease	Increase
SOC	No change	Increase	Mixed	Mixed	No change	Increase	Increase	Decrease
Soil N	No change	Increase	Increase	Decrease	No change	Increase		
Soil P	No change	Increase	Increase	Decrease	No change	Mixed	Decrease	Increase
Soluble N Loss	No change	Decrease	Increase	Decrease	Decrease	Increase		
Soluble P Loss	No change	Mixed	Increase	Decrease	Decrease	Increase	Decrease	Increase
Tile Drain N Loss	No change	Decrease	Increase	Decrease	Decrease	Increase		
Tile Drain P Loss	No change	Mixed	Increase	Decrease	Decrease	Increase		
Yields	No change	Mixed	Increase	Decrease	Increase	Mixed		

Table 13. References from the scientific literature for the expected trends described in Table 14.

Topic or Variable	Source
SOC and no-till	(Iheshiulo et al., 2023)
CO_2 and no-till	(Yue et al., 2023)
CO_2 and manure injection	(University of Vermont, 2017)
Yield and manure injection	(Bierer et al., 2021)
Yield and no-till	(Yue et al., 2023)
Runoff and no-till	(Sun et al., 2015)
P loss and manure injection	(Miller et al., 2019)
P loss and no-till	(Daryanto et al., 2017)
P loss and cover crops	(Carver et al., 2022; Liu et al., 2019)
N loss and cover crops	(Abdalla et al., 2019)
SOC and cover crops	(Joshi et al., 2023)
Yield and cover crops	(Peng et al., 2024)
SOC and high nutrient inputs	(Brown et al., 2014; Han et al., 2016)
CO_2 emissions and high nutrient inputs	(Wang et al., 2022; Wilson and Al-Kaisi, 2008)
CO_2 emissions and cover crops	(Kaye and Quemada, 2017)

Soil N and cover crops	(Johnson et al., 2024)
Soil P and cover crops	(Wang et al., 2021)
Soil P and high nutrient inputs	(Chen et al., 2022)
Soil N and high nutrient inputs	(Li et al., 2021)
Soil P and stocking rates	(Silveira et al., 2013)
N stress and cover crops	(Meyer et al., 2022)
Soil N and no till	(Lafond et al., 2011)
Soil P and no till	(Daryanto et al., 2017)
Bulk density	(Iheshiulo et al., 2023; USDA, 2015)

5. Modeling Results

The following sections (Section 5 of this report) describe the outcomes of *Task 4-1 Calibration/Parameterization/Evaluation of APEX With Respect to Soil Health Metrics* and *Task 4-2 Evaluation of APEX Response to Practice and Management Options* of the Soil Health Calculator Project.

5.1. Site-Specific Calibration

The objective of this multi-objective calibration approach was to select a ‘global’ APEX parameter set that provides a robust performance with respect to multiple modeled processes including phosphorus and nitrogen losses, GHG emissions, carbon sequestration, and soil health. In Section 4 we described the approach used to perform a calibration analysis and two approaches proposed for selecting the ‘best fit’ parameter set to meet this objective. As a final evaluation of which calibration approach leads to the best results, we compared the best parameterizations from the two weighting approaches “Balanced” and “PROCESS-Focus” described in Section 4.1.6.1 and five sensitivity-based approaches described in Section 4.1.6.2. We also ran the 32 site-specific models with variations of three previously available parameterizations to evaluate whether the selected parameter set using our methods resulted in a performance improvement over these previously used parameterizations. These three parameterizations included the APEX default parameterization (parameter values selected based on the 2024 manual ‘default’ recommendations) and the current Farm-PREP parameterization, including one Farm-PREP parameterization that included a specified model ‘spin up’ period.

The parameter sets were ranked (amongst the 2+5+3=10 parameter sets) based on normalized RMSE across sites, where rankings were developed based on the min-max normalization function. We calculated an average rank across each of the normalization methods for each selection and determined which had the ‘lowest’ rank, indicating best performance. The selection method, normalized RMSE, and rank for the key parameters sets is shown in Table 14 and are also plotted in Figure 11. The plots show that the sensitivity-based approach based on minimizing the min-max normalized median site RMSE (Sens30-MnMx-MdAg) produced a parameter set that resulted in lower errors for most outputs than parameter sets selected using other approaches or default and previous Farm-PREP parameterizations. We see that the sensitivity-based (‘Sens-Based’) approach outperforms the classical multi-objective calibration where a single parameter set is chosen versus selecting parameters from different runs based on their unique sensitivity. The final parameter set selected using this approach (‘Sens30-MnMx-MdAg’ = ‘Sens-Based’) is shown in

Table 15.

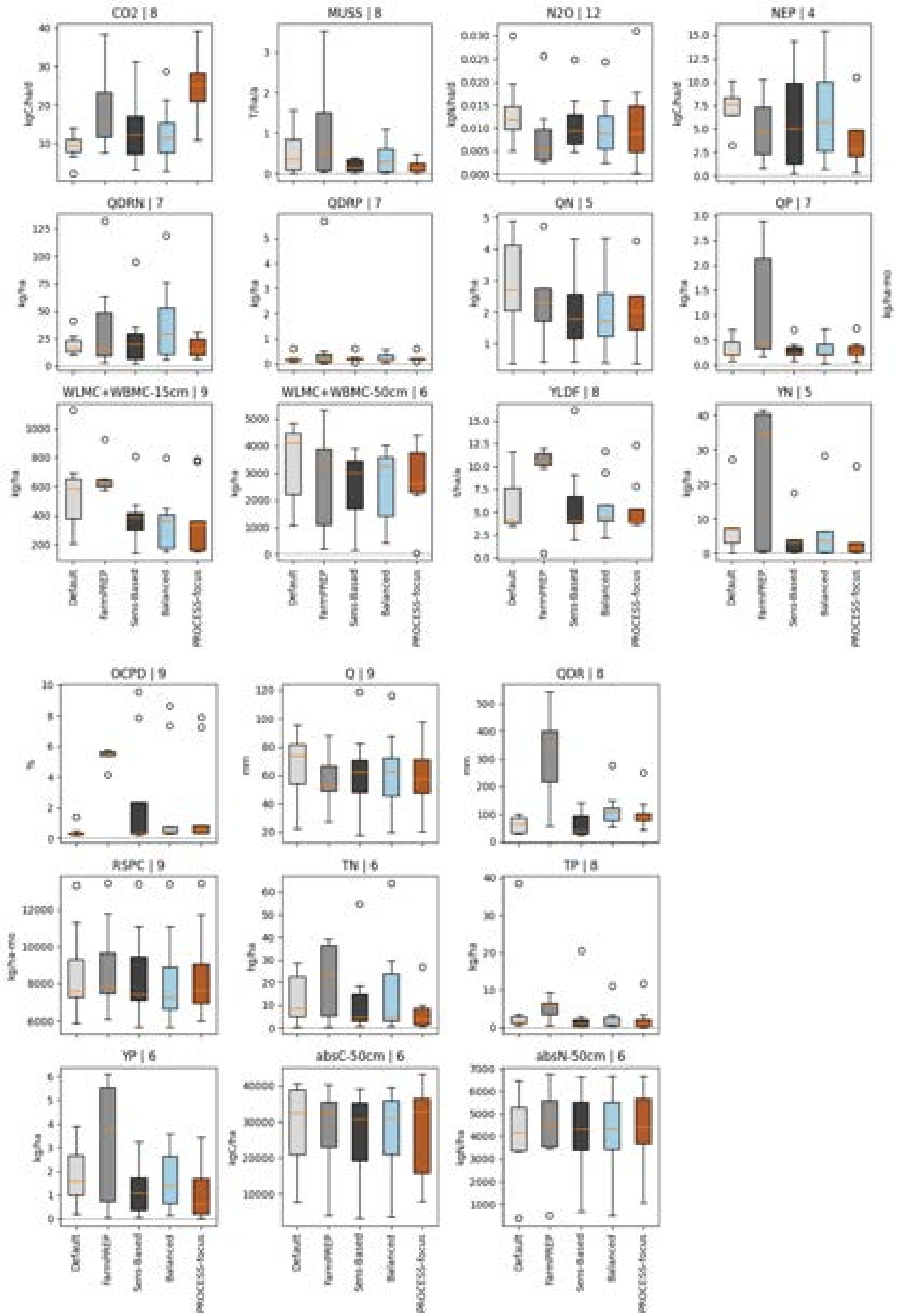

Figure 11. RMSE (not normalized) for the evaluated weighting functions across the 32 sites.

Table 14. Rank of parameter sets chosen based on key selection approaches.

Method/Weighting	Normalized RMSE	Rank
Sens30-MnMx-MdAg	**0.0105**	**1**
Sens2-MnMx-MdAg	0.0106	2
Balanced	**0.0115**	**3**
Sens5-MnMx-MdAg	0.0128	4
Sens10-MnMx-MdAg	0.0130	5
PROCESS-focus	**0.0141**	**6**
Sens20-MnMx-MdAg	0.0164	7
Default	**0.0208**	**8**
FPLong	0.0289	9
FarmPREP	**0.0335**	**10**

Table 15. Final parameter values selected using the sensitivity-based approach (parameters in bold font) with a 30% sensitivity threshold (Sens30-MnMx-MdAg); parameters in normal font were set to these fixed values after the sensitivity analysis.

Parameter	File	Description	Final Value
FHP	**.sol**	**Fraction of Humus in Passive Pool**	0.32
HE	**tillcom.dat**	**Harvest efficiency for grazing - important for N_2O emissions**	0.16
ICP	**APEXCONT.dat**	**ICP**	1
PARM(107)	Parm1501.dat	Maximum rate of uptake of nitrogen during immobilization	0.35
PARM(108)	Parm1501.dat	Half Saturation constant for ammonia immobilization	15
PARM(109)	Parm1501.dat	Half Saturation constant for nitrite immobilization	10
PARM(110)	Parm1501.dat	Half Saturation constant for nitrate immobilization	15
PARM(12)	Parm1501.dat	Soil evaporation coefficient	2.50
PARM(14)	**Parm1501.dat**	**Nitrate leaching ratio**	0.85
PARM(15)	**Parm1501.dat**	**Runoff CN adjustment**	0.02
PARM(17)	**Parm1501.dat**	**Soil evaporation plant cover**	0.14
PARM(19)	Parm1501.dat	Sediment routing coefficient	0.01
PARM(2)	**Parm1501.dat**	**Root-growth-soil strength**	1.18
PARM(21)	Parm1501.dat	Soluble Carbon adsorption Coefficient	10
PARM(23)	**Parm1501.dat**	**Hargreaves PET equation coefficient**	0.0031
PARM(28)	Parm1501.dat	Upper Nitrogen Fixation limit	10
PARM(29)	**Parm1501.dat**	**Biological mixing efficiency**	0.0011
PARM(4)	**Parm1501.dat**	**Water storage N leaching**	0.88
PARM(46)	**Parm1501.dat**	**RUSLE-C factor coefficient**	1.15
PARM(59)	**Parm1501.dat**	**P upward movement by evaporation coefficient**	4.37
PARM(62)	Parm1501.dat	Manure erosion coefficient	0.25
PARM(68)	Parm1501.dat	Manure erosion exponent	0.50

PARM(69)	**Parm1501.dat**	**Coefficient adjusts microbial activity in top layer**	0.57
PARM(7)	**Parm1501.dat**	**N fixation**	0.42
PARM(70)	**Parm1501.dat**	**Microbial decay**	1.34
PARM(71)	Parm1501.dat	Manure erosion exponent -adjusts based on plant material	1.15
PARM(72)	**Parm1501.dat**	**Volatilization/nitrification partitioning**	0.15
PARM(74)	Parm1501.dat	Partitions N flow from groundwater	10
PARM(76)	**Parm1501.dat**	**Conversion of standing dead to flat residue**	0.0046
PARM(8)	**Parm1501.dat**	**Soluble phosphorus runoff coefficient**	11
PARM(83)	**Parm1501.dat**	**Estimates drainage system lateral hydraulic conductivity**	1.32
PARM(84)	Parm1501.dat	Coefficient regulating P flux between labile and active pool	0.0001
PARM(85)	Parm1501.dat	P partitioning between stable/active	0.0001
PARM(86)	Parm1501.dat	N upward movement	0.01
PARM(92)	**Parm1501.dat**	**Runoff Volume Adjustment**	0.80
PARM(96)	**Parm1501.dat**	**soluble p leaching**	1
XKN1	Parm1501.dat	Michaelis Menten constant	0.13
XKN3	Parm1501.dat	Michaelis Menten constant	14.22

5.2. Batch Simulations for Trend and Management Evaluation

The following sections describe the results of batch simulations (Section 4.2), including a comparison of results to additional observed data and an evaluation of results in comparison to established trends related to the impact of particular crops, management options, and/or practice.

5.2.1. Comparison of Additional Observed Data to Model Results

The following subsections present model predicted results for certain soil health metrics that are also measured as part of the CASH framework, and in particular look at how they compare against observed soil health data described in Section 4.2.2. For each of the variables shown in the following section, we bin data (observed and modeled) by soil texture, similarly to the presentation of data in the SSHVT report (White et al., 2022). While soil texture was available in the SSHVT data, for VLTHS pasture fields, soil texture was calculated in R based on sand, silt, and clay percentages following USDA guidelines. The SSHVT report also presented plots where observed data was binned based on crop type. As there was little known about the specifics of management (e.g. what species of crop/s were considered field grains, what species of hay were grown, etc.), we did not further bin and compare modeled and observed data in this format.

The goal we sought to achieve was that model predicted values are similar in magnitude and show similar trends across crop or texture types (which were available attributes of data points in the SSHVT and VLTHS datasets). We acknowledge that there are many additional factors (including slope, other soil characteristics, management details, and other factors) that are critical model inputs but were not available attributes in these observed datasets and therefore could not be used as a basis of comparing model-predicted vs observed data. Model simulations included hypothetical fields with a wide range of slope and soil characteristics and as detailed agronomic management information was also not available for the observations, we simulated multiple management scenarios associated with several crop groups representative of cropland and pasture systems (Table 10). Observed data included corn, hay, vegetable, field crop, and pasture management but details such as timing and type of tillage as well as manure application rates were unknown. These are critical drivers for some metrics; by simulating and including multiple management scenarios in the following comparison, as well as by simulating a large range of soil-weather combinations, we expect to generally bracket the observed data (which includes corn, hay, field crop, vegetable, and pasture management with unknown tillage, manure application timing, rates, and other management details). We then binned predicted and observed data by crop and soil texture, like the summary of SSHVT data (White et al., 2021), for statistical comparison.

For comparison to the SSHVT and VLTHS datasets, we used hypothetical fields located only in locations classified as Cropland or Pasture (Figure 7) and included results from all management scenarios described in Table 10. Fields located in areas classified as forest or wetland or other land uses were not included here as it was considered likely those soils would not be representative of typical agricultural uses and would bias this comparison. Management scenarios are binned as either Cropland or Pasture (Category for Comparison to Observed Data in Table 10) such that results for Cropland management scenarios were compared to SSHVT data and results for Pasture management scenarios were compared to VLTHS data. All results are included in the same plots as we acknowledge overlap in management between the observed datasets. Statistical summaries of these results, binned by Cropland and Pasture are also shown in Appendix C.

Note that in the plots in the following sub-sections, there are some soil categories where there were not both simulated and measured values. For example, there were no fields (grid points) located on clay loam or sandy clay loam and categorized as cropland or pasture based on the NLCD layer, therefore the plots in the following subsections do not have simulated results for these soils. There were also no observed data points for some soil types (e.g., no measurements were taken through the VLTHS or SSHVT efforts on fields characterized as sand).

For each metric in the following subsections, a figure with boxplot comparison is provided within the section. Boxplots in the following section show the median, 25th percentile, and the 75th percentile. Outliers are defined as greater than or less than 1.5 times the interquartile range for each boxplot. Outliers calculated for the entire dataset (rather than by boxplot category) were removed for easier display. Additionally, we calculated statistics for each set of results and present them in tables (Appendix C) added alongside the statistics calculated for the SSHVT and VLTHS datasets.

5.2.1.1. Bulk Density

Bulk density measures the ratio of dry soil mass to total soil volume and is related to soil compaction, porosity, and soil structure, making it a potential indicator of soil health. It affects water infiltration, rooting depth, available water capacity, and microbial activity, as well as is critical for calculating total carbon stores (and other metrics) in soil. Higher bulk density indicates soil compaction, which typically has negative impacts on plant growth and soil health.

While bulk density is one of the key soil inputs entered into APEX simulations (Table 4), the model also simulates changes in bulk density over the course of a simulation, driven primarily by tillage practices. Here we look at average annual bulk density for the top 30 cm of soil (based on a 30-year simulation) in comparison to SSHVT and VLTHS observed data (also based on sampling to a depth of 30 cm). As bulk density is a critical indicator of how soils respond to agronomic management, this comparison demonstrates that the model predicted values are reasonably similar to observed data and are not changing unrealistically through a simulation.

Modeled and measured bulk density for pasture and cropland fields in t/m^3 are shown in Table 21, Table 22, and Figure 12. The range of bulk density values is similar for modeled and measured soils, and the model results generally bracket the observed. As expected, there is more variability in the APEX results because many combinations of management scenarios and field conditions are included. APEX-predicted bulk density for cropland management and cropland locations appear slightly lower than the observed SSHVT bulk density measurements and APEX-predicted bulk density for pasture management on pasture locations appear slightly higher than the observed VLTHS measurements. This is likely due in part to the suite of management schedules included in the APEX simulations (see Section 5.2.3 for further discussion). Note that data shown as horizontal bars are typically where more than one sample (but typically very few) were available and values were very similar. For example, two samples from the SSHVT dataset were classified as sandy clay loam, and the bulk density values were almost identical. No pasture or model predicted values existed for that soil texture.

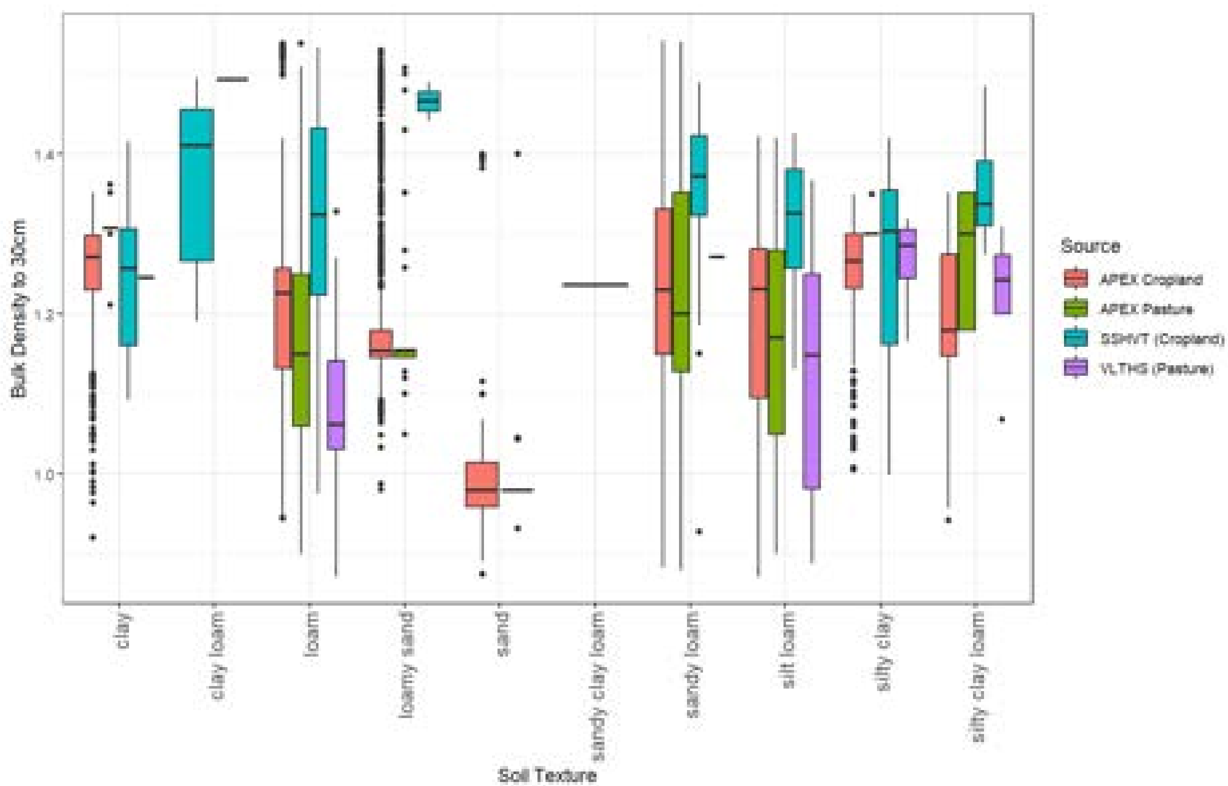

Figure 12. Bulk density for simulated cropland and pasture fields with APEX modeling, SSHVT measurements for croplands in Vermont, and VLTHS measurements for pastures in Vermont.

5.2.1.2. Soil Organic Matter

Soil organic matter is the primarily driver of carbon storage and greatly impacts physical, biological, and chemical properties of soil. Organic matter can act as a long-term carbon sink as well as a slow-release pool for nutrients, as well as contributes to nutrient storage and cycling, soil aggregation, water holding capacity, and provides nutrients to microbial communities (Moebius-Clune et al, 2017).

Initial soil organic matter (in the form of organic carbon percent) is also an input to APEX and like bulk density, the model simulates changes in organic carbon. Soil organic carbon is much more dynamic in APEX than bulk density and we can typically expect more significant variation from the initial value in response to simulated agronomic management (what carbon and nutrient inputs are applied, what crops are grown, tillage practices, etc.).

In Table 23, Table 24, and Figure 13, we compare model predicted and observed soil organic matter. APEX has an available output for percent organic carbon calculated based on the top 15 cm of soil. These values were converted to percent organic matter using a conversion factor of 1.72 to compare with observed data. Note that SSHVT and VLTHS data measured percent organic matter based on samples to a depth of 30 cm. As organic matter typically declines with increasing depth, we might expect observed data to be slightly lower than simulated values because of this difference but for purposes of this assessment, we considered these similar enough to compare the distributions of values. As with all plots in Section 5.2.1, the comparison of simulated and observed organic matter included simulated values for all cropland and pasture field locations and associated cropland or pasture management scenarios.

The range of values for organic matter in soil is reasonably similar for both modeled and measured datasets for both cropland and pasture land use groups, with model results generally bracketing the observed. APEX predicted organic matter for cropland locations and management does appear consistently lower than SSHVT measured organic matter and APEX predicted organic matter for pasture locations and management is generally slightly higher than VLTHS measured organic matter. We expect these differences are largely due to specific management simulated verses actual management implemented on observed sites (see Section 5.2.3 for further discussion).

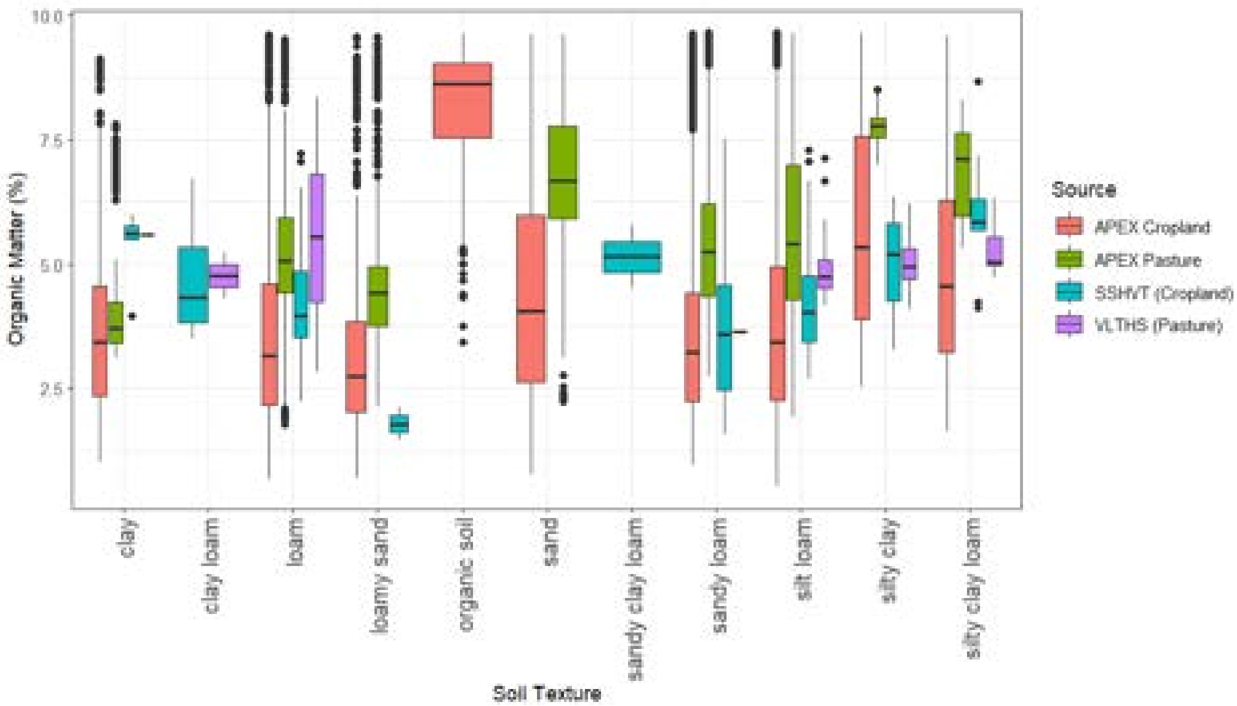

Figure 13. Modeled organic matter in plow depth (to 15 cm) from APEX, measured organic matter to 30 cm from SSHVT cropland fields, and measured organic matter to 30 cm from VLTHS pastures in Vermont.

5.2.1.3. Soil Carbon Stocks

Soil carbon stocks also reflect the organic matter content of the soil but represent the overall mass of carbon stored within a unit area and to a specified depth. The CASH framework also includes a measurement of soil carbon stocks within the top 30 cm of soil. This metric provides another data point for evaluating model performance related to soil carbon and compliments percent organic matter and bulk density comparisons. APEX provides an output of soil organic carbon in tonnes/ha for each of the modeled soil layers. These values were post-processed to obtain carbon stocks in the top 30 cm of soil and converted from tonnes/ha to kg/ha to match observed data.

The comparison shown in Figure 14, Table 25, and Table 26 demonstrates that there is generally good agreement between the ranges of measured and modeled total carbon stocks. Again, APEX simulated values show more variability and typically bracket observed data, except for some soils where simulated pasture stocks are higher than observed. Unlike organic matter percent, soil carbon stocks do not appear generally lower than observed.

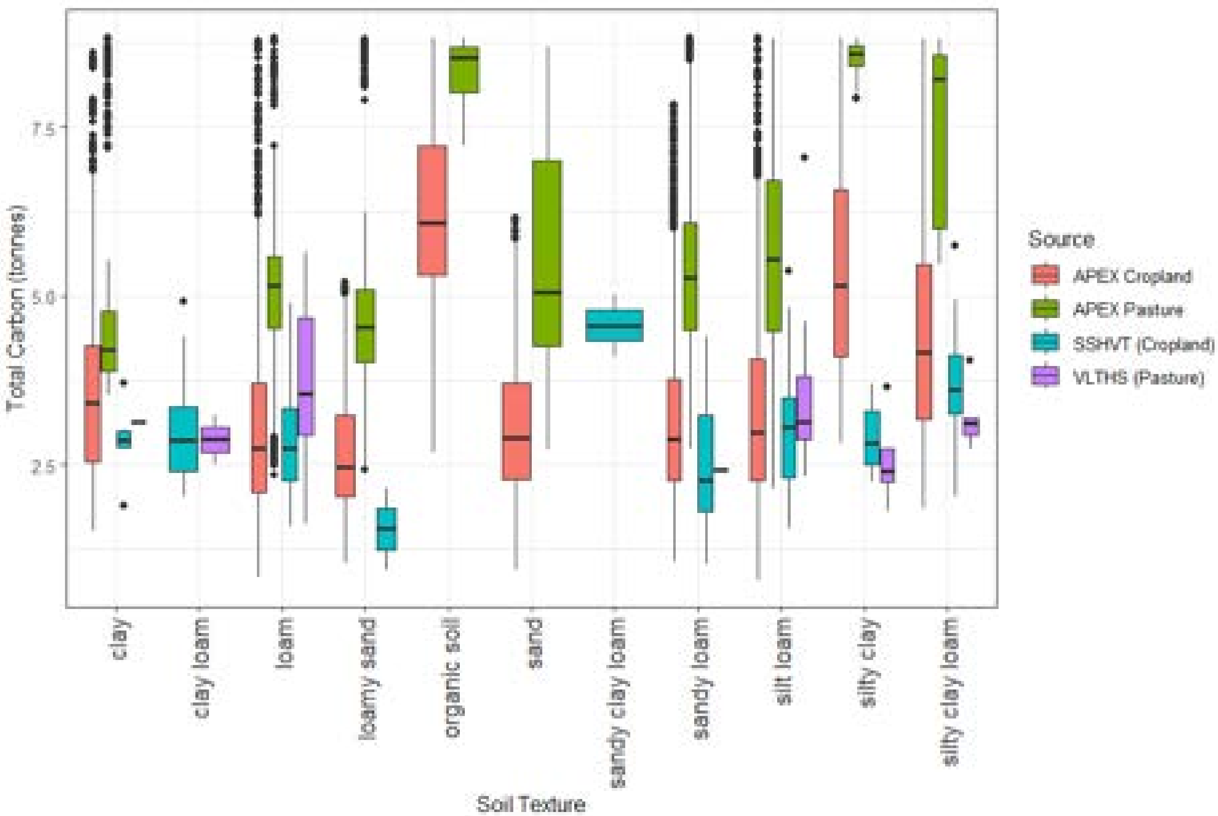

Figure 14. Modeled total carbon from APEX, measured total carbon from SSHVT cropland fields, and measured total carbon from VLTHS pastures in Vermont.

5.2.1.4. Soil Phosphorous

While we reviewed similar plots and statistical comparisons to observed data for soil phosphorus concentrations, it was determined that modeled and observed data for this indicator were not directly comparable. One reason is that soluble phosphorus concentrations are extremely variable and responsive to agronomic management such as the rates of manure/fertilizer inputs and timing of sampling in relation to manure and/or fertilizer applications (which was unknown in observed data). In addition, observed data was in the form of extractable phosphorus (based on Modified Morgan's extractant and indicative of plant available phosphorus), while APEX outputs a larger pool of phosphorus that drives phosphorus losses to the environment. The Farm-PREP tool does convert user-entered Modified Morgan's soil test phosphorus to an initial soluble phosphorus concentration for field simulations, and for batch runs a value of 5 ppm Modified Morgan's was used, using the equation specified in Stone Environmental (2020a, Section 3.2.1.1). However, this conversion is dynamic and would need to be done within the model code, as opposed to as a post-processing step. Therefore, we concluded it did not make sense to compare modeled soluble phosphorus concentrations to observed values for extractable phosphorus in soils.

While this metric was not included in this comparison, average peak daily soluble phosphorus concentration (average of each year's maximum soluble phosphorus concentration) was added to the Farm-PREP tool. Peak values will almost always be associated with fertilizer/manure applications and are indicative of concentrations that could drive soluble phosphorus losses in runoff if precipitation events following applications. The soluble phosphorus concentration shown in the tool is associated with the top 15 cm of soil simulated in APEX and converted to ppm using the equation:

$$P_{ppm} = P_{kg/ha} * \frac{1}{BD * 0.15 * 10}$$

Where BD is bulk density and 0.15 is the depth in meters.

5.2.1.5. Soil Nitrogen

Soil nitrogen as a percent is another indicator included in the CASH framework that APEX has the functionality to simulate. Percent nitrogen impacts plant growth and is sometimes the limiting nutrient for crops, particularly in non-legume grass systems. Soil nitrogen was modeled in kg/ha then converted to a percent value to align with observed data using the following equation:

$$N_{\%} = N_{kgN/ha} * \frac{1}{BD * 0.3 * 100000}$$

Where BD is bulk density and 0.3 is the depth in meters.

APEX predicted soil nitrogen percent values are generally lower than observed but within a similar range (Figure 15). As with carbon, it is expected the simulated long-term agronomic management, particularly in cropland simulations, is driving this tendency. Model results show similar trends with soil texture as observed as well (Table 27, Table 28). Note that these values were missing for many of the VLTHS fields.

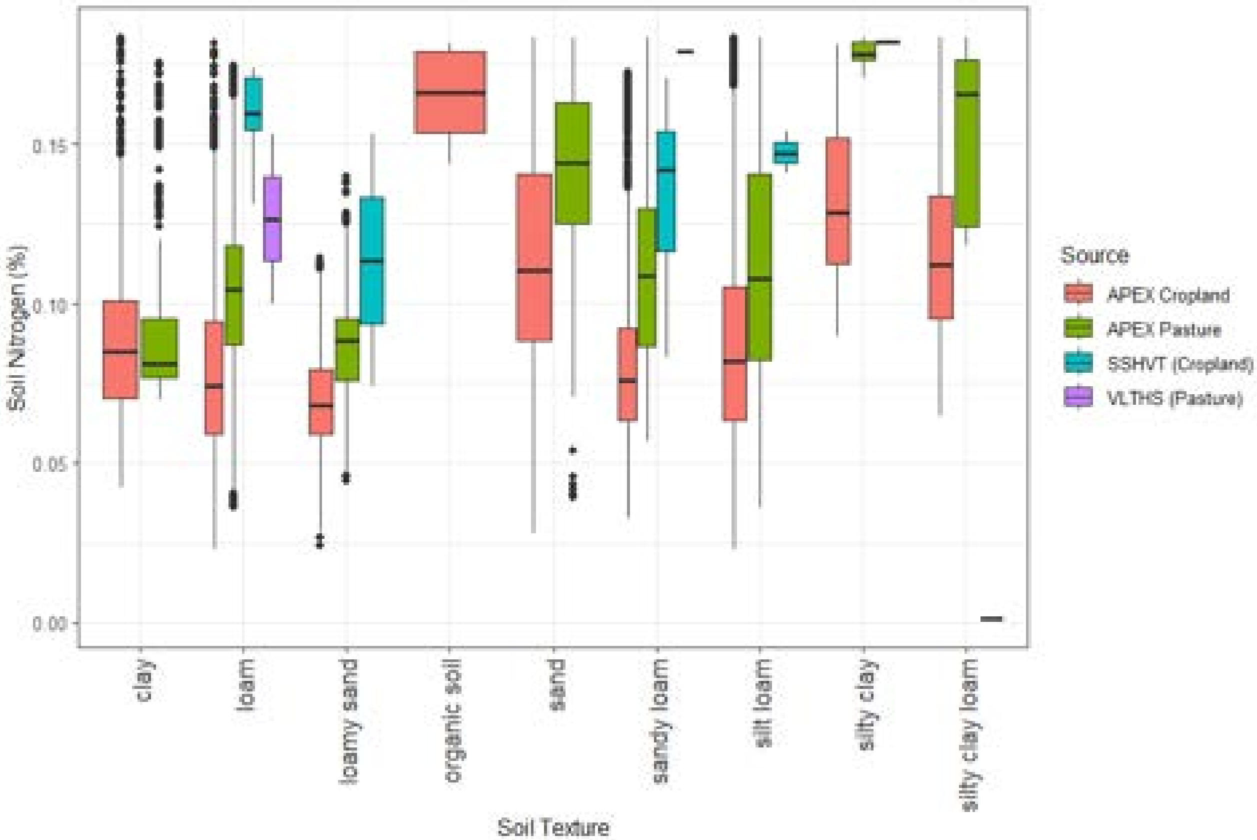

Figure 15. Soil nitrogen for simulated cropland and pasture fields with APEX modeling, SSHVT measurements for croplands in Vermont, and VLTHS measurements for pastures in Vermont.

5.2.1.6. *Respiration*

Soil respiration is representative of microbial activity in the soil. Microbial communities and associated processes are critical for many processes related to soil health including nutrient cycling and accumulation or degradation of organic matter. It is also highly affected by management practices. Respiration is calculated in APEX as the carbon dioxide loss from decomposition processes, and is impacted by soil moisture content, temperature of the soil, and existing carbon and nitrogen stocks (Izaurralde et al., 2017). If the potential supply of electrons exceeds the capacity of the oxygen available to accept them, then this leads to denitrification.

For this metric, we looked only at simulated values during the growing season (May 15 – Oct 15). Respiration was converted from kg/ha to mg CO_2/g with the following equation:

$$RSPC_{mgCO2/g} = 4 * \ RSPC_{\frac{kgCO2}{ha}} * \frac{1}{BD * 1.5 * 100} * 10$$

Where BD is bulk density and 1.5 m is the depth of the soil column over which respiration is calculated in APEX. The multiplication by 4 is to simulate test conditions which occur over 4 days. When reported in Farm-PREP, this metric represents a daily value (not multiplied by 4).

As with other metrics, there is reasonable agreement between soil respiration measurements and model results and more variability in modeled (Figure 16, Table 29, Table 30). Trends across soil textures also follow expectations. For example, higher soil moisture increases respiration up until saturation, meaning that respiration declines in dry soils. Medium-textured soils are often favorable to soil respiration because of good aeration and a high available water capacity. Measurements of soil respiration can also vary widely within a local area because plant roots and compaction both play an important role.

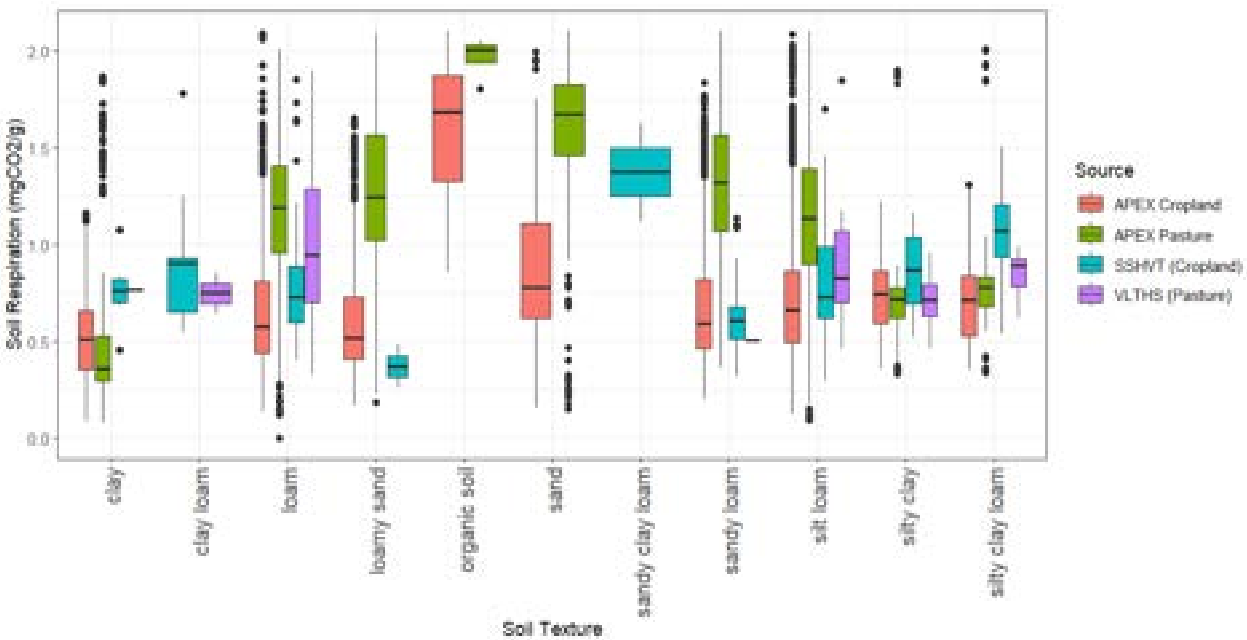

Figure 16. Soil respiration for simulated cropland and pasture fields with APEX modeling, SSHVT measurements for croplands in Vermont, and VLTHS measurements for pastures in Vermont.

Soil tests for respiration measure carbon dioxide released from a soil sample over 4 days as a proxy for microbial activity. As with soluble phosphorus in soil, that created added variability and uncertainty in terms of comparing with measured data. To explore this variability, we aggregated daily respiration results to create a 4-day rolling sum to better understand model-predictions in comparison to real-world sampling. Figure 17 shows a rolling 4-day sum across the 30-year simulation, indicating distinct high peaks in spring followed by generally lower values and dips during winter months. Figure 18 shows these 4-day rolling averages binned by month. This look at the variability confirmed our expectation that taking the growing season average (in comparison to an annual average) would likely better represent observed values.

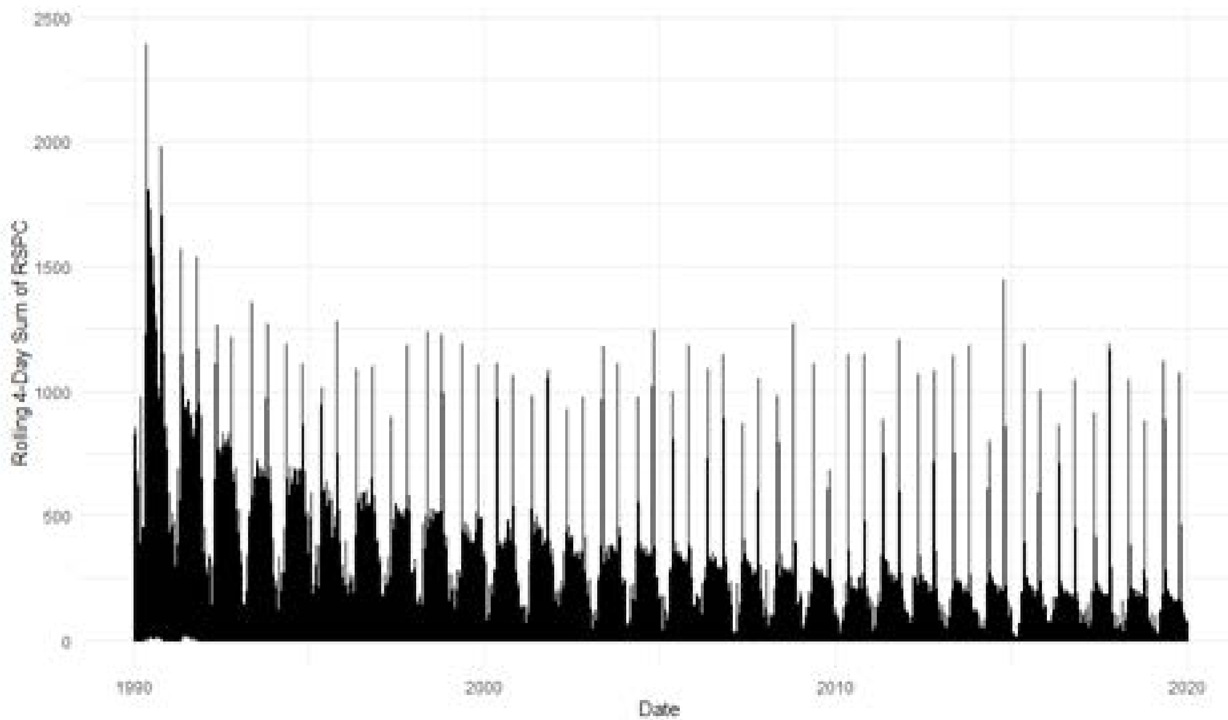

Figure 17. 4-day rolling sum of soil respiration.

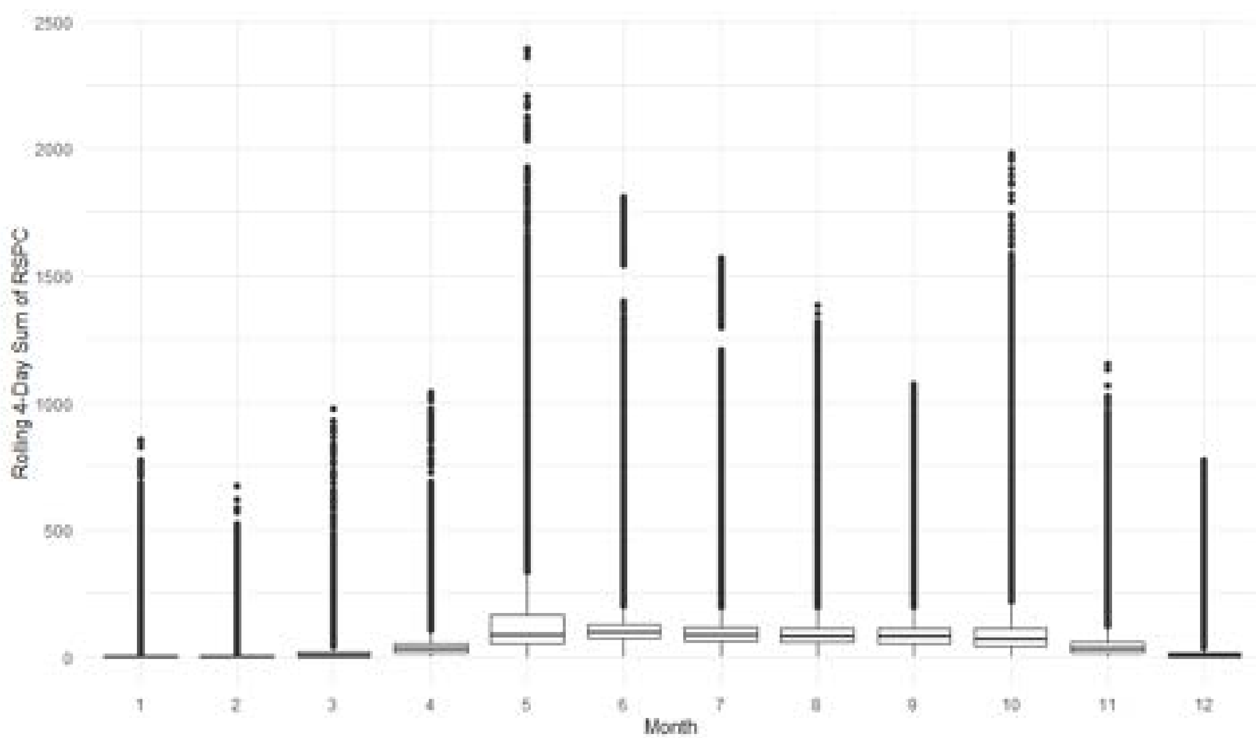

Figure 18. Monthly 4-day rolling sum of soil respiration across all years.

5.2.1.7. *Active Carbon*

Active carbon is representative of the pool of carbon available to soil microbial communities. APEX simulates coupled carbon and nitrogen cycling (as well as phosphorus cycling) between active/microbial, slow, and passive pools. Here we used outputs indicative of only the active pool of carbon ("WBMC") in kg/ha then converted to ppm to compare to observed by the following equation:

$$AC_{ppm} = AC_{kgCO2/ha} * \frac{1}{BD * 0.3 * 10}$$

Where BD is bulk density and 0.3 m is the depth.

The modeled active carbon values are also similar to the measured pasture and cropland active carbon values, and, as expected, the modeled values have a wider range because the simulations contain more variability in inputs (management practices, field conditions) than the observations. Trends across soil textures appear to be generally consistent as well, where fine soils tend to have higher active carbon values. As with other carbon metrics, we again see that modeled values for Cropland management and locations are lower than observed, likely due to simulated management (Figure 19, Table 31, and Table 32).

Results are shown in Figure 19, Table 31, and Table 32.

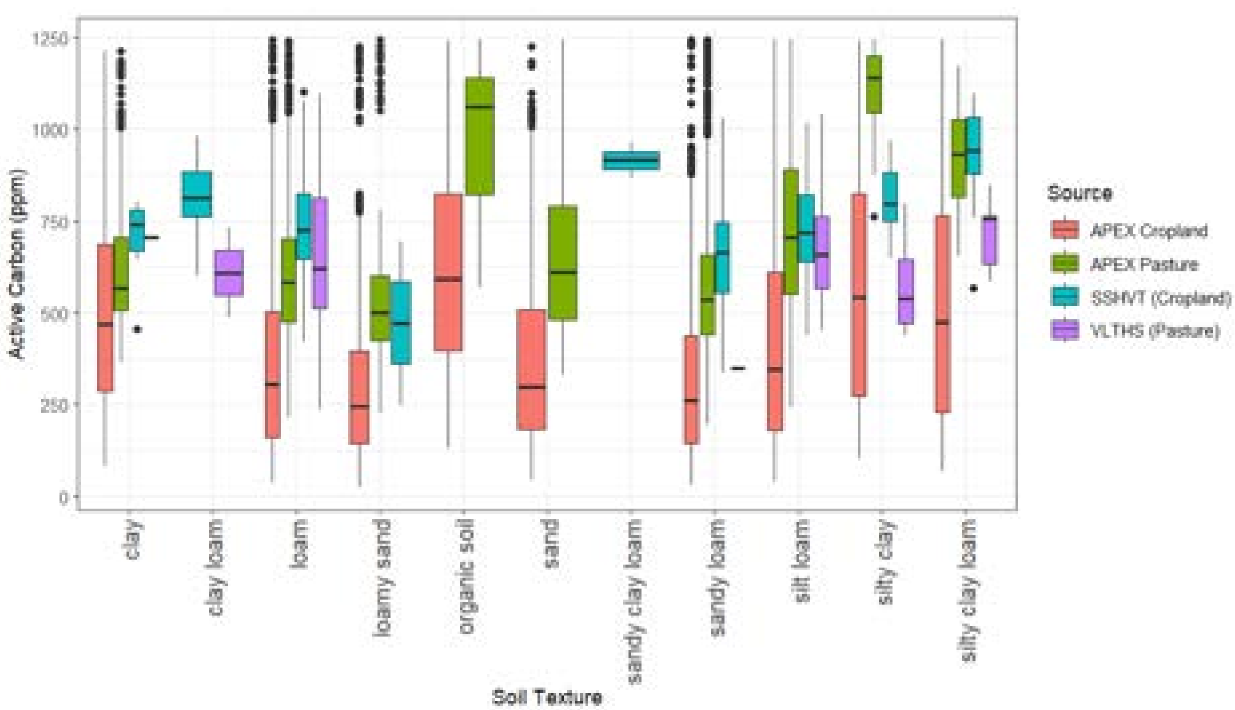

Figure 19. Active carbon for simulated cropland and pasture fields with APEX modeling, SSHVT measurements for croplands in Vermont, and VLTHS measurements for pastures in Vermont.

5.2.1.8. *Available Water Capacity*

Available water capacity (AWC) is indicative of porosity and represents the amount of water stored in the soil that is available for plant uptake. To evaluate this metric from APEX, it was defined as the difference between field capacity where the soil is fully saturated and wilting point where plants can no longer extract water. Available water capacity was calculated with the following equation:

$$AWC = \frac{1}{100} * (\sum_{1}^{365} FC_{15cm} - \sum_{1}^{365} S15)$$

Where FC_{15cm} is the field capacity and S15 is the wilting point, both in kPa. Here they are summed on an annual basis and then converted to g/g.

There is strong agreement between modeled and measured AWC in both cropland and pasture soils (Figure 20, Table 33, and Table 34)

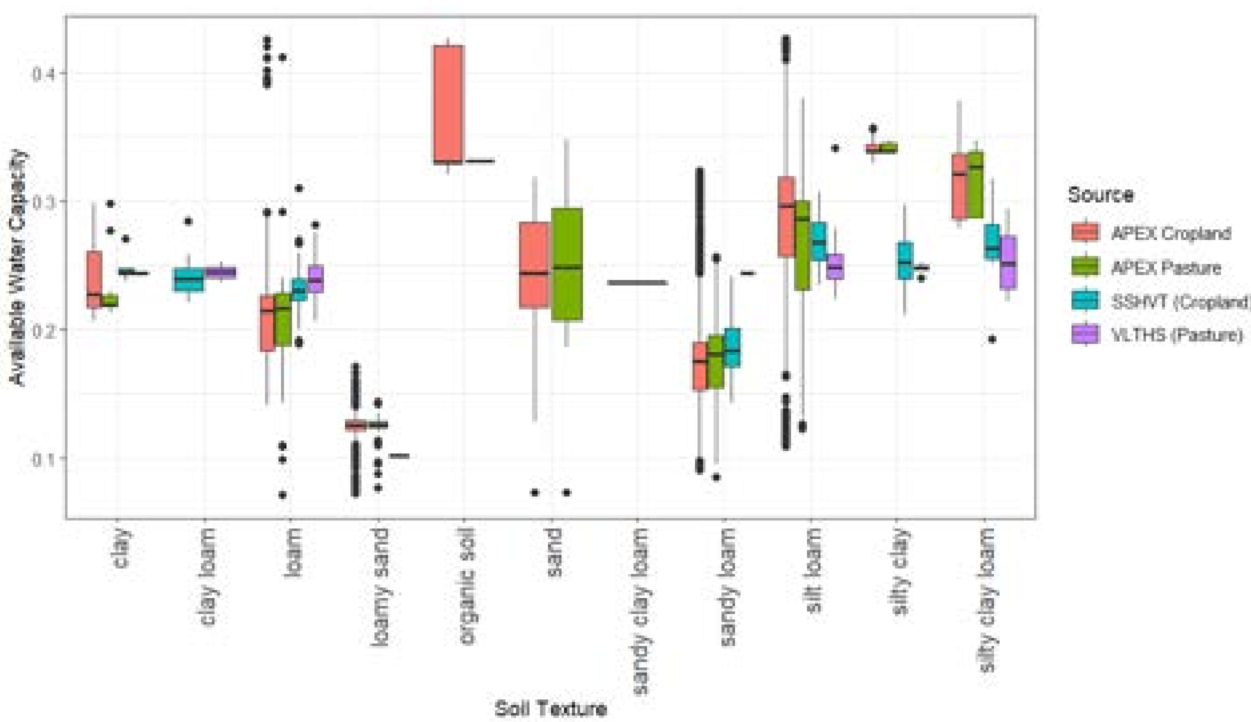

Figure 20. Available water capacity for simulated cropland and pasture fields with APEX modeling, SSHVT measurements for croplands in Vermont, and VLTHS measurements for pastures in Vermont.

5.2.2. Evaluation of Expected Trends in Model Results

The following sections assess whether we see the expected trends in APEX-predicted metrics based on peer-reviewed literature and accepted knowledge of simulated crops and management practices. Each section provides evaluation of cropland management scenarios on a particular indicator metrics (as calculated in Section 5.2.1), where we calculate a percent change from each practice scenario in comparison to the corresponding baseline management simulated on the same field. The baseline management for cropland simulations is representative of conventional tillage and incorporated manure/fertilizer applications (see Section 4.2.1.4, Table 10, for further description). Simulated practice scenarios for cropland include cover crops, high and low nutrient inputs (changes in manure application rates), manure injection (no change in application rate), mulching, no till, reduced tillage, and no-till combined with manure injection.

5.2.2.1. Bulk Density

Soil management practices can change the soil structure; one way this can be measured is through changes in bulk density. APEX predicts that in general, cover cropping, no-till, reduced-till, and manure-injection result in slightly higher annual average bulk density in the top 30 cm of cropland soils (Figure 21). Figure 21 shows the simulated percent change in annual average bulk density from each practice scenario and the corresponding baseline.

The research on whether many of these practices increase or decrease bulk density in other locations is very mixed because it depends on the original soil structure, moisture content, cropping system, historical practices, and the timeframe over which bulk density is measured. This is reflected in the range of percent change predicted across different soils, slope, and weather conditions, where we see that for all practices, there are some fields that show higher bulk density under that management and other fields that show a lower bulk density in response. Both mulching and high nutrient inputs generally decrease bulk density, potentially because new, lighter material is incorporated into the soil, providing aeration and pore space. Bulk density is known to slightly increase over time depending on the cover crop (Denton et al., 2021), in agreement with the model, while no-till increases bulk density due to the lack of soil disturbance. However, neither an increase nor a decrease necessarily has a negative impact on overall soil health, particularly when the change is less than 10%. Differences in bulk density between scenarios should be considered in context of differences in other metrics, not as a standalone indicator of soil health.

We show here that APEX generally shows realistically small differences in bulk density across management scenarios. It also demonstrates, however, that for some fields, management could have a more significant impact on bulk density. Field specific simulations of management scenarios in Farm-PREP would indicate if bulk density of soils on particular fields are likely to respond to alternative management strategies.

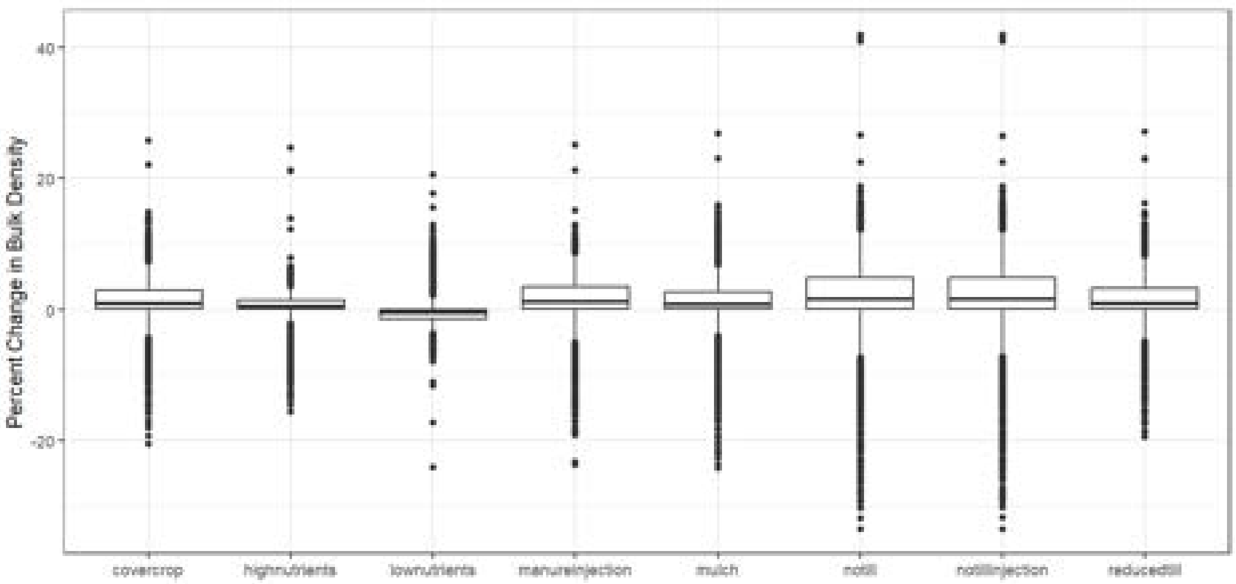

Figure 21. Percent change in bulk density from baseline scenarios with management practices.

5.2.2.2. Soil Organic Carbon

Here we show the percent change of each practice scenario in comparison to the conventional tillage baseline (Figure 22). All management scenarios except the low nutrient scenario show higher predicted annual average percent soil organic carbon, where no till and reduced till generally resulted in the most significant increases in comparison to the conventional baseline. This is consistent with research on soil carbon that has demonstrated that cover crops increase soil organic carbon (Abdalla et al., 2019; Bolinder et al., 2020; Poeplau and Don, 2015; Wortman et al., 2012) as well as the general conclusion that long-term no till systems increase organic matter (USDA, 2015). The Comprehensive Assessment of Soil Health manual (Moebius-Clune et al., 2017) suggests that cover cropping increases carbon capture from the atmosphere, some of which can remain in the soil as organic matter. This document also suggests that reducing tillage slows decomposition of soil organic matter and release of CO_2 into the atmosphere, and that adding additional amendments such as mulch, manure, compost, etc., serve to add additional carbon sources to soil. The low nutrient input scenario limits plant growth in comparison to other scenarios, thereby reducing the amount of carbon-containing biomass. By similar mechanism, the high nutrient scenario enables more crop growth and biomass accumulation, leading to higher soil organic carbon. Manure injection reduces loss of soil and nutrients.

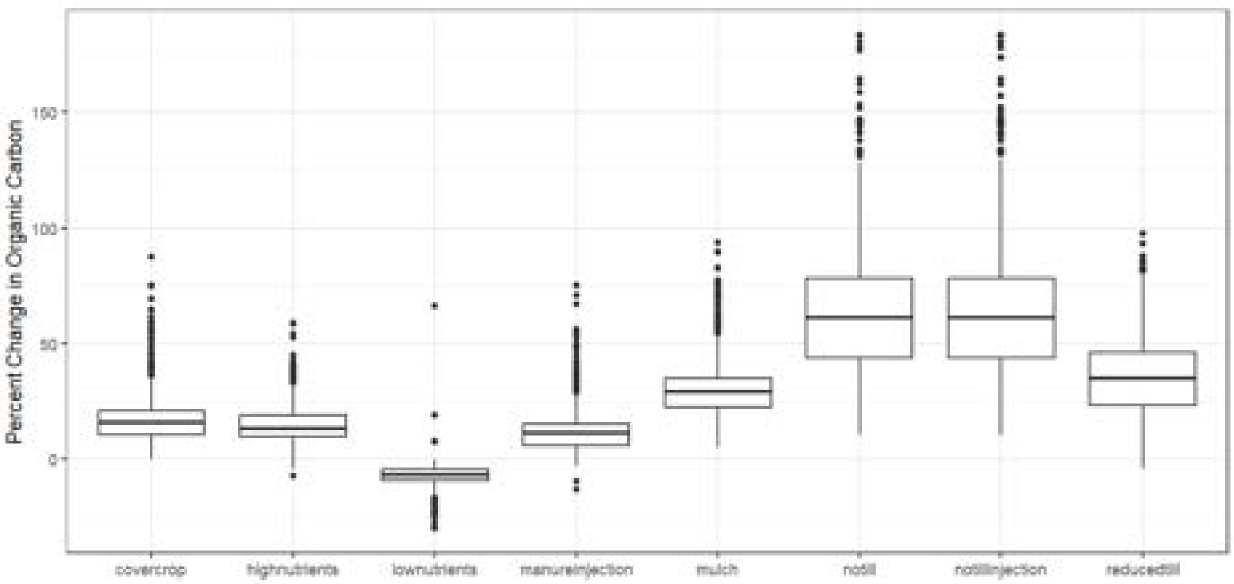

Figure 22. Percent change in organic carbon percent (top 15 cm) from the baseline scenarios with management practices.

Not unexpectedly, soil carbon stocks show similar trends to organic carbon % in this section and active carbon in the following section and therefore those plots were not included as additional material here.

5.2.2.3. Active Carbon

As with the response of percent soil organic matter, the model response in simulated active carbon to management practices is consistent with expectations. The active carbon pool in cropland soils increases with no-till, reduced till, no-till with manure injection, manure injection, and high nutrient inputs (Figure 23). Many of the mechanisms mentioned that impact percent soil organic matter also similarly impact active carbon. It is expected that no and reduced tillage systems slow decomposition of organic matter, cover cropping increases atmospheric capture, higher nutrients and mulching represent additional inputs into the system, and injection reduces losses to the environment. Also as with soil organic carbon, the range in percent change is larger with no till and reduced tillage systems. Note we found no data to validate the magnitude of practice impacts for active carbon, though would expect similar trends to organic carbon and higher sensitivity to practices that increase residue and microbial decay (as with no and reduced tillage). Active carbon is the most dynamic, fast-responding pool of carbon and responds more quickly to management than overall soil organic carbon.

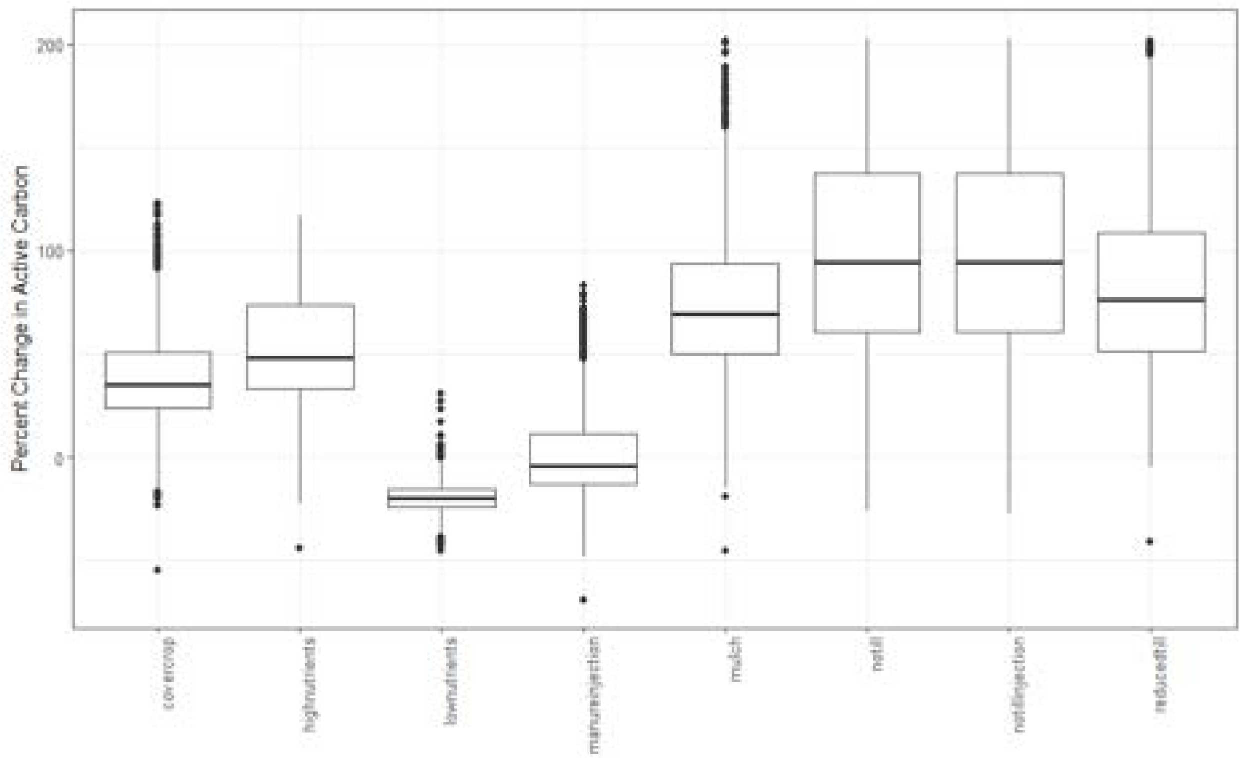

Figure 23. Percent change in active carbon from baseline scenarios with management practices.

5.2.2.4. Respiration

The APEX model results for respiration by management practice are consistent with long-term trends from prior research studies (Figure 24). Most of these practices either reduce soil disturbance and/or increase carbon sources, resulting in an increase in annual average growing season respiration. No-till and reduced tillage systems generally increase soil moisture as well as result in more surface residue, both of which also lower soil temperatures. These factors slow microbial decomposition and therefore soil respiration. Cover cropping scenarios do not include a fall tillage and cover crops enhance microbial activity with increased carbon inputs, resulting in higher respiration. Other practices that increase available nutrients like mulching and high nutrient inputs also represent additional carbon inputs, favoring plant root growth by providing additional carbon and nitrogen, and increasing respiration.

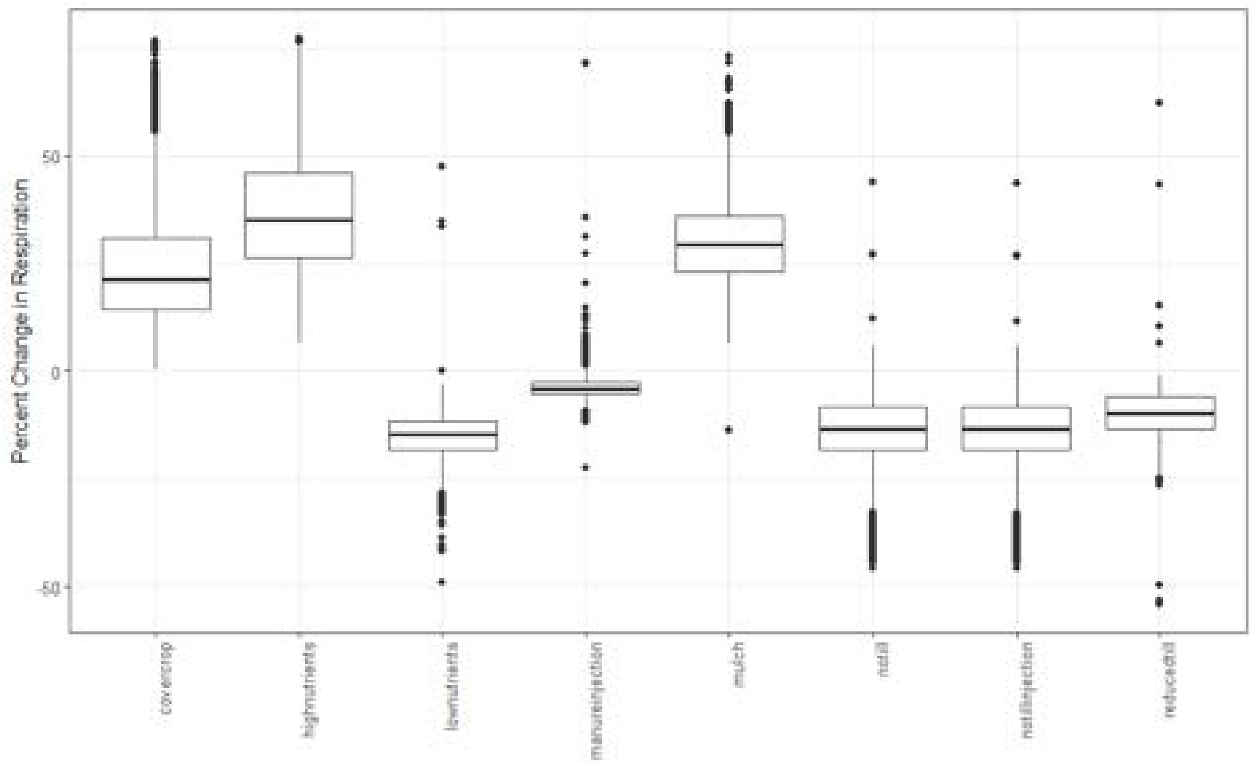

Figure 24. Percent change in growing season soil respiration from baseline scenarios with management practices in croplands.

5.2.2.5. Surface Losses

While surface losses were not part of the comparison to SSHVT or VLTHS datasets, surface losses are still a core component of Farm-PREP so it is important to evaluate the response in nitrogen and phosphorus losses to management changes. Impacts of these practices on surface loss are more established, though long-term studies that specifically monitor edge of field losses to establish effectiveness of practices is still limited.

Here we look at annual average total nitrogen edge of field loss (as the sum of soluble nitrogen loss and nitrogen loss in erosion) in response to management scenarios (Figure 25). Modeled total nitrogen loss declines with most management practices either due to decreased runoff and erosion, such as with no-till and reduced tillage, or increased nitrogen utilization, such as with cover cropping systems. High and low nutrient input scenarios showed no significant change from the conventional tillage baseline scenario in these simulations, and the median change from high nutrient applications actually shows a slight decrease in nitrogen losses. This is likely due to enhanced plant growth which increases land cover and further reduces runoff and erosion in comparison to the conventional tillage baseline. The high nutrient scenarios, as well as other practices scenarios, generally show an increase in average annual percent soil nitrogen (Figure 26). Low nutrient scenarios indicate a lower annual average percent nitrogen in comparison to the conventional tillage scenario.

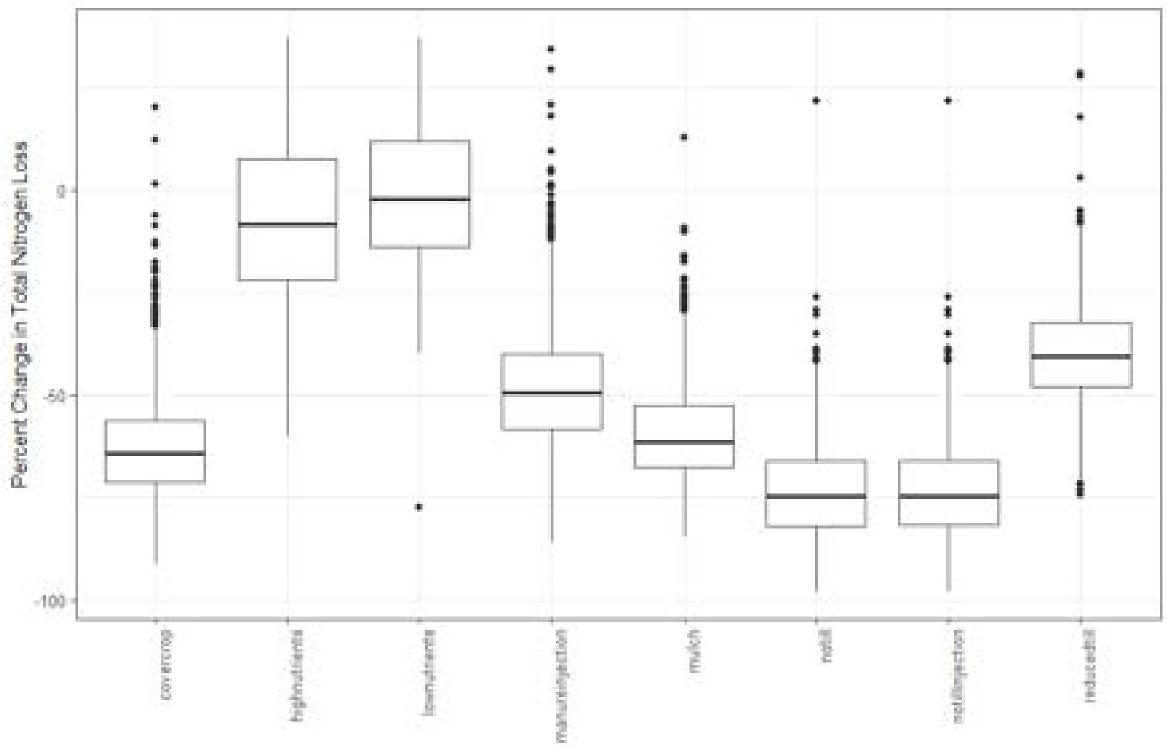

Figure 25. Percent change in total N loss from the baseline scenarios with management practices.

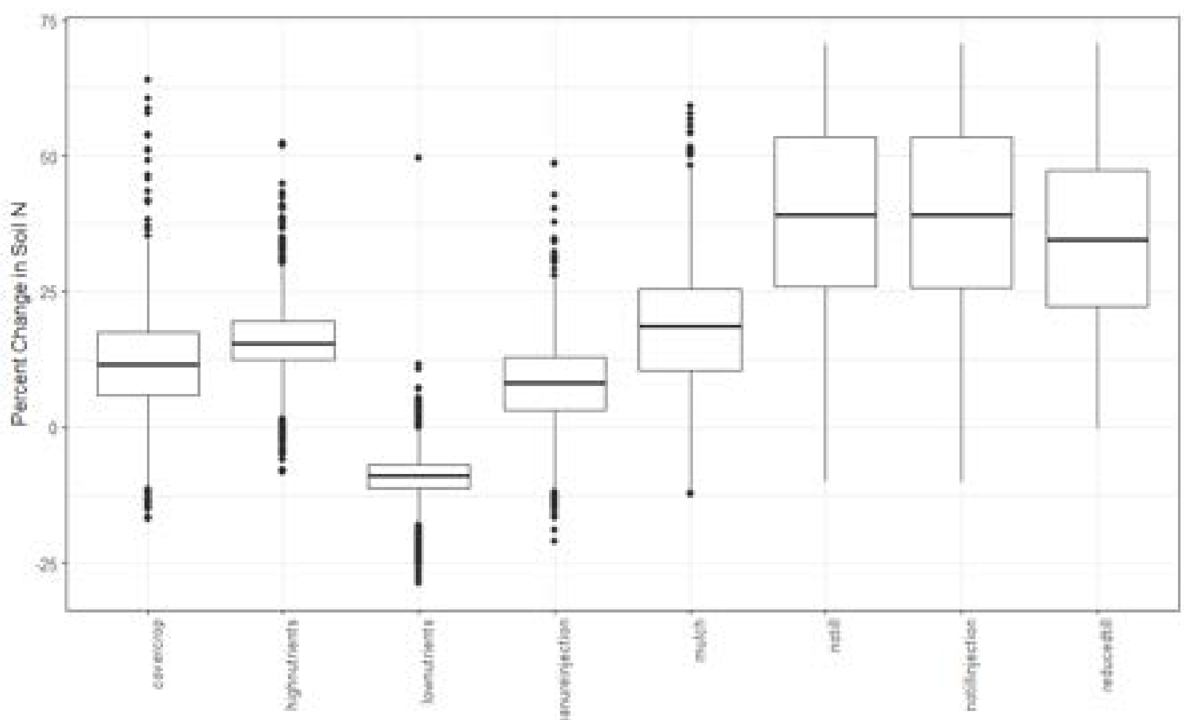

Figure 26. Percent change in soil N (to 30 cm) from the baseline scenarios with management practices.

The percent change in edge of field phosphorous (as the sum of soluble phosphorus loss via runoff and sediment bound phosphorus via erosion) are shown Figure 27. As expected, high nutrient inputs in the modeled cropland system cause increased phosphorous loss as crops cannot uptake all available phosphorous before it is lost from the system. All other management practices show lower annual average total phosphorus loss either through reducing runoff and erosion (and therefore phosphorus loss) and/or by decreasing the amount of excess phosphorus that that is available for runoff (e.g. cover crops scenarios show reduced erosion due to increased land cover and also lower levels of soluble phosphorus in soils).

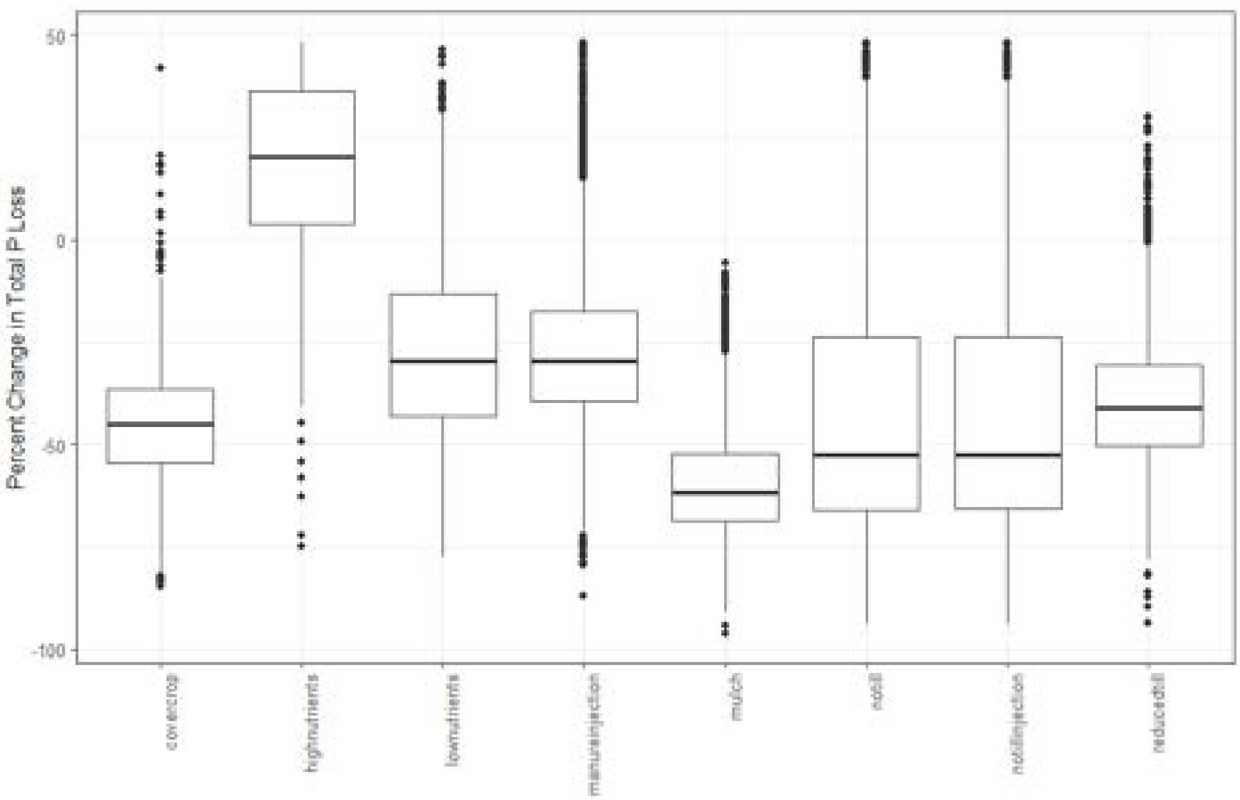

Figure 27. Percent change in total P loss from the baseline scenarios with management practices.

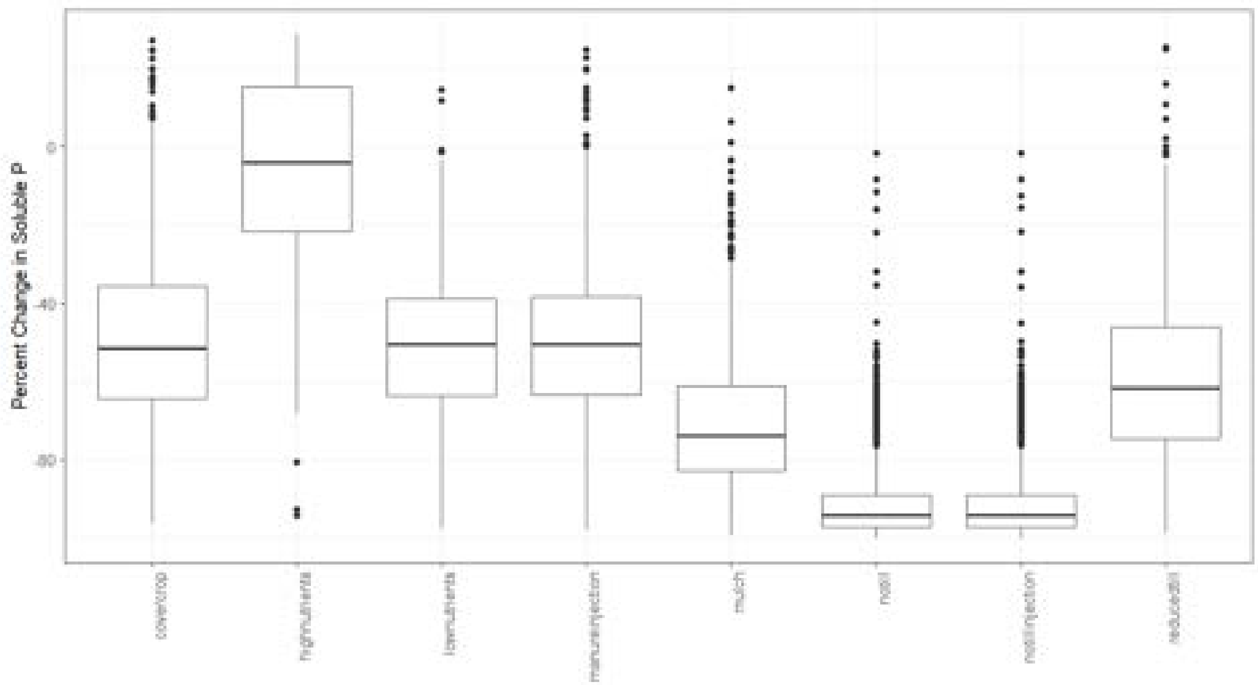

Figure 28. Percent change in soluble P concentrations from the baseline scenarios with management practices.

5.2.2.6. Available Water Capacity

Minimal changes were seen in the annual average growing season available water capacity metric in response to practices (Figure 29). Most practices result in a slight increase in median available water capacity, except the low nutrient scenario. We expect that most practices are increasing organic matter and microbial activity in comparison to the conventional tillage scenario, where that in turn increases infiltration and allows more water to be held in pore spaces. It is not unexpected that soil characteristics are the primary driver of variability in plant available water capacity.

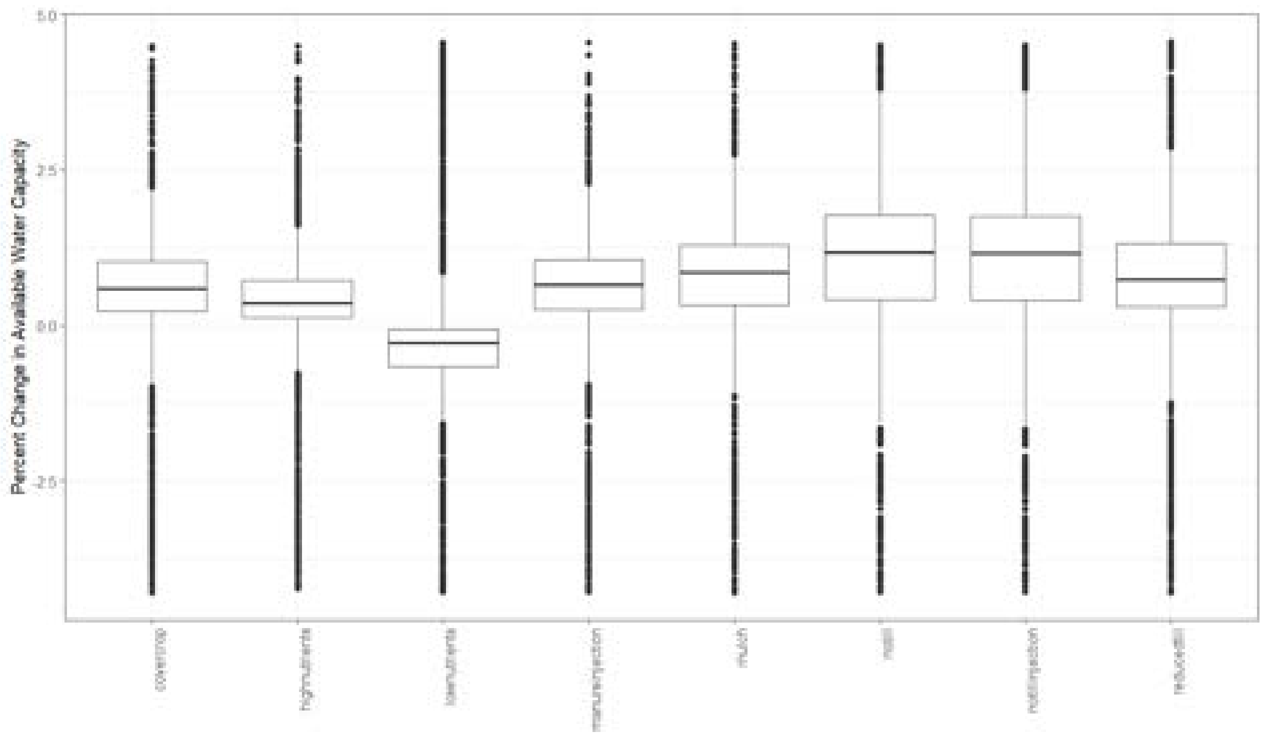

Figure 29. Percent change in available water capacity from the baseline scenarios with management practices.

5.2.3. Discussion

5.2.3.1. Summary of Cropland Results

The comparison between APEX predicted values and observed data from the SSHVT and VLTHS datasets demonstrates reasonable agreement across multiple soil health variables. The model generally brackets the observed values and reproduces expected trends across soil texture classes for bulk density, soil organic matter, carbon stocks, soil nitrogen, respiration, active carbon, and available water capacity. Some outliers were noted and were found to be related to unique soils that are likely not representative of cropland. We did not adjust model parameters based on the existence of these outliers.

We acknowledge that carbon-related metrics are consistently lower than observed. We expect this is largely due to the model set up for these simulations, where agronomic management is repeated over a 30-year time series. In addition, we simulated more management scenarios for continuous row crop rotations (which are more likely to show long-term draw down of organic matter) than continuous hay rotations (which are more likely to store carbon in soil over time). This may be biasing the distributions of simulated values low. However, management for soil health data used in the comparison to batch simulations was largely unknown and simulated values were generally within a reasonable range and/or bracketing observed results. Therefore, we did not consider this to indicate the need for any additional model calibration efforts or evaluation.

It should be noted that the specifics of simulated management, for example nutrient application rates, also have a critical impact on many of these metric values. It is possible that if both baseline and practice simulations had higher manure (carbon) inputs, we might see generally higher annual average organic matter and microbial activity in all scenarios (and higher phosphorus and nitrogen edge of field losses). For batch simulations, we based management scenario rates and timing based on existing Farm-PREP schedules, developed in collaboration with UVM Extension, crop consultants, and VAAFM (Stone Environmental; 2018, 2020a, 2020b), and used manure application rates based on modeling conducted for Vermont's TMDL (Tetra Tech, 2015). We did not evaluate a larger range in application rates in this scope of work. In the Farm-PREP tool, users enter field-specific manure and fertilizer application rates (as well as tillage timing and type, etc., Section 6.2.4), such that the model-predicted response to management practices simulated in the tool is specific to those inputs.

The evaluation of expected trends in response to management practices also demonstrates that APEX is responding appropriately to the selected management practices. The predicted increases in soil organic carbon and active carbon under no-till and reduced-till align with the literature demonstrating conservation tillage benefits for soil carbon sequestration. Similarly, APEX's prediction that cover cropping increases soil carbon is consistent with the literature. The nutrient loss patterns predicted by APEX also agree with the literature and known responses in runoff and erosion processes to the specified management alternatives. Practices that reduce erosion also decrease total nitrogen and phosphorus loss, while high nutrient inputs increase phosphorus loss when crop uptake capacity is exceeded. Soil respiration decreases as soil disturbance increases and/or as carbon inputs increase. These results demonstrate that APEX is effectively simulating key interactions between management, soil properties, and environmental outcomes.

As previously discussed, simulated management is one component driving the wide range in values for many of these metrics. However, another significant driver of this variability within management scenario results is the simulated field conditions (soils, slope, weather). In Figure 30 – Figure 33, we show simulated values of soil carbon and respiration for each cropland management group, further broken out by hydrologic group or field slope. The median and percentiles of soil carbon stock estimates vary by both hydrologic group and slope for all management scenarios (Figure 30 and Figure 31). While respiration results show similar sensitivity to slope (Figure 32), respiration estimates for no till and reduced tillage systems appear less sensitivity to hydrologic group than other practices (Figure 33).

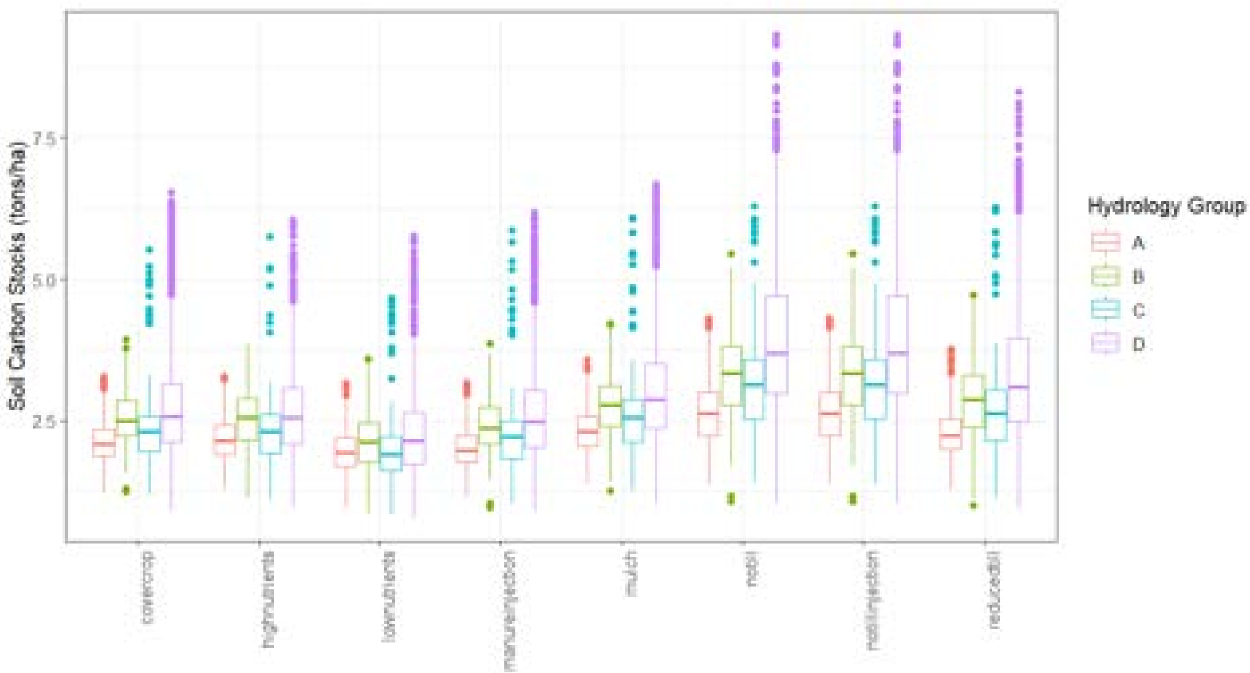

Figure 30. Carbon stocks in cropland soils by hydrologic group.

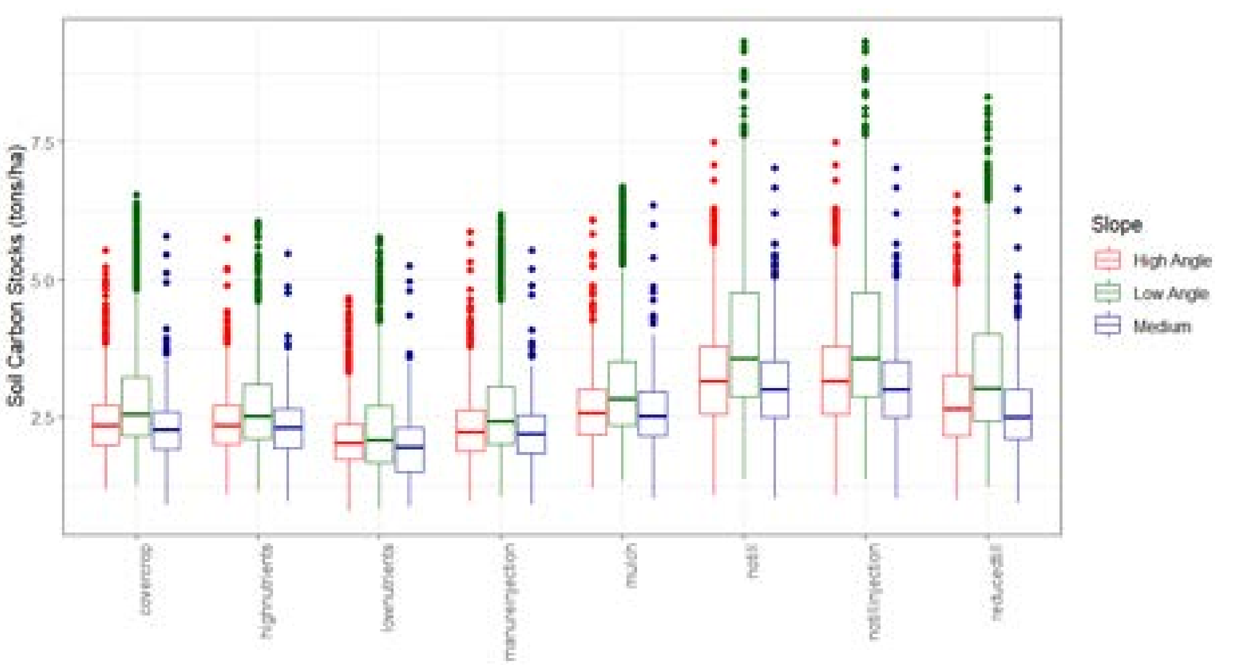

Figure 31. Carbon stocks in cropland soils by slope.

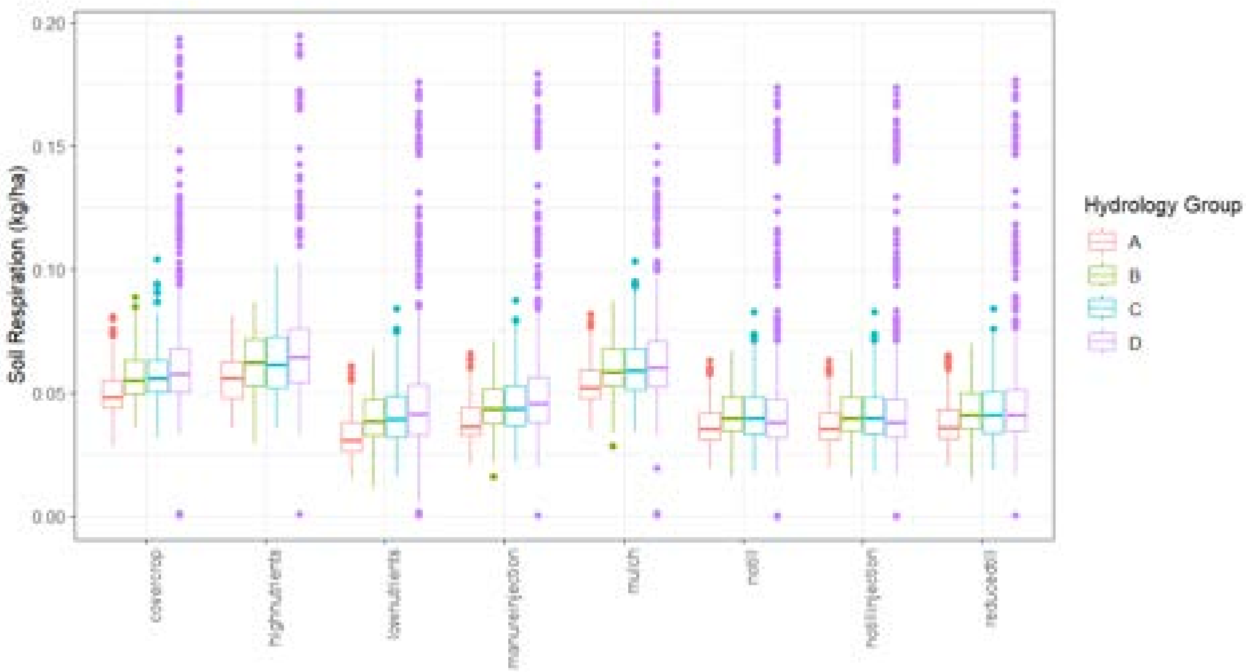

Figure 32. Respiration in cropland soils by hydrologic group.

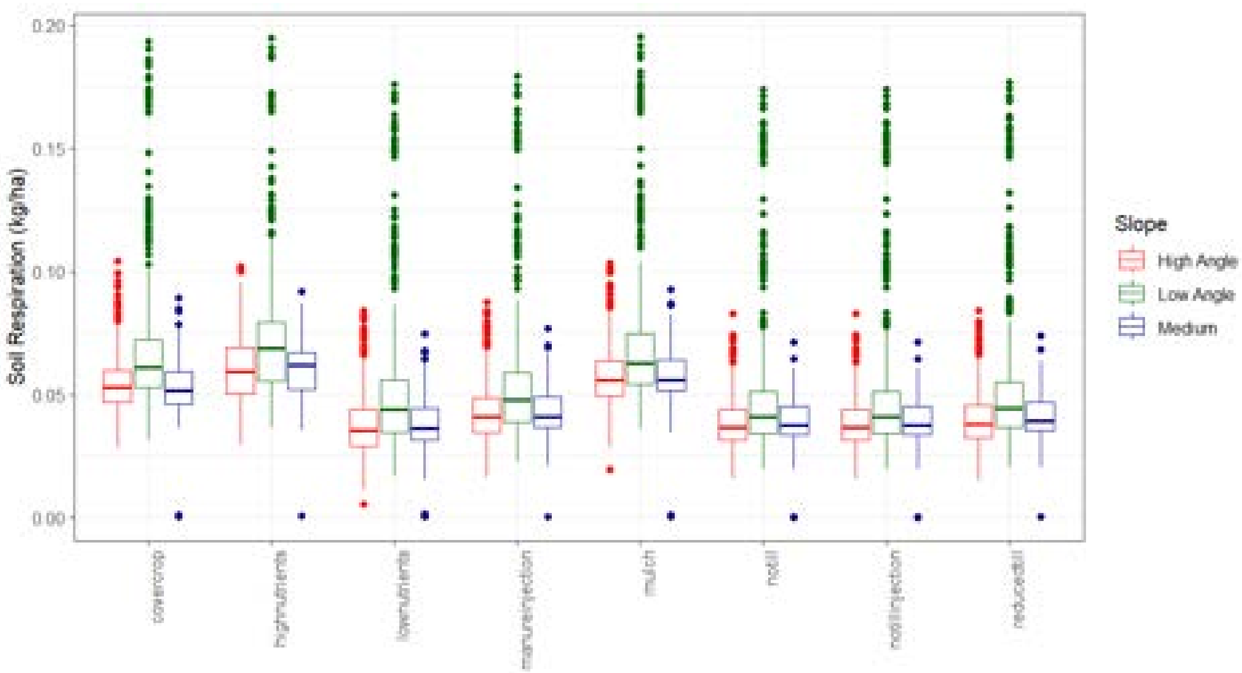

Figure 33. Respiration in cropland soils by slope.

Overall, the agreement between modeled and observed data shows that Farm-PREP can provide reasonable estimates of key soil health metrics for comparative scenario analysis. The wide variability in responses across different field conditions (soil type, slope, hydrologic group) emphasizes the value of this field-specific modeling approach to help farmers understand the relative impacts of their management decisions.

5.2.3.2. Pasture Trend Results

While we included pasture management scenarios to compare with observed soil health data (Section 5.2.1), the scope of this work was intended to focus primarily on cropland management. Additional work is being conducted under a separate scope of work to further evaluate the impact of pasture management on carbon, nitrogen, and greenhouse gas processes. These practices include changes in stocking rates, rotation changes, nutrient inputs, grass type, and simulation of hay cutting prior to grazing (Table 10). Pasture management scenarios generally respond similarly to the primary drivers of changes (increase in carbon inputs, slowing of microbial decomposition, nutrient stress due to high forage removals and/or nitrogen stress), however it can be more difficult to tease out how pasture management impacts those drivers. For example, several grazing management choices such as the length of grazing rotations, rest time between rotations, overall time on the field, as well as stocking rate, have interconnected non-linear impacts on simulated processes. For the purposes of this report, we do not include detailed results of pasture management but can summarize a few key trends we observed in pasture results:

- There was negligible difference in bulk density or available water capacity in response to pasture management scenarios. APEX does not simulate compaction from animals, though it does estimate the impact of over-grazing on grass growth and availability as forage.
- Most simulated management scenarios reduced soil carbon stocks in comparison to the baseline because of the significant difference in nutrient inputs. The baseline pasture management is a continuous dairy grazing scenario (with a stocking rate 0.4 ha/hd or approximately 1 animal per acre, and where cows are on the field 14 hours per day) on grass hay with no cuttings or additional manure inputs other than what cows are estimated to produce when on the field. All other management scenarios either modify the stocking rate or implement rotational grazing where cows are on the field for less than half the time of the continuous grazing scenario.
- Simulated pasture systems are often nitrogen limited.
- Most pasture simulations show higher soil carbon stores than most cropland simulations.

6. The Soil Health Calculator Tool

The Soil Health Calculator was developed within the Farm-PREP system (Stone Environmental, 2018; 2020a; 2020b). Farm-PREP is a web-based tool that enables users to delineate fields anywhere in the state of Vermont, and through an intuitive interface, enables users to enter custom soil and management information for each of their fields. When users are ready to run an 'assessment', the tool writes APEX input files using user-entered data for each field selected. Assessments are run through Amazon cloud services, on the fly, results are returned to the backend postgresql database through custom python scripts, and the tool then presents results back to the user in the web-interface. We leveraged this architecture and existing data collection such that the data collection and workflow required minimal changes. Public or 'soil health' users (users who are not enrolled in the VAAFM Pay for Performance [VPFP] program) can now access Farm-PREP to run assessments focused on a suite of environmental outcomes, including analysis and reporting focused specifically on soil health outcomes. Section 6 of this report described the implementation of *Task 4-5 Development of a Soil Health Calculator as a Module of Farm-PREP*.

6.1. User Management

While the soil health calculator was built into the existing Farm-PREP system, users that are not part of VPFP are able to gain access through a soil health account. Using role-based functionality and data partitioning on the backend, the tool keeps soil health users' data separate and allows minor changes to the workflow for these users. Farm-PREP is a secure web-based tool, such that soil health users can only view and access their own data (their own farms and fields and associated information) through the web interface. For new users, an account can be requested on the login page by clicking 'Request Access to Soil Health Calculator' (Figure 34). Users then receive a username and password via the email address they provided.

Soil Health Calculator url: https://farm-prep-ag-www-dev.stone-env.net/#!/login

Figure 34. Soil Health Calculator Login Page.

6.2. Data Entry

While previous reports provide guidance on using Farm-PREP (Stone Environmental, 2018; 2020b), the following sections provide descriptions and illustrations of the components/steps required to set up and run assessments as a soil health user.

A high-level summary of steps to run an assessment follows. Each of these is described in the sections below:

1. Create a farm (only required once)
2. Define field boundaries (only required once)
3. Create an assessment
4. Enter field-specific data and assessment options
    a. Enter manure nutrient information (optional)

   b. Enter field-specific soil and management information
   c. Enter prioritization for practices (optional and only for optimization assessments)
5. Run assessment
6. View Results

6.2.1. Create a Farm

The primary unit of analysis in Farm-PREP is the farm. While the tool creates and runs APEX simulations for each user-defined field within a farm, reporting and analysis is conducted at the farm scale and therefore the first step is to create one or more farms (Figure 35). Once a farm is created using the "Add Farm" button, multiple assessments can be run on the same farm, so this step is only required once for each farm (or for each set of fields that a user is interested in evaluating together).

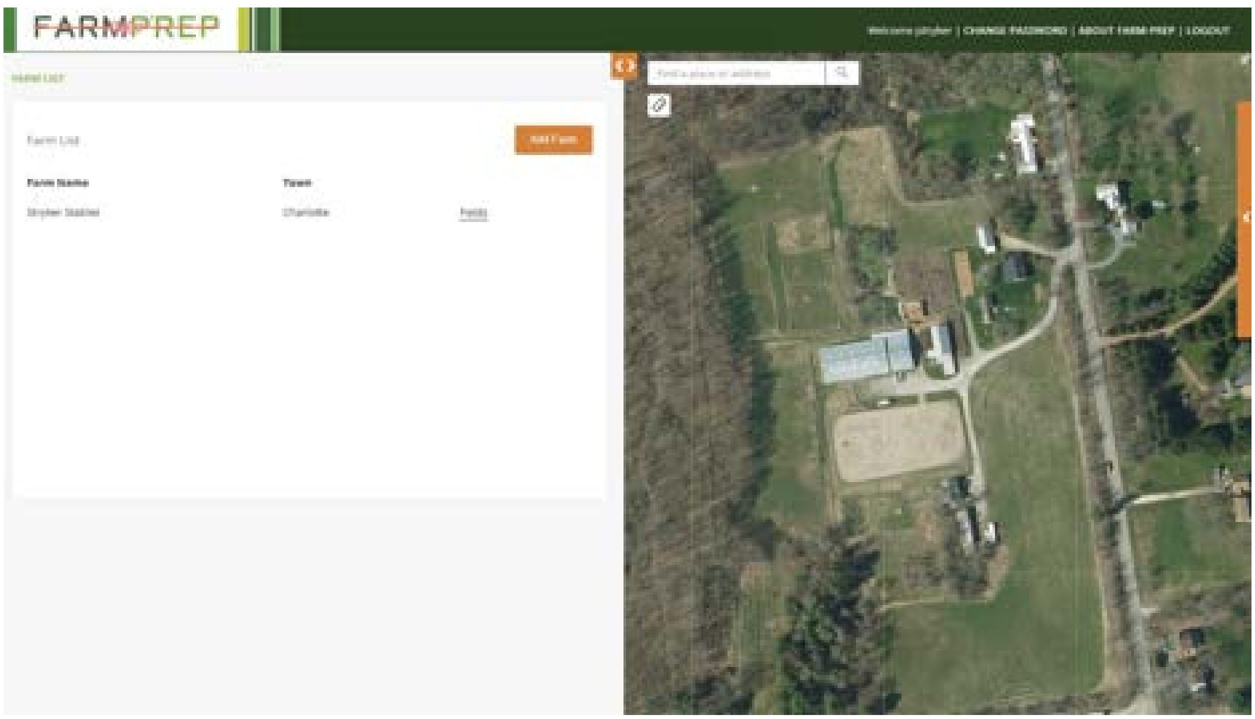

Figure 35. User Specific Farm List.

6.2.2. Define Fields

After a user has created a field, users must define the boundaries. To create a field, first click on the 'Fields' button from the Farm List module to access both the Field and Assessment modules. Create fields by either delineating on the map or uploading a shapefile. The tool provides brief instructions for delineating fields on the map as well as shapefile requirements if uploading (Figure 36). Users may create more than one field sequentially by drawing them on the map or simultaneously by uploading shapefiles.

Note that when a field is created, the tool queries several spatial layers in the background to obtain and/or calculate field area, average field slope (based on a 10-m digital elevation model, Section 4.1.1.3), slope length using the equation shown in Section 4.2.1.2, dominant soil and associated attributes based on the soil database described in Section 4.2.1.2, and the closest weather station based on the same weather stations described in Section 4.2.1.3 (Figure 37).

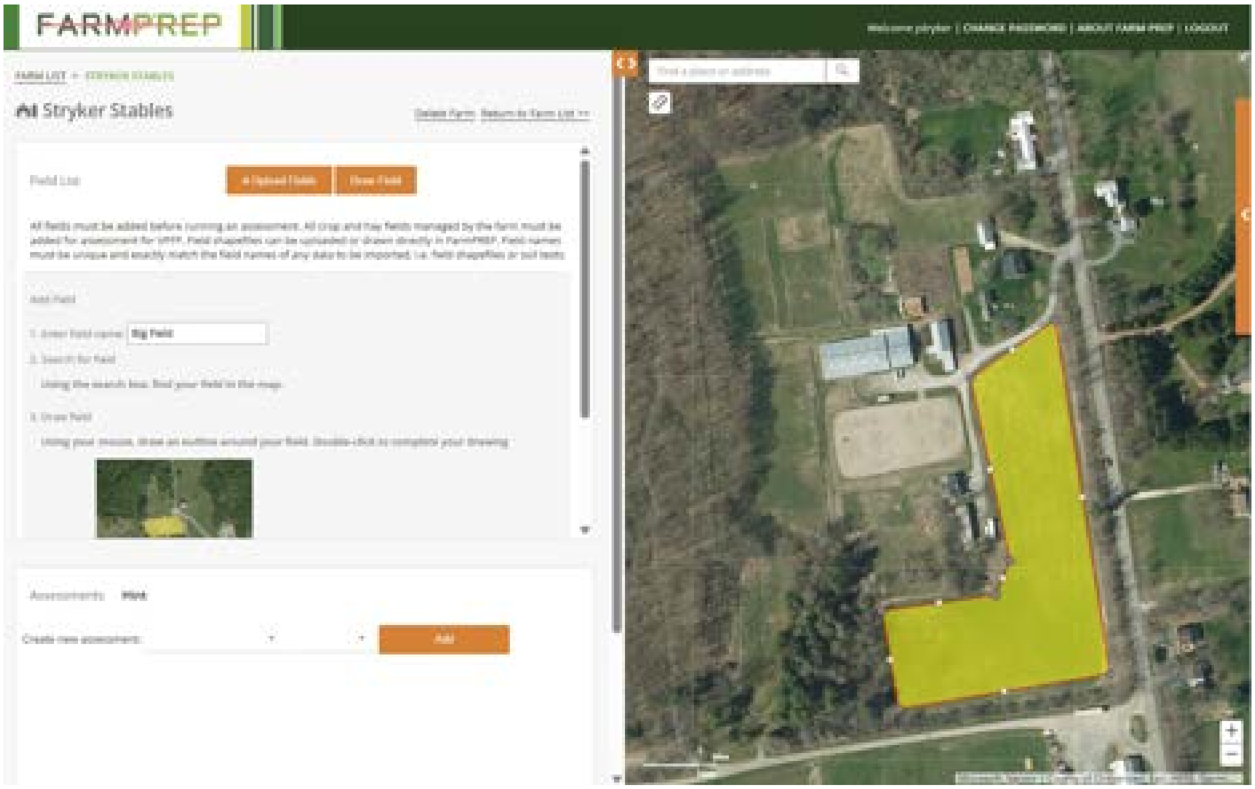

Figure 36. Field List Module where Users Delineate or Upload Field Boundaries.

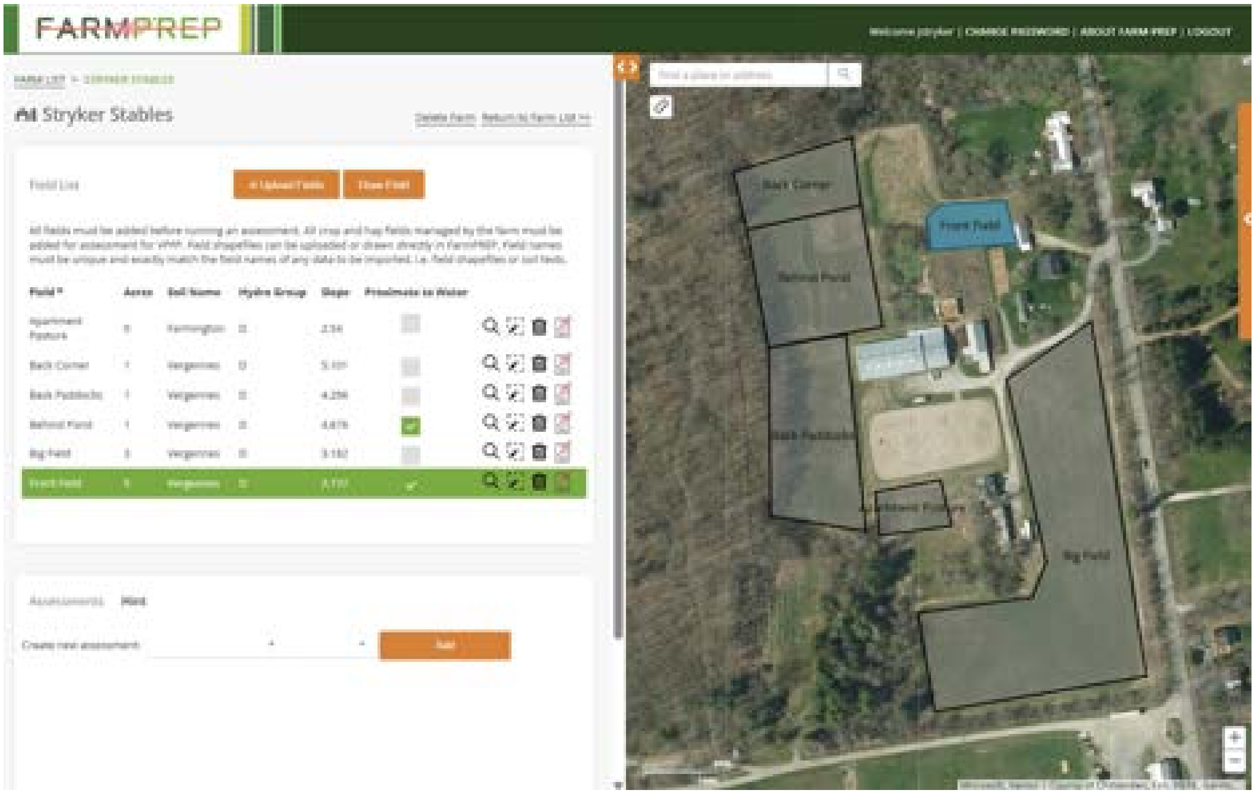

Figure 37. User Entered Fields with Attributes.

6.2.3. Create an Assessment

The term ‘assessment’ in Farm-PREP is used to refer to the unit of simulations conducted to evaluate the impact of management on a farm. It comprises APEX simulations of each field defined and selected for inclusion in the tool. To run APEX and evaluate outcomes in Farm-PREP, a user must create one or multiple assessments of their fields/farm. Soil health users can select from two types of assessments in Farm-PREP: ‘Alternative Practice’ and ‘Alternative Optimization’ (Figure 38). The term ‘alternative’ is assigned because Pay for Performance users also run Planned and Actual assessments, so this nomenclature is maintained for soil health and public users for consistency. Users select the a) type of assessment to run, b) either to start from a blank assessment or select to copy an existing assessment, and c) provide a name for the assessment (Figure 38).

Figure 38. Assessment list including Alternative Optimization and Alternative Practice Assessments.

Alternative optimization assessments also require users to enter a phosphorus reduction target (as a percent reduction in a fourth input box), which represents a desired farm-scale reduction in phosphorus edge of field loss (based on total phosphorus losses as the sum of soluble phosphorus loss in runoff, soluble phosphorus in tile drainage (if applicable), and sediment bound phosphorus associated with erosion). The user also has the option of prioritizing practices either on each field or at the farm level (Figure 45). When an optimization assessment runs, the tool automatically creates and executes simulations comprised of numerous combinations of practices implemented on some or all fields in various combinations. The order in which practices are tested is determined based on the user-defined practice priorities or the default prioritization. As scenarios are run, the tool identifies the first 10 solutions that accomplish the desired farm-scale reductions within a 5% tolerance. The user is provided with results for their 'current' (user-entered) management, a baseline management scenario reflective of no practice implementation, and the 10 solutions of the optimization algorithm (see Section 6.3).

Alternative practice assessments automatically create and run practice-based management scenarios based on adding to or modifying the 'current' user-entered management (Table 16). For buffer and cover cropping scenarios, these practices are added to current management. Buffers are applicable to all crop rotations and cover cropping is applicable to all crop rotations except hay and small grains. No till and reduced tillage scenarios are applicable to row crops and vegetable rotations. However, there are many permutations of tillage and manure application management options built into Farm-PREP and not all of these can be mapped to existing no till or reduced tillage systems. These scenarios (no till – injection, no till – surface, reduced – incorporated, and reduced – injected) are developed by matching the occurrence of spring and/or fall tillage as well as the occurrence of spring and/or fall manure applications between current management and an existing no till or reduced management schedule in the Farm-PREP database. If matching conditions do not exist, this scenario remains the same as the current. The user is provided with results for their current management as well as each of the practice management scenarios (see Section 6.3).

Table 16. Practice assessment management scenarios.

Management Scenario	Definition	Eligible Crop Rotations	Constraints
Current	User entered management		
Buffer	User entered management with 25 foot buffer. If existing buffer >=25 ft, then simulate existing buffer width.	Corn grain, Corn silage, Mixed vegetables, Soybean, Hay, Small Grains	
No-Till Injected	Existing tillage-manure application system replaced with no-till, injected manure.	Corn grain, Corn silage, Mixed vegetables, Soybean	Existing management must include spring/fall tillage and manure options that match available no till systems and are more conservative than no till.
No-Till Surface	Existing tillage-manure application system replaced with no-till, surface applied manure.	Corn grain, Corn silage, Mixed vegetables, Soybean	Existing management must include spring/fall tillage and manure options that match available no till systems and are more conservative than no till.
Reduced-Incorporated	Existing tillage-manure application system replaced with reduced tillage, surface incorporated manure.	Corn grain, Corn silage, Mixed vegetables, Soybean	Existing management must include spring/fall tillage and manure options that match available no till systems and are more conservative than reduced till.
Reduced-Injected	Existing tillage-manure application system replaced with reduced tillage, injected manure.	Corn grain, Corn silage, Mixed vegetables, Soybean	Existing management must include spring/fall tillage and manure options that match available no till systems and are more conservative than reduced till.
Cover cropping - winter hardy, by 9/15	Existing management with winter hardy, early cover cropping.	Corn grain, Corn silage, Mixed vegetables, Soybean	
Cover cropping - winter hardy, by 10/15	Existing management with winter hardy, late cover cropping.	Corn grain, Corn silage, Mixed vegetables, Soybean	
Cover cropping - winter hardy, By 10/1	Existing management with winter hardy, mid cover cropping	Corn grain, Corn silage, Mixed vegetables, Soybean	
Cover cropping - winter kill, by 9/15	Existing management with winter kill, early cover cropping.	Corn grain, Corn silage, Mixed vegetables, Soybean	

6.2.4. Enter Field Information and Management

When a user creates an assessment, the tool directs the user to a set of input forms that inform the current field conditions and management.

For both optimization and practice assessments there are tabs for 1) Farm Manure Characteristics and 2) Fields; for optimization assessments there is also a tab for 3) Farm BMP Prioritizations.

Farm Manure Characteristics is an optional input. This tab allows users to customize manure characteristics (e.g., nutrient contents) based on site-specific nutrient tests such that simulated manure applied to fields reflects the specified nutrient composition (Figure 39). Several default options are also available based on Table 15 in the Nutrient Recommendations for Field Crops in Vermont (UVM Extension, 2020). Users can also specify the units in which they want to enter manure application rates.

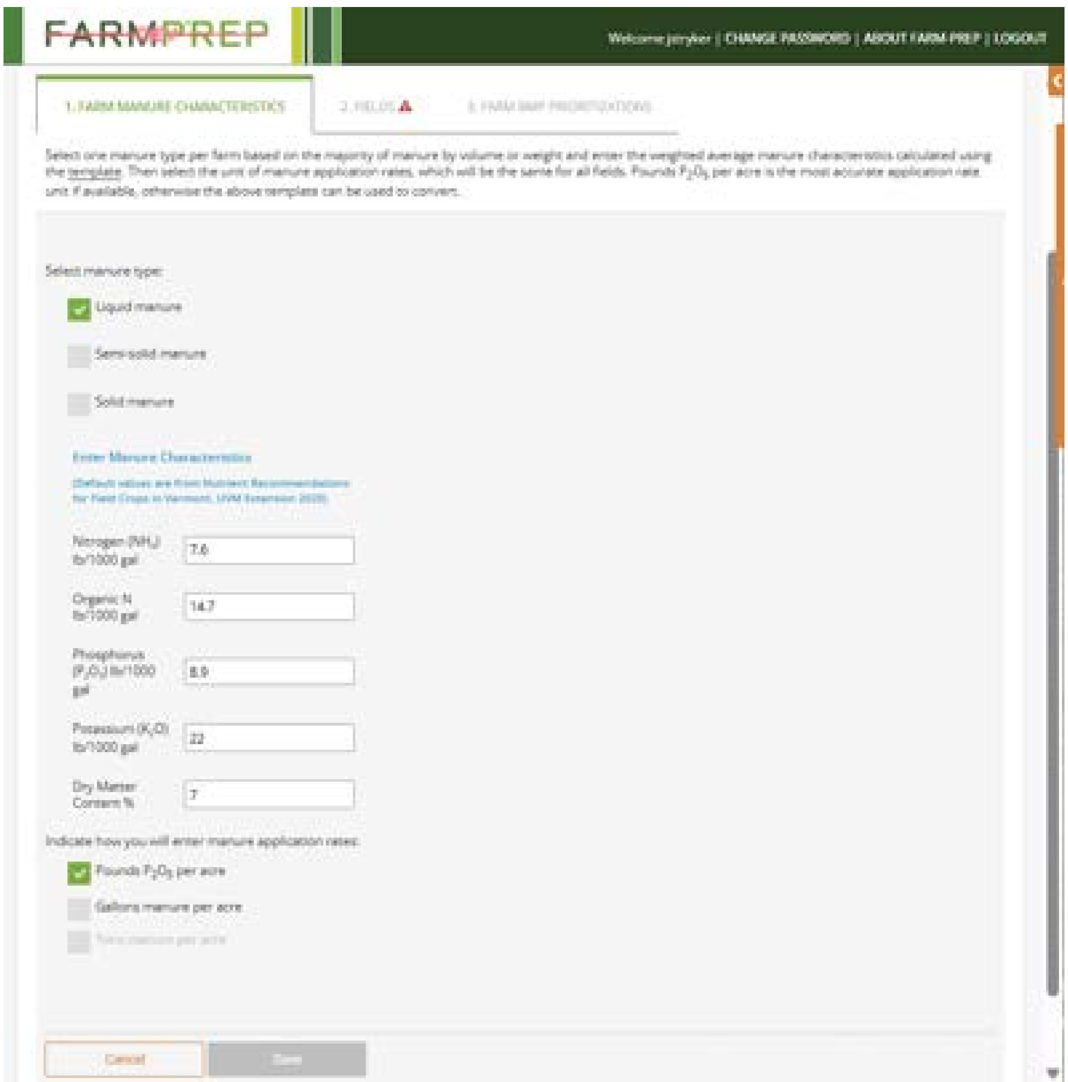

Figure 39. Farm manure characteristics input form – optional input.

The Field tab is where users enter field-specific soil and agronomic management. Field information is broken into 3-4 sub-categories: Soils, Crop/Tillage/Manure Information, Buffers, and in optimization assessments only there is a Best Management Practice Prioritization section.

Soils information is populated by default based on values in the gNATSGO database described in Section 4.2.1.2 for the map unit comprising the most area within each field boundary, and is therefore an optional input (Figure 41). Users can modify this data based on soil test information if available. Tile drain depth and spacing can also be entered if available and is used to parameterize the representation of tile drainage in the associated field model. The default is no tile drainage. Users can also import soil information for multiple fields by clicking on 'Import Data' and following the prompts to upload a csv (template provided in application).

Agronomic management is specified in the Crop/Tillage/Manure Information section and is the only mandatory data entry required to run an assessment (Figure 42). A series of dynamic dropdowns help guide users through the selection of crop rotation, timing and type of tillage, timing and type of manure applications, as well as timing and type of cover cropping. Numeric entry of manure and fertilizer application rates are entered manually. A Field Notes section is also available for users to keep text notes associated with each field (optional). While management is required for each field, the orange button near the crop rotation dropdowns allow users to apply management selections to one or many other fields in the assessment (Figure 43). The same button exists in the soils tab, such that users can apply tile drainage characteristics to other fields (Figure 43). Users can then edit or customize each field further if/as needed. This allows for streamlined data entry across multiple fields.

The Buffer section allows users to specify whether a buffer or grassed waterway exists on each field (Figure 44). If a buffer is selected, the model assumes that buffer is downslope of the field and all flow and sediment is routed across the specifies buffer width. Buffers are assumed to be external to the field (do not affect field area) and assumed to have minimal slope. Grassed waterways are assumed to be within the field, such that the area of the grassed waterway is subtracted from the area of the field. Grassed waterways are assumed to have the same slope as the field. The default is no buffers or grassed waterways.

For optimization assessments, users can optionally define priorities for specific conservation practices (Figure 45). This can be done either at the farm or field scale. If done at the field scale, those selections will override farm-level selections. Users can select the priority number associated with each practice type, which moves that practice to the associated priority box. Practices can also be excluded from optimization if not relevant for specific users' fields or farms, in which case these practices will not be tested as a potential solution to meet the desired phosphorus reduction.

When all required data has been entered, a 'Run Assessment' button becomes enabled on the top right of the page. Clicking this will execute the process that writes APEX input files for each field and management scenario (depending on type of assessment), runs APEX using AWS cloud services, and returns model outputs to the backend database. The Assessments form associated with each farm provides a list of assessments and their status (Figure 38). When an assessment is complete and results are available, users click on the Results link to view.

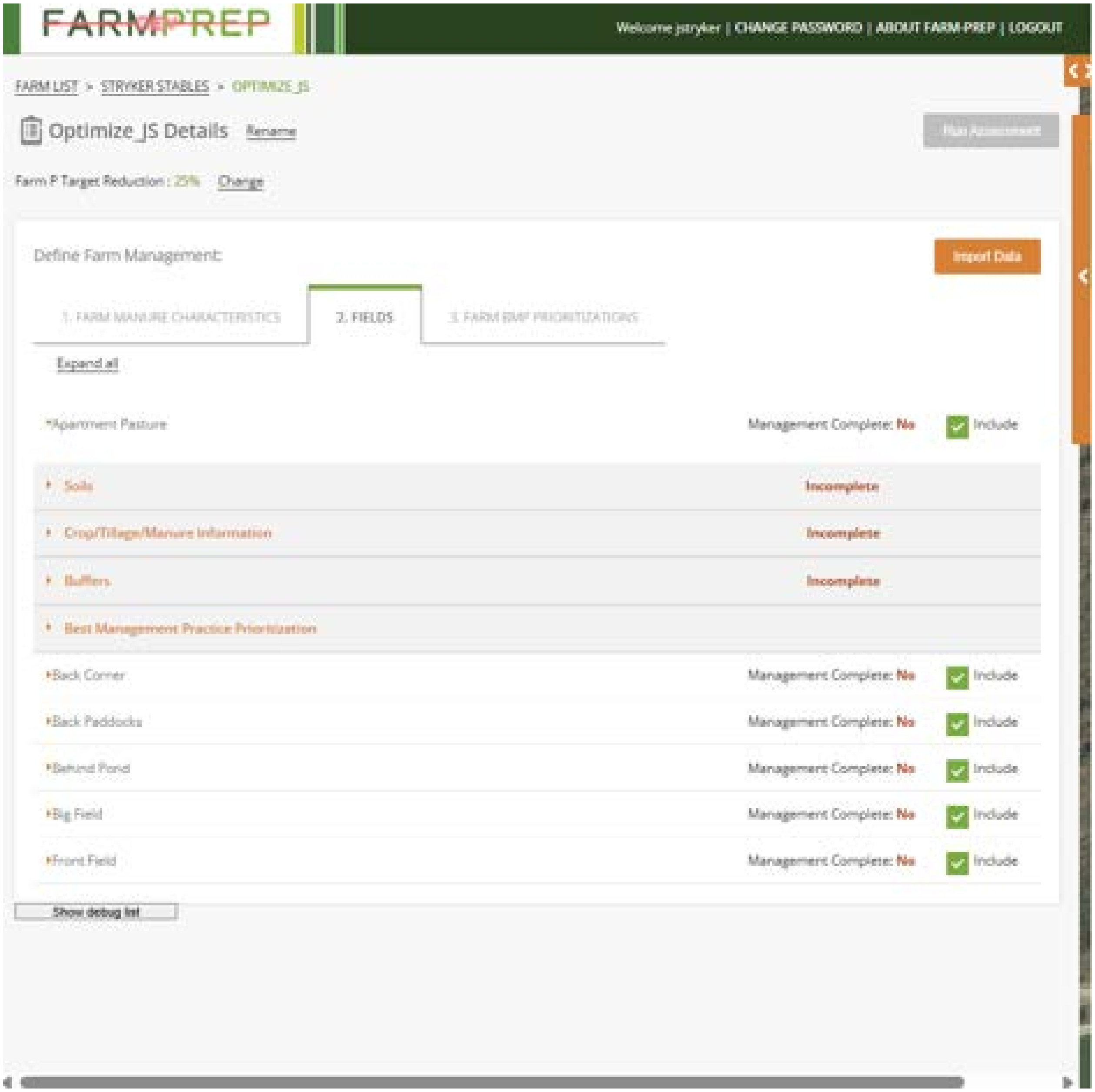

Figure 40. Fields input tab, including field-specific input forms for soils, crop/tillage/manure, buffers, and practice prioritization (in optimization assessments).

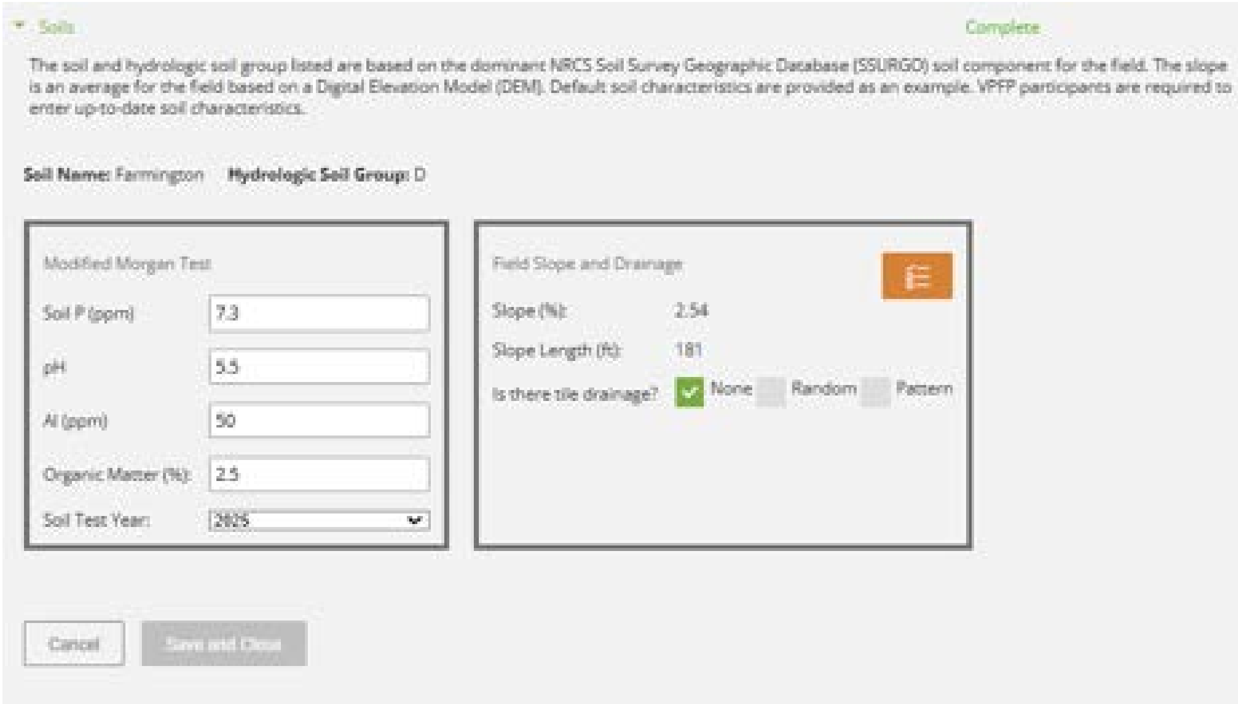

Figure 41. Field-specific soils inputs – optional input.

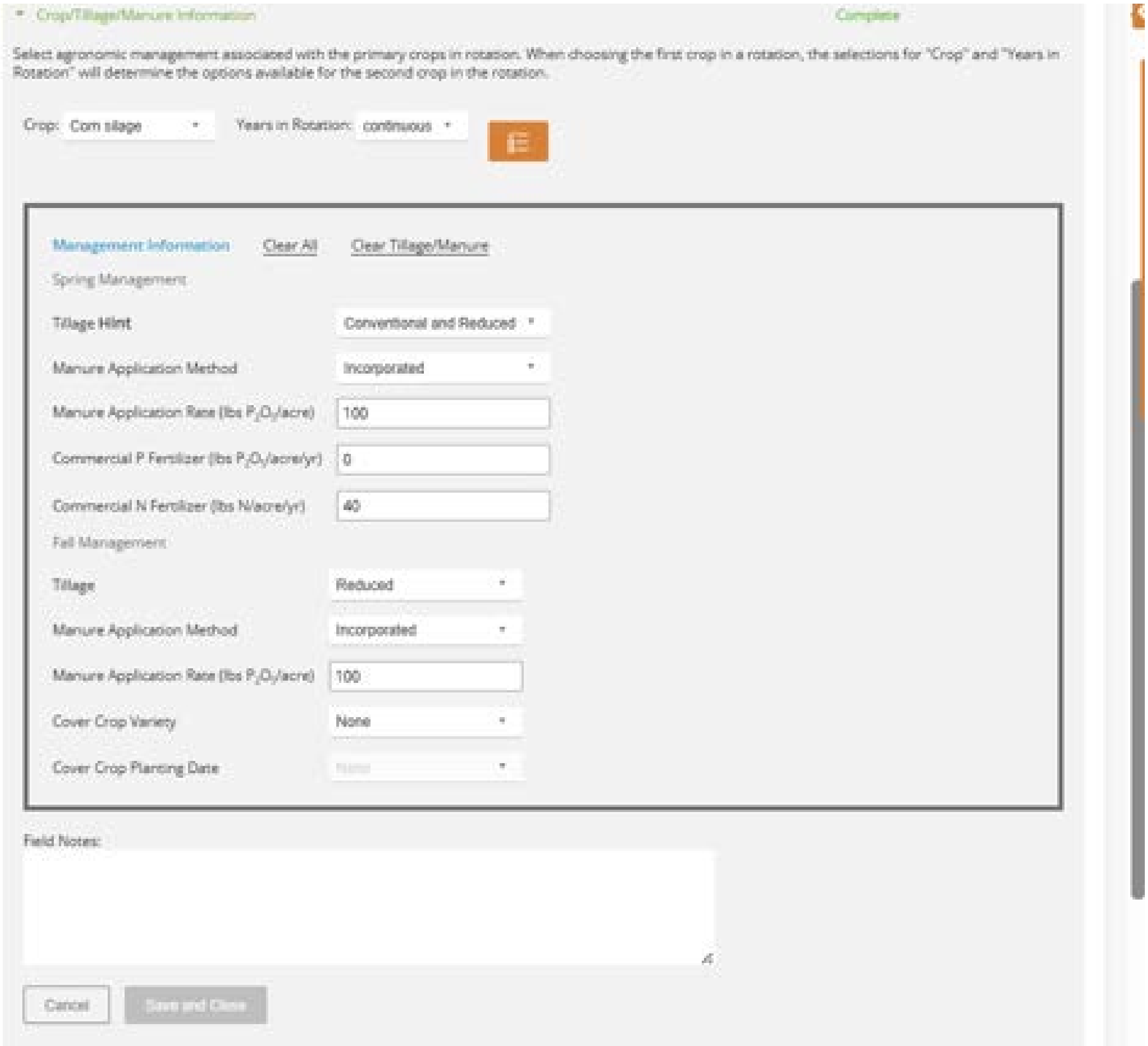

Figure 42. Field-specific Crop/Tillage/Manure Information inputs – required user input.

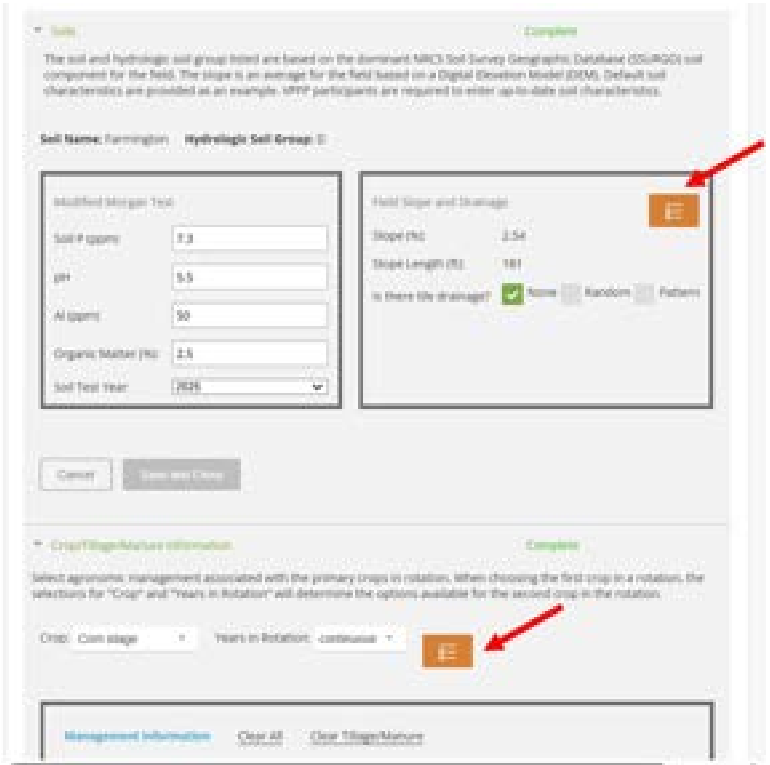

Figure 43. Field input form, highlighting button for copying to other fields.

Figure 44. Buffer and grassed waterway input form - optional input.

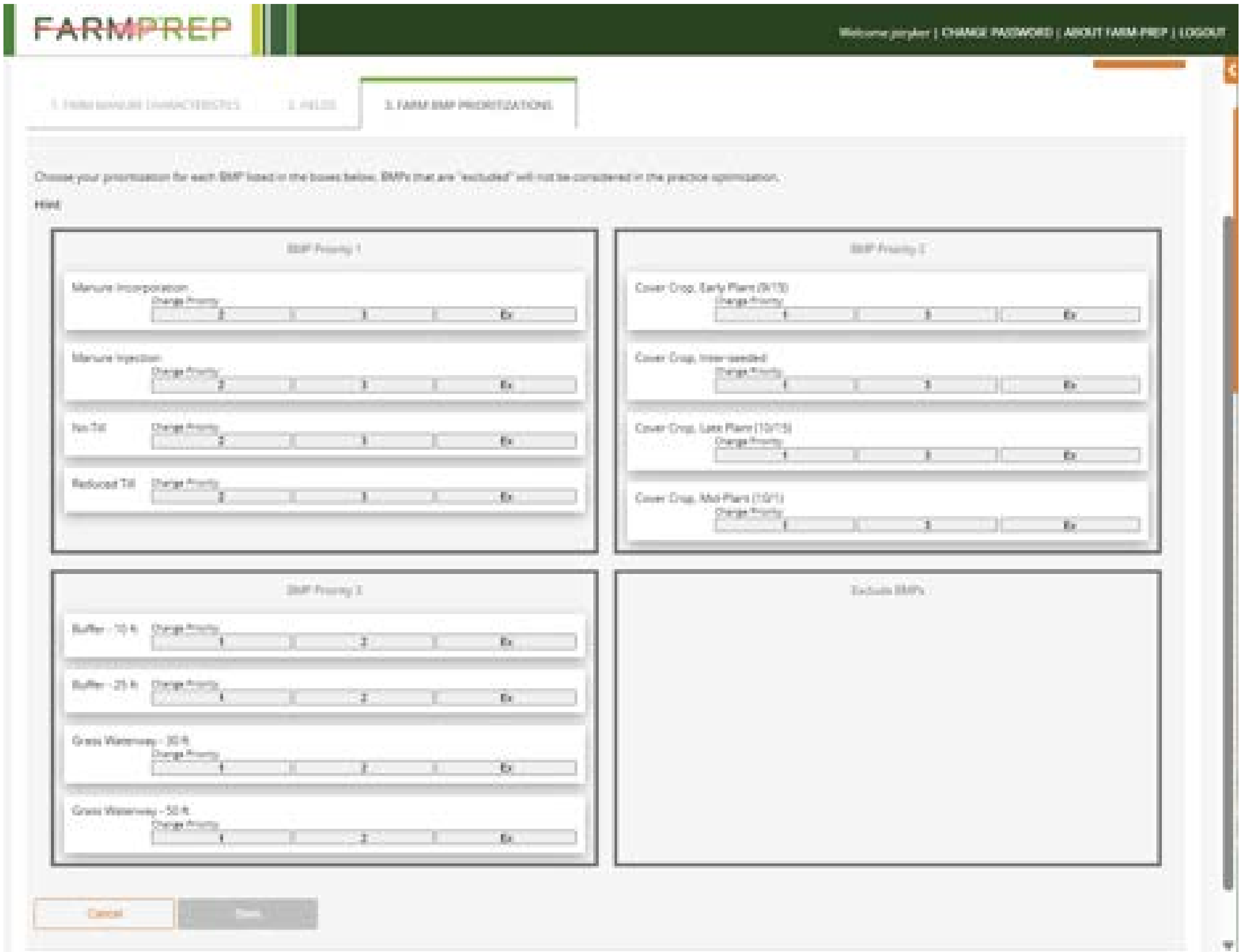

Figure 45. Farm BMP Prioritization form - optional input for optimization assessments. Note that field-level prioritization is also available in the Fields tab and will override farm level selections.

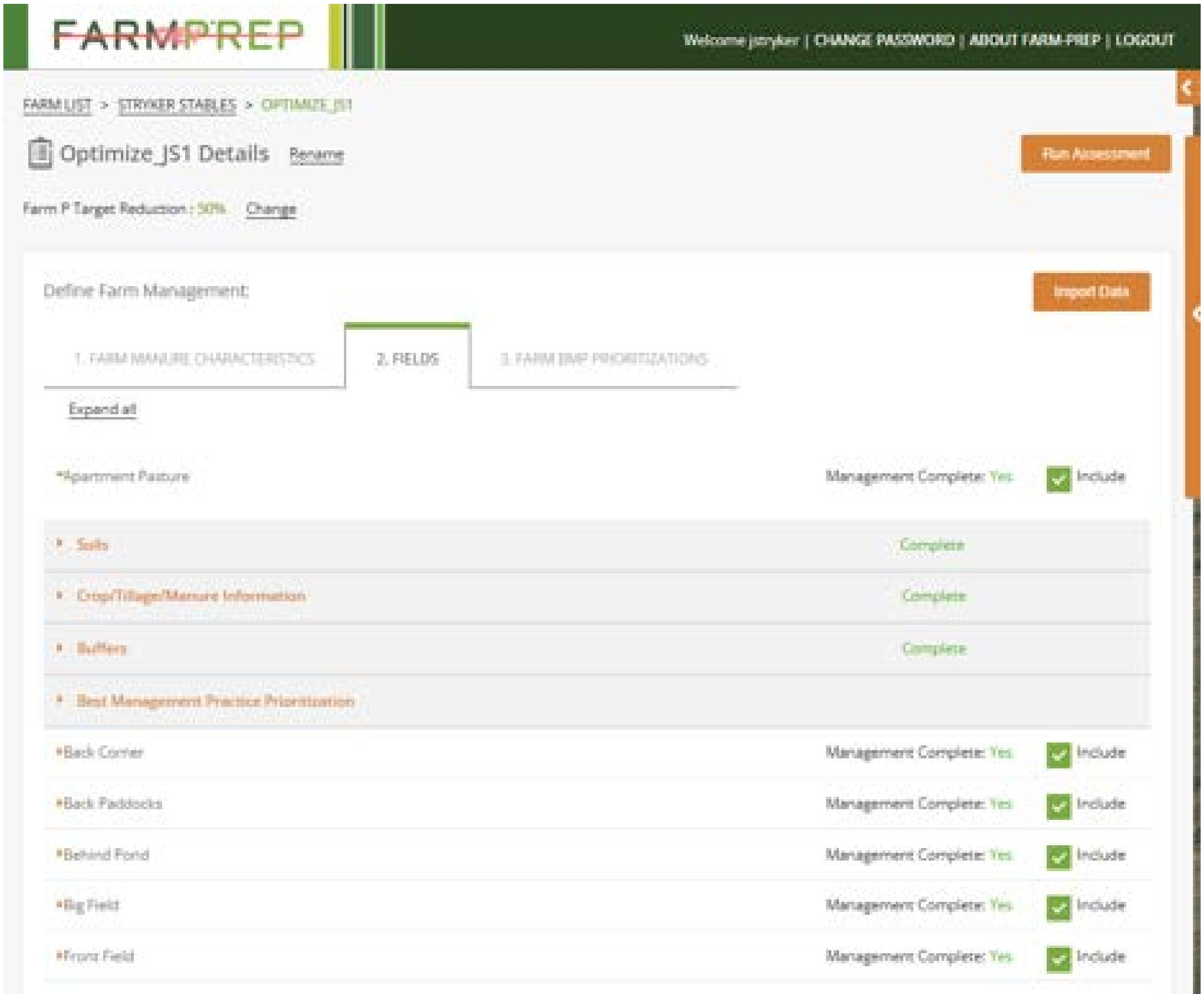

Figure 46. Completed entry enables 'Run Assessment' button.

6.3. Results/Reporting

Farm-PREP provides soil health users with a multi-tabbed report that shows model outputs related to Soil Health, Greenhouse Gases, Crop Metrics, and Surface Losses. Model results are initially present at the farm level, where field results are aggregated to the farm-scale (Figure 47), and field results are nested under each Farm Management Scenario (Figure 48). Most output metrics are reported as annual average or daily average values (based on a 30-year simulation). In addition, the change in bulk density and the change in plow depth (15 cm) percent soil organic matter from start of the simulation to end of the simulation is reported. Note that in the case of soluble phosphorus in soil, the calculator reports average annual peak growing season soluble phosphorus in the top 15 cm of soil (in other words, the average of each simulated year's maximum daily value) As soluble phosphorus is not directly comparable to a Modified Morgan soil test value, and this output is highly variable and difficult to track over a season, we suggest a near surface peak value is more useful as a relative measure of concentrations that drive soluble phosphorus loss in runoff. Units and output metrics descriptions are provided in Table 17.

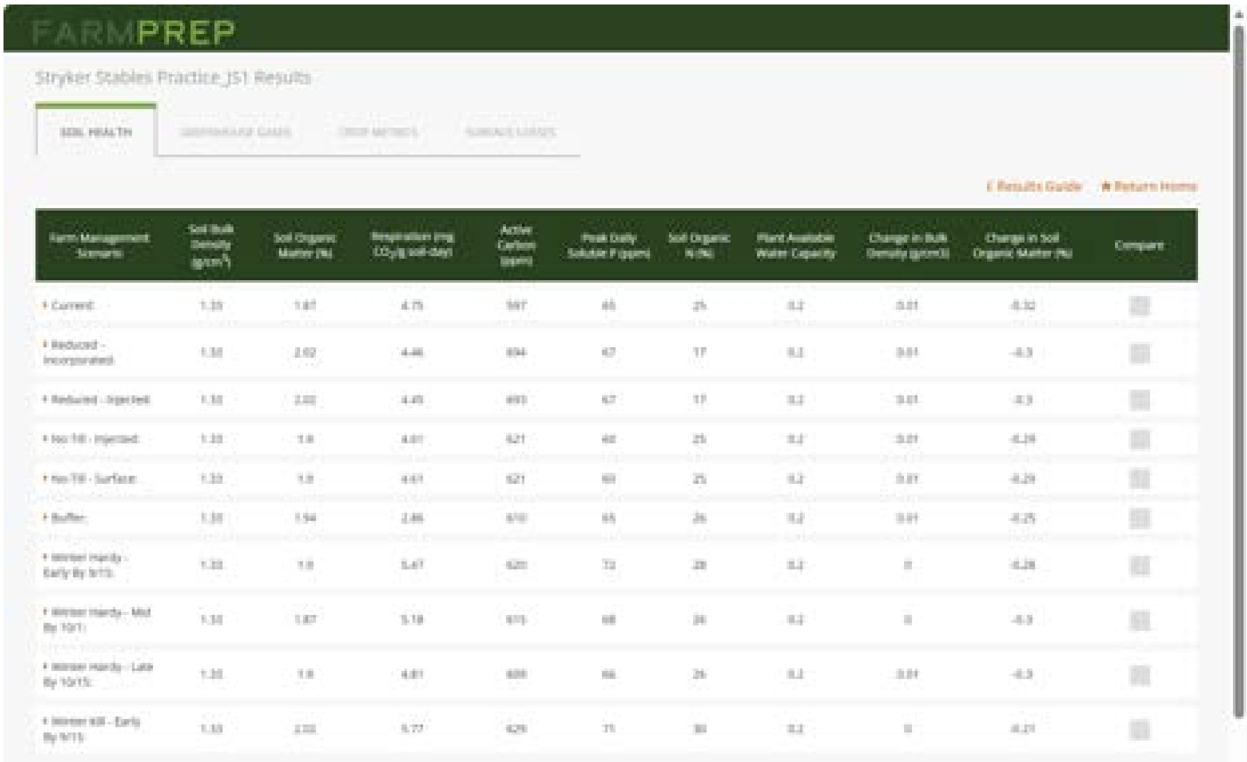

Figure 47. Results page showing farm-scale results of soil health metrics.

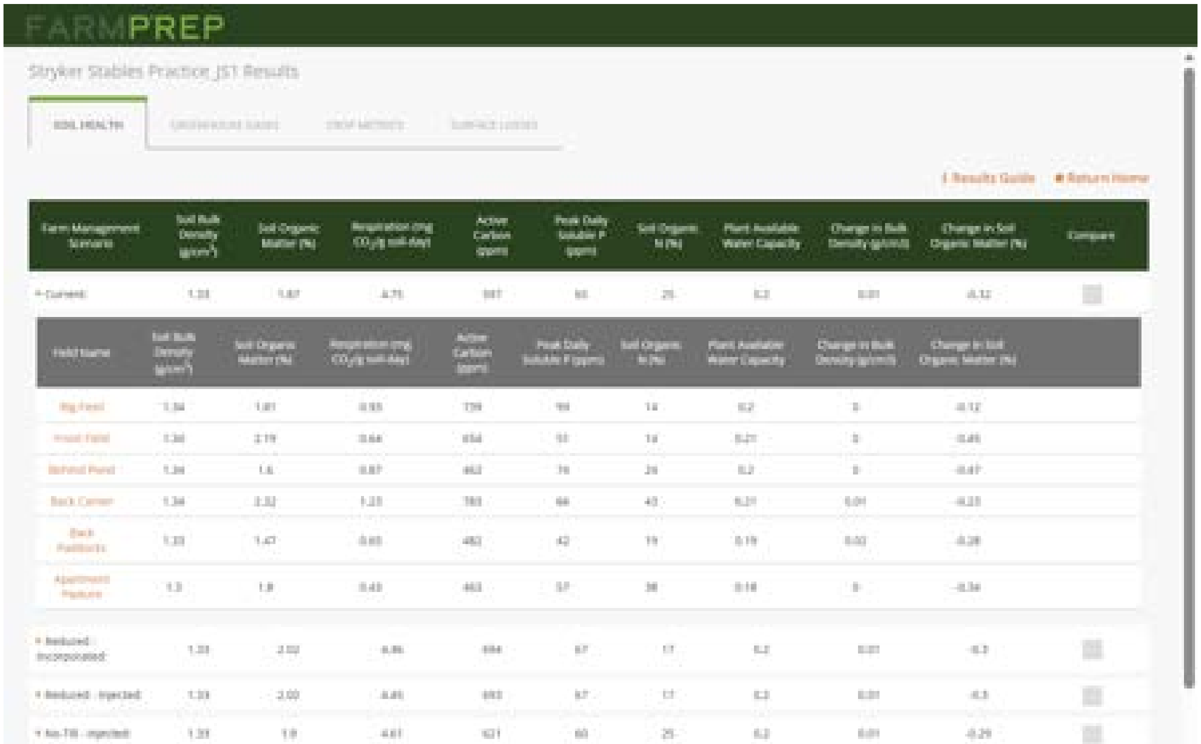

Figure 48. Results page showing nested field level results for soil health metrics.

Table 17. Reported metrics in the Farm-PREP Soil Health Calculator Tool.

Report Tab	Output Metric	Units	Depth	Description
All	Farm Management Scenario			
Soil Health	Soil Bulk Density	g/cm^3	30 cm	Average soil bulk density over simulation period
	Soil Organic Matter	%	15 cm	Average soil organic matter over simulation period
	Respiration	Mg CO_2 / g soil-day	30 cm	Average daily growing season respiration
	Active Carbon	ppm	30 cm	Average daily growing season active carbon
	Soil Soluble P	ppm	30 cm	Peak daily growing season soluble phosphorus concentration. Note this is NOT directly comparable to Modified Morgan's soil test P.
	Soil Organic N	%	30 cm	Average percent nitrogen of soil over simulation period
	Plant available water capacity		30 cm	Average growing season plant available water capacity (difference between wilting point and field capacity) over simulation period
	Change in Bulk Density	change in g/cm3	30 cm	Change in bulk density from beginning to end of 30-year simulation
	Change in Soil Organic Matter	change in %	15 cm	Change in near surface soil organic matter from beginning to end of 30-year simulation

[2]Greenhouse Gases	CO2 Flux	[1]tons CO^2 equivalent		Represents average annual flux of carbon dioxide to atmosphere (negative indicates net emissions/flux out)
	N2O Flux	[1]tons CO^2 equivalent		Represents average annual flux of nitrous oxide to atmosphere (negative indicates net emissions/flux out)
	Gross GHG Flux	[1]tons CO^2 equivalent		Total carbon dioxide and nitrous oxide flux to atmosphere
	Net GHG Flux	[1]tons CO^2 equivalent		Net emissions, gross carbon dioxide and nitrous oxide emissions minus respiration
	Carbon Sequestered in Soil	tons organic carbon	1.5 m	Represents annual average amount of additional carbon sequestered in soil carbon (positive represents increase)
	Carbon Storage in Soil	tons organic carbon in soil	1.5 m	Annual average organic carbon in soil
Crop Metrics	Crop 1 / Crop 2 P Stress	days		Annual average days crops experience phosphorus stress
	Crop 1 / Crop 2 N Stress	days		Annual average days crops experience nitrogen stress
	Crop 1 / Crop 2 Yield	tons/ac		Annual average crop yield
	Total P Applied	lb/ac		Annual average total phosphorus applied to fields (input)
	Total N Applied	lb/ac		Annual average total nitrogen applied to fields (input)
Surface Losses	Precipitation	inches		Annual average precipitation (input)
	Runoff	inches		Annual average runoff
	Percent Runoff	%		Annual average percent runoff
	Percent Infiltration	%		Annual average percent infiltration
	Nitrogen Surface Losses	lb/ac		Annual average total nitrogen edge of field loss (includes soluble N in runoff, sediment N in erosion, and soluble N in tile drainage)
	Nitrogen Volatilization	lb/ac		Annual average nitrogen volatilization
	Phosphorus Surface Losses	lb/ac		Annual average total phosphorus edge of field loss (includes soluble P in runoff, sediment P in erosion, and soluble P in tile drainage)
	Erosion	tons/ac		Annual average sediment loss (metric tons)

[1]CO2 equivalents are calculated based on global warming potentials from the Intergovernmental Panel on Climate Change's Fifth Assessment Report.

[2]Greenhouse gas results are being further validated under a separate scope of work and should be considered preliminary, or may be disabled, until that work is complete (expected to finish April 2026).

Farm-PREP also offers a module that allows users to easily compare farm management scenario results and better understand driving factors of differences between field and scenario results. This feature has been updated to include the metrics shown in Table 17. Users select scenarios from the primary reporting page and click 'Compare' (Figure 49). The tool reformats results to allow a more direct comparison of results across either a) each field across different scenarios or b) fields within each scenario. If users select to compare by field (a), the tool shows a table of each field's results where values that differ from the Current management scenario are highlighted in green (Figure

50). If a practice scenario could not be mapped to an alternative management scenario representative of that practice, an asterisk is shown at the top of the scenario indicating this result matches Current. For example, in Figure 50, the ‘Apartment Pasture’ field included a 50-ft buffer as part of Current management therefore the result of the ‘Buffer’ practice scenario is the same as Current. Similarly, the management on that field included no manure in the fall and therefore could not be mapped to a no-till injection system (because the tool does not add a manure input if not part of current management). Both inputs and results are included in this table, so that the user can see what inputs and results differed across fields (e.g., perhaps for one field with hydrologic group B soils no till was more effective at increasing organic matter than on a field with D soils). With optimization scenarios, farm management scenarios are not prescripts as with practice scenarios and are referred to as ‘Alternative 0, Alternative 1’, etc., so using the compare feature to identify what practices are different across those scenarios and what is driving the changes in indicator values is critical.

If users select to compare by scenario (b), the tool transforms the data so that all field results and associated key inputs within a single scenario are shown in the table (Figure 51). In this format, users can also select to map key results onto their field boundaries for a visual representation of how inputs and model results differ spatially across a farm. In Figure 51, we easily see what fields are responsible for higher phosphorus loss rates relative to others. This compare feature can help identify reasons driving certain results (e.g. did one field have a considerably higher soil test phosphorus value that drives higher phosphorus loss, or did one field have higher slope or different soils, etc.). It can also help identify where practices might be more or less effective and help us think about what the driving factors of practice effectiveness might be (e.g. perhaps cover cropping was more effective at increasing organic matter on a field with B soils in comparison to a field with D soils, or a buffer was more effective on a field with higher slope than a field with low slope).

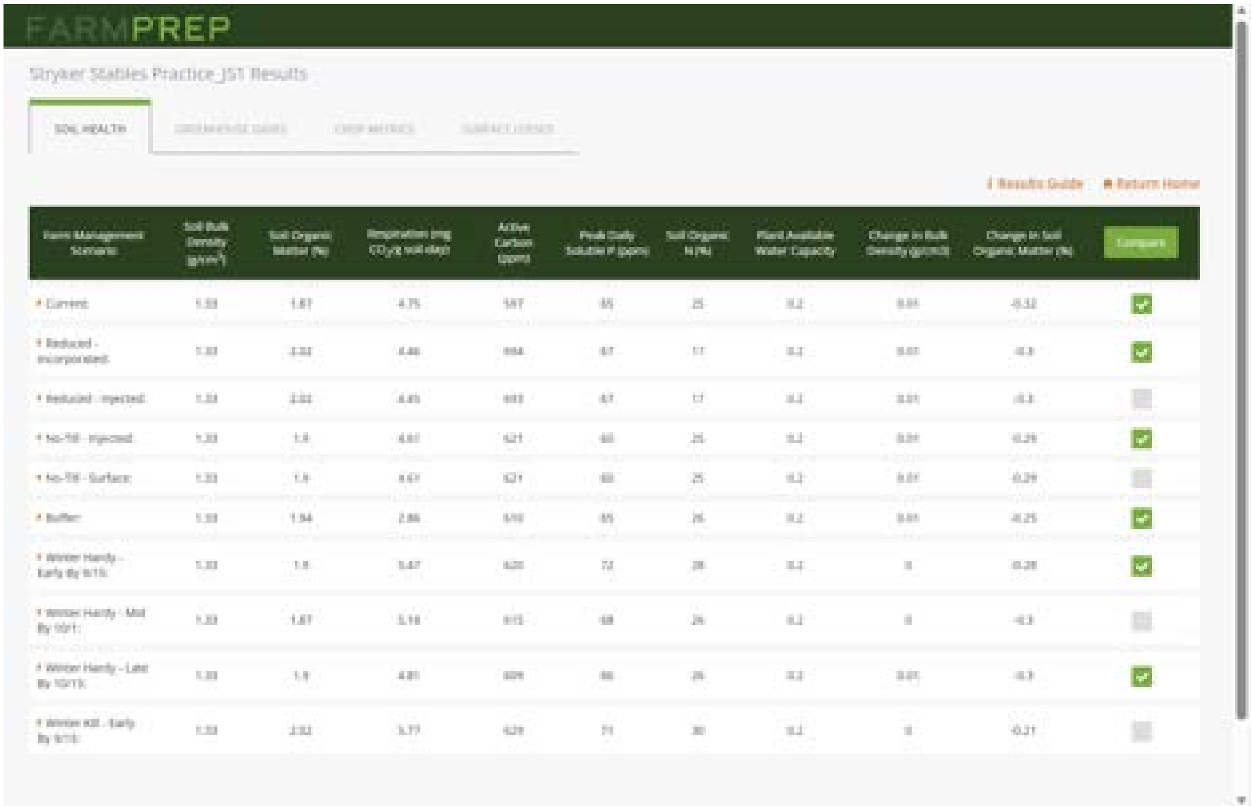

Figure 49. Select scenarios to directly compare results across fields and/or scenarios.

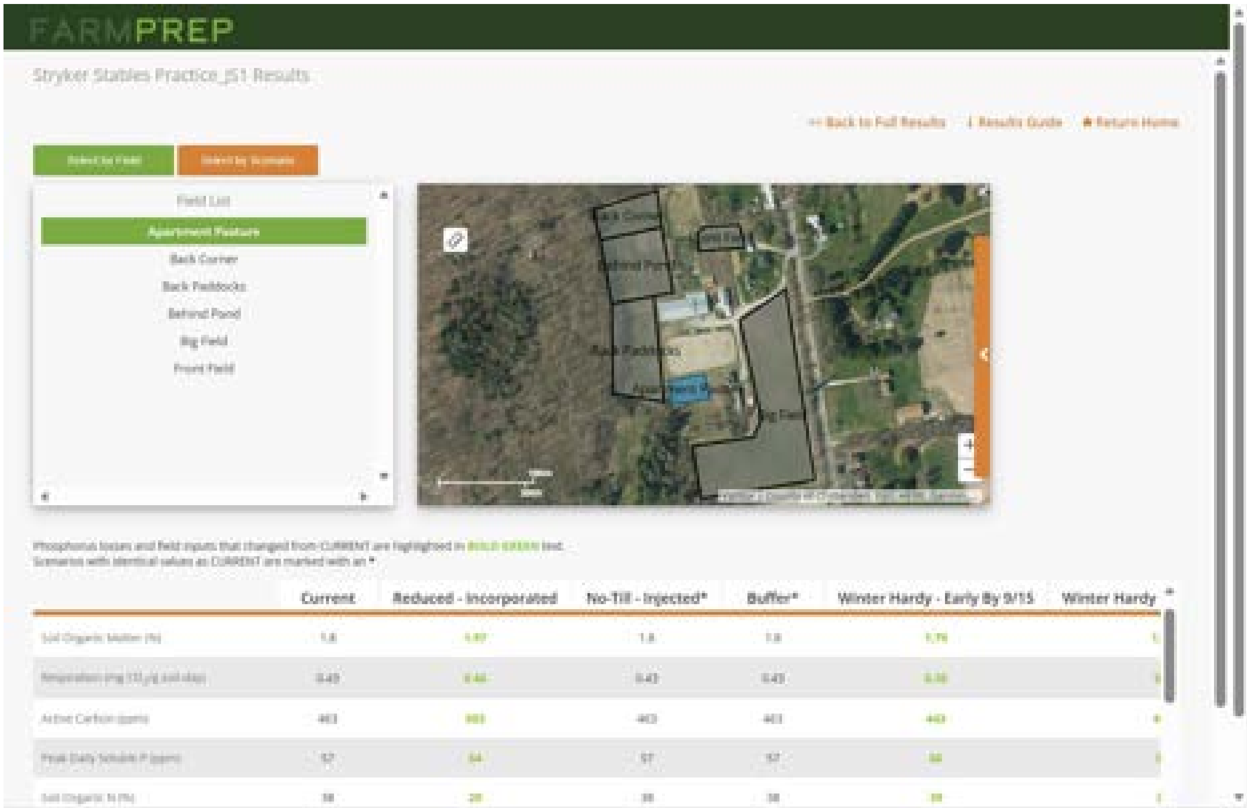

Figure 50. Compare by field module.

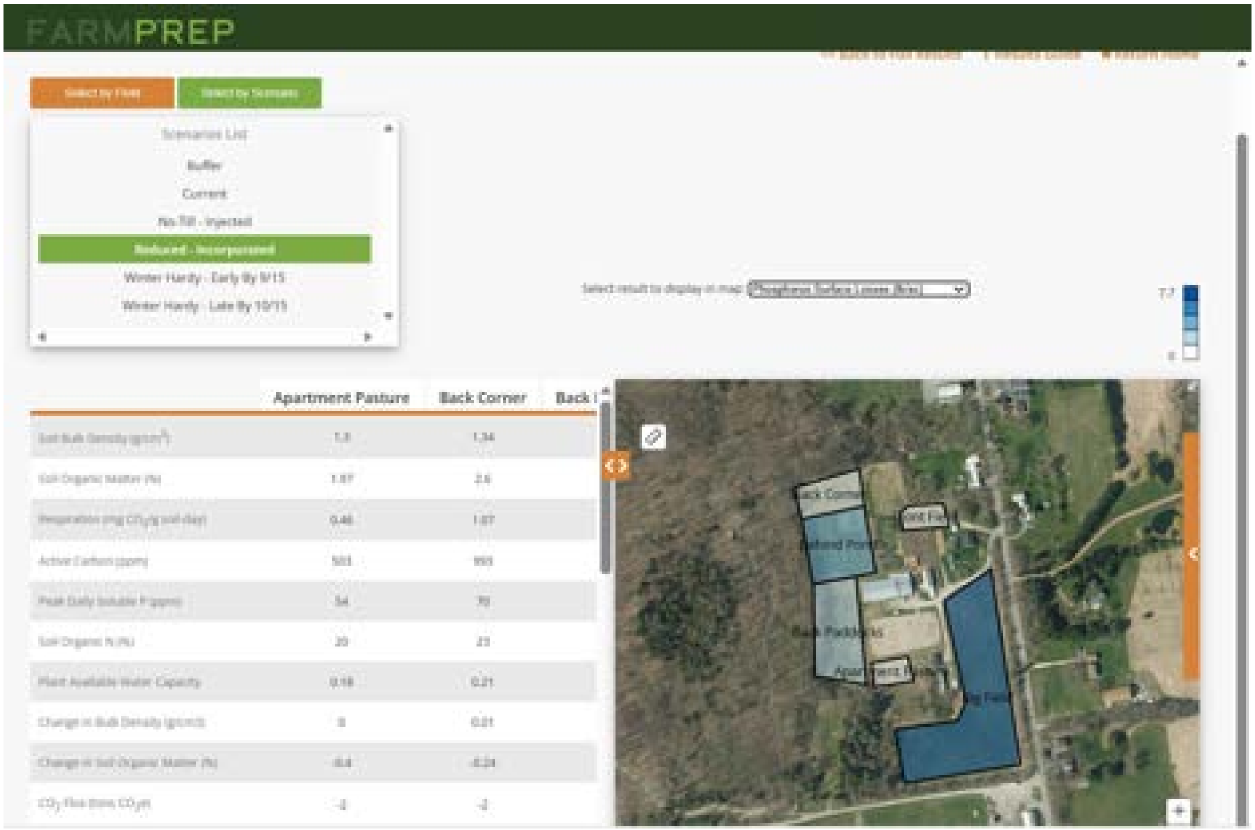

Figure 51. Compare by scenario module and mapping of key results.

7. Server Support and Maintenance

The current Farm-PREP tool is hosted by Stone Environmental and supported financially by VAAFM through a contract that extends through the duration of the Soil Health Calculator Project. *Task 4-4 Server Support and Maintenance* instead included testing of server resources to accommodate a potentially larger user base as well as the effort to establish a login option to allow public users to request a login from the tool. VAAFM users receive logins through assignment by an admin user when enrolled in Pay for Performance. For this work we established a new soil health role in the Farm-PREP system to keep those users' data separate and distinct from users who are administering or enrolled in the VAAFM Pay for Performance program. Anyone can now request a login from the login page of the tool and will be established as a soil health user.

8. Training

A virtual training session on the Farm-PREP Soil Health Calculator was conducted on February 18th (*Task 4.5* of the Soil Health Calculator project), It was advertised primarily through VAAFM's partner email list. This training was geared towards new users of the tool but was also suitable for users familiar with Farm-PREP and who want a refresher on data entry, interpreting alternative assessments, and/or those who were interested in new reporting metrics. Jody Stryker, from Stone Environmental, conducted the training and Hannah Rubin from Stone took meeting notes. The training objectives were:

1. Demonstrate how to set up and run assessments in Farm-PREP as a soil health user.
2. Describe framework of 'assessments' (will guide users in how to interpret results).
3. Demonstrate how to compare results of management scenarios.

The training covered:

- Introduction to the Soil Health Calculator project (10 minutes)
- Brief description of model and tool framework (5 minutes)
- Data entry walk through (15 minutes)
- Assessment framework (5 minutes)
- Results and comparison module (10 minutes)
- Discussion/questions (15 minutes)

The first two topics above were presented in slide format, and then the Soil Health Calculator tool was used to walk people through creating a farm, delineating field boundaries, what are required inputs in comparison to inputs we provide a default value for, and entering required information (agronomic managements schedules comprised of tillage, manure application method and timing, and manure/fertilizer application rates). The optimization vs practice assessments were described and we looked at results of each type to distinguish how management scenarios simulated in those assessments differ from each other. We demonstrated how results are provided to the user and how to use the compare feature to identify differences in outputs across fields within a management scenario or across management scenarios on a single field. The compare feature also includes management options run in each particular field scenario, to assist the user in identifying how management and field conditions may be driving differences across soil health (and other) results. No questions were asked during the training.

This training session was very lightly attended; however, the session was recorded and will be made publicly available either through VAAFM's and/or Stone's websites.

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Appendix A

Soil Model Parameter Database Compilation Documentation

STONE
ENVIRONMENTAL

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Soil Model Parameter Database Compilation Documentation

Contents

1. Documentation Overview

This document describes the process of compiling a soil parameters database that completely covers the continental US (CONUS). For any location and area in the CONUS, the final soil database provides a complete set of valid soil physical and chemical parameters that can be used as inputs for a variety of simulation models. In fact, although the database compilation was focused on considering parameter soil inputs used by the Agricultural Policy / Environmental eXtender model, APEX (Steglich et al., 2019), many other models, e.g., DNDC (Li et al., 1992), SWAT (Arnold and Fohrer, 2005) or ALMANAC (Kiniry et al., 1992), require most of the same inputs. In addition, the methodology developed to compile this soil database can easily include any set of soil parameters not specifically considered here.

The main source of soil data is the gNATSGO geodatabase, a USDA-NRCS Soil & Plant Science Division (SPSD) composite database that provides complete coverage of the best available soils information for all areas of the United States and Island Territories. The gNATSGO database contains a raster of the soil map units and 70 related tables of soil properties and interpretations. It was created by combining data from the Soil Survey Geographic Database (SSURGO), State Soil Geographic Database (STATSGO2), and Raster Soil Survey Databases (RSS) into a single seamless ESRI file geodatabase. The State-wide geodatabases contain a 10 meter raster while the national database contains a 30 meter raster. Current data (released on 11/2021) can be downloaded at https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcseprd1464625 (Accessed 9/2022).

Soil data are continuously extended and updated by the USDA-NRCS. However, although the gNATSGO database is spatially gapless, a remarkable number of data elements have no valid value reported. This includes specific soil parameters for a given record, soil records present in the database but with no valid parameter values reported, as well as entire soil data records that are missing from the database. A methodology was developed to fill missing soil model parameters and entire soil data records. The method starts from the data gap filling procedure described for the development of the US-ModSoilParms-TEMPLE database (TAM, 2016 and Di Luzio et al., 2017) and has been modified to address missing data issues more thoroughly.

The soil database compilation process developed here, is accomplished by python routines that process the source soil data in two main steps: 1) extraction of the needed source data element, initial manipulation, and compilation of an intermediate soil model parameter database and 2) filling all soil model parameters gaps. Since the gNATSGO database is continuously updated, it is worth noticing that the entire soil model parameter database compilation process is fully automated. Should new soil data become available, the user can collect the necessary gNATSGO source tables, update additional supporting tables (discussed in more details below), and rerun the python scripts.

Below, the methodology to compile the CONUS soil model parameters database and fill data gaps is explained in detail. After describing all data source used as inputs for the soil database compilation process, the initial compilation of the database is presented, followed by the description of the data gap filling procedure. All deliverables are listed in the following section. Finally, detailed instructions are provided on how to execute the python routines to compile and fill the soil model parameter database starting from scratch. Column description of all tables produced is included in Appendix A.

2. Data Sources

As a first step, all input tables containing all the needed soil parameters necessary for compiling the soil model parameter database were gathered in one input database.

The primary source of soil data were the national gNATSGO mapunit, component, and chorizon tables. The mapunit represents the spatial unit of gNATSGO. Soil components represent the soil series present within each mapunit. The soil horizons represent the soils horizon/layer properties within each soil component. Some additional information was drawn from other gNATSGO tables. In total, seven tables from the gNATSGO CONUS database were used in this work (see Table 1).

Besides the gNATSGO tables, a conus_mukey table was created using ArcMap 10.5.1 by building the attribute table for the raster resulting from clipping the gNATSGO mapunit raster by a CONUS boundary polygon. This step allowed identification of all the map units in the CONUS and, more importantly, to count the 30 m x 30 m cells in each map unit (this is used later to calculate mapunit areas since it is not always available from the source gNATSGO mapunit table although an area column is in the table).

Finally, component and horizon default soil tables, defaultsoil_component and defaultsoil_horizons, were extracted from the US-ModSoilParms-TEMPLE database (TAM 2016) to be used, where applicable, as a last resort soil parameter input source in the soil data gap filling procedure.

All these source tables were collected and saved in an SQLite database.

Table 1. List of input tables used for compiling soil model parameter database.

#	Source	Table	Short Description	Level of Detail
1	gNATSGO*	*legend*	Provides information related to the soil survey area	Soil Survey Area
2		*mapunit*	Map units included in the referenced legend and data related to the map unit as a whole	Map Unit
3		*muaggatt*	Variety of soil attributes and interpretations that have been aggregated from the component level to a single value at the map unit level to express a consolidated value or interpretation for the map unit as a whole	Map Unit
4		*sapolygon*	attributes for survey area polygons	Map Unit
5		*component*	Map unit components identified in the referenced map unit, and selected properties of each component	Soil Component

#	Source	Table	Short Description	Level of Detail
6		*chorizon*	Horizon(s) and related data for the referenced soil component	Soil Horizon
7		*chtexturegrp*	Range of textures for the referenced horizon as a concatenation of horizon texture and texture modifier(s)	Soil Horizon
8	gNATSGO/ CONUS boundary	*conus_mukey*	Cell count for each map unit in the CONUS	Map Unit
9	TAM 2016	*defaultsoil_component*	Default soil component record and default parameters	Soil Component
10		*defaultsoil_horizons*	Default soil horizon records associated with the default component and default parameters	Soil Horizon

* In the input database all these tables were renamed by adding the prefix *gnatsgo*_

3. Initial Database Table Compilation

The initial compilation of the soil database consists of extracting all model input soil parameters from the source tables. Some initial data manipulation is also conducted to rescale parameters to model-required units, calculate derived parameters, and conduct some data accuracy checks. This data extraction and processing is conducted at the mapunit level, the soil component level, and the soil horizon level. These new intermediate tables, which contain model soil parameter input columns and other data columns necessary to perform the soil parameter gap-filling procedure, are saved in an SQLite database. Derivation of each of these initial tables is provided below.

3.1. Mapunit Level Table

This table is not directly necessary for deriving model soil parameter inputs once soil component and horizon tables have been compiled. However, this table stores some useful general information about the map units, e.g. survey source (SSURGO or other), and collects the ensemble of all map units in the CONUS. Joining this table with the component table on the *mukey* column guarantees that each mapunit in the CONUS has also component and horizon records (either readily available or filled).

Steps to compile this table are described below.

1. Collect data from several gNATSGO tables:
   a. *mapunit* – To gather basic mapunit information (table columns: *musym, mukey, muname, mukind, muacres, lkey*)
   b. *component* – To count the total components in each mukey (table columns: *mukey, cokey* and count/group by cokey to get the count)
   c. *sapolygon* – To get the source of data (table columns: *lkey, source)*
   d. *legend* – To get the Soil Survey Area (SSA) (table columns: *lkey, areasymbol*)

2. Calculate the area in each mukey as *muacres=cell count x cell resolution*^{2} *x unit conversion factor*
   Note: Although there is a column with area in the gNATSGO *mapunit* table, this step is necessary since many records have no area reported. The cell resolution for the analysis described here was 30 m (900 m^2) with a unit conversion factor m^2 to acres of 0.000247105.

3. Join all the tables on the common keys and save the final table in an SQLite database as *mapunit_model*.

3.2. Component Level Table

This table contains all the information to characterize components level soil attributes. The primary soil component model parameters which are taken directly from gNATSGO data columns are:

- Hydrologic Group
- Soil Albedo
- Minimum Depth to Water Table

Component level model parameters that are derived from gNATSGO data columns include:

- Soil Weathering Code - see below for calculation details
- Soil Grouping - see below for calculation details

In this initial compilation, not only are the parameters above gathered or calculated, but also various other soil attributes are also collected, e.g. component percentage to calculate the area that each soil component occupies in each mapunit or soil taxonomy classes and soil survey areas (SSA), to be used in the gap-filling procedure of soil records that are not complete.

The steps taken to compile this table are described below:

1. Read the gNATSGO component table for the following parameters:
    - *compname* – Component Name (Name assigned to a component based on its range of properties.)
    - *comppct_r* – Component Percent, Representative Value (The percentage of the component of the mapunit.)
    - *mukey* – Mapunit Key (A non-connotative string of characters used to uniquely identify a record in the Mapunit table.)
    - *hydgrp* – Hydrologic Group (A group of soils having similar runoff potential under similar storm and cover conditions. Examples are A and A/D.)
    - *cokey* – Component Key (A non-connotative string of characters used to uniquely identify a record in the Component table.)
    - *taxclname* – Taxonomic Class (A concatenation of the Soil Taxonomy subgroup and family for a soil (long name).)
    - *taxsubgrp* – Subgroup (The fourth level of Soil Taxonomy. The subgroup is below great group and above family.)
    - *taxgrtgroup* – Great Group (The third level of Soil Taxonomy. The category is below the suborder and above the subgroup.)
    - *taxpartsize* – Particle Size (Particle-size classes are used as family differentiae. Particle-size refers to grain-size distribution of the whole soil and is not the same as texture. (Soil Taxonomy).)
    - *taxsuborder* – Suborder (The second level of Soil Taxonomy. The suborder is below the order and above the great group.)
    - *taxorder* – Order (The highest level in Soil Taxonomy)
    - *albedodry_r* – Albedo Dry, Representative Value (The estimated ratio of the incident short-wave (solar) radiation that is reflected by the air dry, less than 2 mm fraction of the soil surface.)

2. Join the component level records and columns listed above with the associated mapunit level records on the *mukey* column.

3. Process component percentage, *comppct*, to correct inaccuracies (i.e. cases where the total sum of component percent in the mapunit is not equal to 100 or components where no area percentage is provided):
    a. Calculate the sum of *comppct* per map unit,
    b. Remove component records where *comppct* is null and the sum of the other *comppct* values for the associated mapunit is 100% or greater. These removed components are assumed to be insignificant because remaining components for the mapunit comprise 100% of the mapunit according to their *comppct* values.

c. For mapunits where the sum of the *comppct* is less than 100, equally partition the missing component percentage to null components *comppct* to achieve 100% in the map unit.
d. Renormalize all percentages to make the total mapunit component percentage equal to 100%.

4. Add a component number column, *compnum*, to each component level record which is based on the descending sort order of the *comppct* for the components within the mapunit (i.e., component with highest *comppct* gets a value of 1). This information is useful if, for example, one is interested in identifying dominant components in the map units.

5. Calculate APEX model specific soil weathering code (*xids*) according to the rules in Table 2 below (TAM 2016).

Table 2. Rules to calculate soil component xids parameter

Rules*	**Value**
taxclname string includes "Calc"	0
taxorder = "Inceptisols" OR *taxorder* = "Entisols"	1
taxorder = "Ultisols" OR *taxorder* = "Oxisols"	3
taxorder = "Alfisols" AND *taxorder* = "Udalfs" AND [*taxclname* string includes "MESIC" OR *taxclname* = "Aqualfs"] AND *tacxlname* string includes "thermic"	3
taxorder = "Vertisol" AND [*taxsuborder* = "Uderts" OR *taxsuborder* = "Ustepts"]	3
Else	2

* All rules are assumed NOT case sensitive

6. Calculate the APEX model specific soil grouping (*xidk*) according to the rules in Table 3 below (TAM 2016).

Table 3. Rules to calculate soil component xidk parameter

Rules*	**Value**
taxclname string includes"Active" OR *taxclname* string includes "SuperActive" OR taxclname string includes "Smectitic"	3
taxclname string includes "Mixed"	2
Else	1

* All rules are assumed NOT case sensitive

7. Add horizons count, *nhorizons*, per component record using the gNATSGO *chorizon* table and join by *cokey*. This column is useful to identify all component records with missing horizons data (nhorizons=NULL).

8. Assign the minimum depth of water table as the *wtdepannmin* column from the gNATSGO *muaggatt* table and join with the component level attributes table by the *mukey* column.

9. Calculate total component area coverage as: *coacres = muacres x comppct*

10. A new cokey column is created, *cokey_custom*, as concatenation of the *mukey* and *compnum* so that each record has a unique 'simple' string (often the original cokey is a 'complicated' string).
Note: This is also necessary, because some map units from the gNATSGO database have no component record associated. In this way, an empty record with a *cokey_custom* is created nonetheless and will be filled in the data gap-filling step.

11. Save this intermediate soil component level table in an SQLite database as *component_model*.

3.3. Horizon Level Table

This table contains all the information for soil horizon attributes. It also includes the *texture* parameter which is used as a soil property in the filling procedure of horizon records that are incomplete.

The steps taken to compile this table are described below:

1. Read the gNATSGO chorizon table for the following parameters:
   - hzname – Designation (The concatenated string of four kinds of symbols (five data elements) used to distinguish different kinds of layers in the soil.)
   - *hzdepb_r* – Bottom Depth, Representative Value (The distance from the top of the soil to the base of the soil horizon.)
   - *wfifteenbar_r* - 15 bar H2O, Representative Value, or "Wilting Point" (The volumetric content of soil water retained at a tension of 15 bars (1500 kPa), expressed as a percentage of the whole soil.)
   - *wthirdbar_r* – 0.33 bar H2O, Representative Value, or "Field Capacity" (The volumetric content of soil water retained at a tension of 1/3 bar (33 kPa), expressed as a percentage of the whole soil.)
   - *sandtotal_r* – Total Sand, Representative Value (Mineral particles 0.05mm to 2.0mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.)
   - *silttotal_r* – Total Silt, Representative Value (Mineral particles 0.002 to 0.05mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.)
   - *claytotal_r* – Total Clay, Representative Value (Mineral particles less than 0.002mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.)
   - *ph1to1h2o_r* – pH H2O, Representative Value (The negative logarithm to the base 10, of the hydrogen ion activity in the soil using the 1:1 soil-water ratio method. A numerical expression of the relative acidity or alkalinity of a soil sample.)
   - *om_r* – Organic Matter, Representative Value – (The amount by weight of decomposed plant and animal residue expressed as a weight percentage of the less than 2 mm soil material. Used to calculate organic carbon content oc_r as oc_r = om_r/1.724)
   - *sieveno10_r* - #10 Sieve, Representative Value (Soil fraction passing a number 10 sieve (2.00mm square opening) as a weight percentage of the less than 3 inch (76.4mm) fraction. Used to calculate rock percentage (%) rock_r as rock_r = 100 - sieveno10_r)

- *dbthirdbar_r* – Db 0.33 bar H2O, Representative Value, of "Bulk Density" (The oven dry weight of the less than 2 mm soil material per unit volume of soil at a water tension of 1/3 bar.)
- *ksat_r* – Ksat, Representative Value, or "Saturated Conductivity" (The amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient.)
- *cokey* – Component Key (A non-connotative string of characters used to uniquely identify a record in the Component table.)
- *chkey* – Chorizon Key (A non-connotative string of characters used to uniquely identify a record in the Horizon table.)
- *sumbases_r* – Sum of Bases, Representative Value (The sum of NH4OAc extractable bases (pH 7.0), reported on less than 2mm base.)
- *caco3_r* – CaCO3, Representative Value (The quantity of Carbonate (CO3) in the soil expressed as CaCO3 and as a weight percentage of the less than 2 mm size fraction.)
- *cec7_r* – CEC-7 , Representative Value, or "Cation Exchange Capacity" (The amount of readily exchangeable cations that can be electrically adsorbed to negative charges in the soil, soil constituent, or other material, at pH 7.0, as estimated by the ammonium acetate method.)
- *dbovendry_r* – Db oven dry , Representative Value, or "Dry Bulk Density" (The oven dry weight of the less than 2 mm soil material per unit volume of soil exclusive of the desication cracks, measured on a coated clod.)
- *ec_r* – EC, Representative Value, (The electrical conductivity of an extract from saturated soil paste.)

2. Read soil texture parameters from *chtexturegrp* gNATSGO table:
   a. Read parameters:
      - *rvindicator* – RV (A yes/no field that indicates if a value or row (set of values) is representative for the horizon.)
      - *texture* – Tex Mod & Class (Name for the concatenation of TEXTURE_MODIFIER and TEXTURE_CLASS.)
      - *texdesc* – Texture Description (The full texture description for a horizon, using full texture class and in lieu of names rather than abbreviations.)
      - *chkey* – Chorizon Key (A non-connotative string of characters used to uniquely identify a record in the Horizon table.)

   b. Sort in descending order by *chkey* and *rvindicator* columns
   c. Keep only the first row for each *chkey*. **Note:** The goal is to select records with *rvindicator* = Yes if possible. However, sometimes there is only one texture record for a given *chkey* and that is selected in those cases regardless the *rvindicator* value.

   Note: A *tex_attr* table is also saved to lookup texture codes and full description by saving the table of unique values of *texture* and *texdesc* columns of the final horizon-texture table.

3. Join horizon level attributes from the *chorizon* and *chtexturegrp* tables on *chkey* to associate texture to each soil horizon.

4. Join cokeys from component table and horizon table on cokey to remove all records outside the CONUS and add *cokey_custom* column to the horizon table

5. Rescale/calculate desired soil parameters:
   - Horizon Depth (m): *hzdepb_r (m) = hzdepb_r (cm) *0.01*
   - Organic Carbon (%): *oc_r (%) = om_r (%)/ 1.724*
   - Rock Percentage (%): *rock (%)=100 - sieveno10_r (%)*

- Saturated Conductivity (mm/hr): ksat (mm/hr)=ksat_r (µm/s)*3.6
- Process particles content percentages, *sandtotal_r, silttotal_r* and *claytotal_r*, for records where a valid value is provided for all three but the sum does not equal to 100%: If the sum is greater than 33.3%, the three values are renormalized to make the total equal to 100%, otherwise they are all changed to a null value. All records having at least one null value among the three soil particle percentages are treated in the gap-filling procedure described below. Exceptions to this rule are soil horizons whose texture is identified as water or permanently frozen water, "W" or "PF-W". In this case, all three soil particle fractions are set to zero.

6. Enumerate soil horizons 1 to n (where n equals the number of soil horizons for the component) in a new column *horizonnum* from the shallower to the deeper soil horizon.
7. To simplify the horizon key *chkey*, create a new column *chkey_custom* by concatenating *cokey_custom* and *horizonnum*.
8. Save this intermediate soil horizon table in an SQLite database as *horizon_model*.

4. Data Gap-Filling Procedure

4.1. General Approach Description

The general rule is to try keeping what is available from the soil surveys in each soil record even if only partial data is available. The filling of the missing parameters is achieved by identifying and using data available from the rest of the gNATSGO soil database. Below is a general description of the filling procedure (special exceptions are described below when applicable):

1. Consider what is known about a record with missing parameters, e.g. missing albedo dry parameter but known hydrologic group (hydgrp), component name (compname) and soil survey area (SSA) (this example considers a component record but the logic to fill a soil horizon missing parameter is identical);
2. Check if in the soil database there is a matching record (or a group of records) with the same known properties, e.g. same compname, hydgrp and SSA but with a valid albedo dry parameter.
3. Use the matching value to fill the missing parameter (the process for deciding between matching records is detailed below). If no matching value is found, go back to step (1) and progressively consider increasingly less specific, more general known soil record descriptors with the missing parameter. For example, choose records with more general soil descriptors* and/or within a larger spatial region** or consider relaxing what is matched for the soil (e.g. look for a match only by soil descriptors and spatial region without requiring a matching *hydgrp*). The main idea is to start filling using the most specific soil record matching conditions, i.e., identify records with same *compname* within the same SSA. As parameter filling progresses, considering more generic or less specific matching conditions, i.e., same soil taxonomy within the same state, may allow identification of soil records with valid parameters that can be used for parameter gap-filling. These later selections of gap-filling parameters may not be as specific to characterize the soil properties with missing parameters, but they will be better than applying default soil parameter values.

   (*) Soil records can be identified and grouped according to various soil descriptors, from the most specific soil component name (*compname*) to the more general soil taxonomy classes and groups: *taxclname*, *taxsubgrp*, *taxgrtgroup*, *taxpartsize*, *taxsuborder*, *taxorder*, *compname_custom*.
   Note: The last group, *compname_custom*, considers soil component name grouping where the *compname* is simplified to provide uniformity across a broader group of components. For example, records with compnames that contain words such as 'water' are all classified as 'WATER', 'pits' as 'PITS' , 'wet' as 'WETSOILS', or considering only the first part of the *compname* if the *compname* string contains words such as 'family', 'variant', '-like', 'and similar'. For future use, a column *compname_custom* is added to the table with the simplified compnames.

   (**) Soil attribute groups are considered at three different spatial scales: SSA, State, CONUS.

4. If a matching record is not found after all the attempts above, a default parameter value is assigned, or the record is completely replaced by an unnamed default soil in case all soil parameters are still missing.

A guiding principle of this general gap-filling approach is the assumption that soil records that are the most complete with respect to soil parameters are of the highest quality. Therefore, if there are multiple matching records, parameter completeness is given highest importance, e.g. between two matching soil records with a valid albedo parameter, the one from the most complete soil record is used for gap-filling. Where applicable, this also allows use of the most complete record to fill as many other missing parameters as possible. This procedure has two additional benefits: (1) having soil parameters coming from the same soil record may also better account for any parameter correlations and, (2) the gap-filling process is more computationally efficient.

Below are the detailed steps for gap-filling all soil records in the component-level and horizon-level tables.

4.2. Component Level Table

Soil records of this table have two possible sets of missing information:

1. Soil component parameters: hydrologic group (*hydgrp*), soil albedo (*albedodry_r*) and minimum depth of water table (*wtdepannmin*).
2. No soil horizon records are associated with the soil component record.
   Note: A new column, *horizons_cokey_custom,* is added to the component table. This column represents the key to join the soil horizons related to each soil component record. For soil components that have related soil horizons, this key is equal to the *cokey_custom* value (see Note in item 10 in the component table section above on why *cokey_custom* has been defined). For all records that initially have no horizon data, this key is going to be treated as a missing component parameter to be populated by a *cokey_custom* value identified in the filling process. At the end of the filling process, this column will not have unique values for each component record (as opposed to the *cokey* or *cokey_custom* columns) but there will be a valid *horizons_cokey_custom* value for each soil component record.

The component level table gap-filling process occurs over three main consecutive steps:

1. First, the focus is filling the *hydgrp* parameter. Not only is *hydgrp* one of the most significant soil component parameters, but its value is used as a soil component property to identify other valid soil parameters in step 2 of the component filling step.
   a. For each descriptor and for each geographic region (going from the more specific, e.g. *compname* and SSA, to the more general, e.g. *taxorder* and CONUS):
      i. For each soil record, create a “label” by concatenating soil descriptor and region
      ii. Identify the list of all the unique labels from records with a missing *hydgrp*
      iii. Identify records that have the same labels as in step ii. but with valid *hydgrp* values.
      Note: If for a given label there are more than one record identified as a possible gap-filling record, these records are initially sorted in descending order by parameter completeness, the total area occupied by the matching *hydgrp* value, then by the soil component area. The first record in the list is selected as the gap-filling record for the considered label.
      iv. Fill the *hydgrp* based on the matching label and fill also all other record missing parameters when possible.
      Note: *horizons_cokey_custom* is used as the component parameter to be filled in cases where there are no soil horizons for a given record.
2. Once the *hydgrp* filling procedure is exhausted, all other missing component parameters are explicitly attempted to be filled. A difference from above is that, in this step, the *hydgrp* is initially also used for grouping parameters.
   a. For each soil component parameter (*horizons_cokey_custom, albedodry_r* and *wtdepannmin*), for each soil descriptor, and for each geographic region (going from to the more specific, e.g. *compname* and SSA, to the more general, e.g. *taxorder* and CONUS):
      i. For each record create a label by concatenating soil descriptor, *hydgrp* and region
      ii. Identify the list of all the unique labels from records with missing parameter

iii. Identify records that have the same labels as in ii. but with valid parameter values
Note: Similarly to what was done in step 1 for *hydgrp* filling, if for a given label there are more than one record identified as a possible gap-filling record, these records are initially sorted in descending order by parameter completeness, the total area occupied by the matching parameter values, then by the soil component area. The first record in the list is selected as the gap-filling record for the considered label.
iv. Fill the missing parameter based on the matching label and fill also all other missing parameters when possible.

b. If a matching soil record is not found, then remove the *hydgrp* as a known parameter (group only by soil descriptor and region) and repeat step 2a.

3. Finally, still missing component level parameters are filled using soil component default values:
   a. All component records that still have either missing *hydgrp* or no associated soil horizons are replaced by a default 'unnamed soil' record that was extracted from the US-ModSoilParms-TEMPLE database (TAM 2016) with *cokey_custom* and *horizon_custom_cokey* set to 'unnamed_comp'.
   b. Similarly, component records missing any other individual parameters are filled by default parameter values defined in the same soil database (TAM 2016).

   It is worth noticing that all these records still missing parameters are generally soil components in non-agricultural areas.

4. The final filled component table is saved in an SQLite database as *component_model_filled*

4.3. Horizon Level Table

Other than soil horizon depths (*hzdepb_r*), all other parameters may be missing. The process to identify valid soil horizon parameters uses the same general approach described above for filling the component table: identify records by soil descriptor, geographic region, and *hydgrp*; with the addition here of soil *texture* and *horizon number* parameters that are used to specifically characterize each soil horizon. Therefore, to gap-fill the soil horizon records, the first step is to join the horizon level table with the component level table by *cokey*. This step joins to each horizon level record several additional soil component attributes used in the next step.

The horizon level table gap-filling process occurs over three main consecutive steps:

1. Fill horizon records *texture* parameter. Similar to what was done with *hydgrp* in the component level table filling, the horizon level table filling process first focuses on filling *texture* in records where it is missing.
   a. For each soil descriptor and for each geographic region (going from the more specific, e.g. *compname* and SSA, to the more general, e.g. *taxorder* and CONUS)
      i. For each record create a label by concatenating soil descriptor, hydgrp, horizon number, and region
      ii. Identify the list of all the unique labels from records with missing *texture*
      iii. Identify records that have same labels as in ii. but with a valid *texture* value
      Note: If for a given label there are more than one record identified as a possible gap-filling record, these records are initially sorted in descending order by parameter completeness, the total area occupied by the matching *texture* values, then by the soil component area. The first record in the list is selected as the gap-filling record for the considered label.
      iv. Fill the missing *texture* value based on the matching label and fill also all other possible missing horizon level parameters when possible.

2. Once the texture filling procedure is exhausted, all other horizon level parameters are explicitly attempted to be filled. A difference from above is that, in this step, the *texture* is also used as a soil horizon attribute for grouping soil record parameters.
   a. For each soil horizon level parameter*, for each soil descriptor and for each geographic region (going from to the more specific, e.g. *compname* and SSA, to the more general, e.g. *taxorder* and CONUS)
      i. For each record, create a label by concatenating the soil descriptor, texture, horizon number and geographic region
      ii. Identify the list of all the unique labels from records with missing values for the parameter being filled
      iii. Identify records that have same labels as in ii. but with a valid parameter value
      Note: If for a given label there are more than one record identified as a possible gap-filling record, these records are initially sorted in descending order by parameter completeness, the total area occupied by the matching *parameter* values, then by the soil component area. The first record in the list is selected as the gap-filling record for the considered label.
      iv. Fill the missing parameter value based on the matching label and fill also all other possible missing horizon level parameters when possible.

   (*) Some soil horizon parameters are known to be highly correlated: wilting point and field capacity; and the sum of sand, silt, and clay percentages should equal 100. In this case, if one parameter of the group is missing, they are always simultaneously filled/replaced from a matching soil horizon record that has valid values for all.
   b. During the process of identifying soil horizon record matches, step 2a is repeated several times, each time by further relaxing a known attribute for each soil horizon record. The progression for relaxing known attributes is as follows:
      i. Identify only by soil descriptor/*hydgrp*/*texture*/geographic region (horizon number removed)
      ii. Identify only by *hydgrp*/*texture*/geographic region (horizon number and soil descriptor removed)
      iii. Identify only by *texture*/geographic region (horizon number/soil descriptor/*hydgrp* removed)
3. Finally, still missing horizon level parameters are filled by default soil horizon parameter values that were extracted from the US-ModSoilParms-TEMPLE database (TAM 2016).
   a. For horizon records still missing all parameter values (other than soil depth), they are filled using the soil horizon parameters from the 'unnamed_soil' described above (soil horizon parameters in 'unnamed_soil' are the same regardless of the horizon) and extracted from TAM 2016.
   b. Horizon records still missing just a few parameters are filled by default horizon level parameter values defined in the same default soil horizon table (TAM 2016).
   c. Horizons records for the 'unnamed soil' are also added to the table with 'unnamed_comp' as *horizon_cokey_custom*.

4. The final filled horizon table is saved in an SQLite database as *horizon_model_filled* after renaming *cokey_custom* column to *horizon_cokey_custom*. In this way, every soil component and its horizons will be identified via the *horizon_cokey_custom* in both tables.

4.4. General Notes

The following are general notes associated with the data gap-filling procedure:

- Both final component level and horizon level tables have a *fill_flag* column of strings concatenating the filled parameter name and either the record key they are coming from (*cokey_custom* for the component table and *chkey_custom* for the horizon table) or 'default' if it came from the 'unnamed soil' or default parameters.

- All soil component records associated with a given mapunit can be identified using the mapunit key column, *mukey*, present in the component table.

All soil horizons associated with each of these soil component records, can be identified using the *horizon_cokey_custom* column present in both the component level land horizon level tables (in the horizon level table, this column was obtained by simply renaming the *cokey _custom* column).

When this data compilation procedure was applied to the 2021 gNATSGO soil database and without considering preliminary data processing to address initial data inaccuracies, out of a total of 1,125,768 component records identifying soil characteristics in the CONUS, 800,512 (~71%) needed to be gap-filled for at least one model parameter. Similarly, 2,179,166 soil horizons records of the total 3,510,115 (~62%) needed some data gap filling.

5. Deliverables

5.1. Soil Input SQLite Database (conus_soil_inputtables.db)

This database contains 10 tables described in the Data Sources section above, whose data is used as the source for the compilation of the soil model parameter database:

- Seven tables with name starting *gnatsgo_* extracted from gNATSGO database and used in the initial table compilation steps
- Tables of default soil records, *defaultsoil_component* and *defaultsoil_horizons*
- Table *conus_mukey* with the cell count for each mukey in the CONUS

5.2. Soil Output SQLite Database (2021_conus_soil_model.db)

Filled soil model parameter database containing:

- Initial compiled soil tables – *mapunit_model*, *component_model* and *horizon_model* tables
- *tex_attr* table - lookup table of horizon texture code and full names
- *component_model_filled* table - final soil component level table with no missing soil model parameters
- *horizon_model_filled* table - final soil horizon level table with no missing soil model parameters

5.3. Python Scripts

Commented scripts used to accomplish this entire soil gap-filling process (based on 64-bit python 3.7):

- main_prog.py to perform the entire procedure from the initial table compilation to the gap-filling of component and horizon tables. This program uses the scripts listed below:
- initial_tables_compilation.py script to perform the initial tables compilation
- soil_component_fill.py to perform all gap-filling steps for component level records
- soil_horizon_fill.py to perform all gap-filling steps for horizon level records
- soil_fill_utils.py contains a collection of functions used in all gap-filling steps. Main functions are: (a) identification of records with missing parameters, (b) identification of candidate records with valid parameters, (c) perform gap-filling.

5.4. Documentation

This document describing the steps for soil model parameter database compilation and gap-filling procedure.

6. Script Execution Instructions

Described below are the steps for compiling the soil model parameter database from scratch by executing the python routines.

It is assumed that the user has Python 3 installed on the computer. Given the significant size of the soil database tables, a Python 64-bit installation is required (execution of routines were tested using 64-bit python 3.7).

The python scripts described in this documentation use sqlalchemy and pandas packages.

User execution steps are:

1. Assemble an SQLite database containing all the tables as described in the Data Sources section.
2. Open the python script main_prog.py and edit in the main part of the module:
   a. Path to the input database created in step 1
   b. The desired path of the output database that will have the compiled initial and gap-filled soil tables

   Note: The main part of the module also allows editing of input table names should they be different from the ones delivered.
3. Execute the script main_prog.py

   Notes:
   - To monitor the database compilation process progress, messages are printed at various points during execution.
   - Depending on the machine, it may take several hours to completely execute the entire database compilation process (approximately 9 hours on a 64-bit 2.60 GHz Windows Server 2012 with 64 GB of RAM installed).
   - Uncommenting the specially identified commented lines of code in the script (commented code lines starting with the text string 'Intermediate save' or 'Intermediate read') allows the user to save/read intermediate tables after a major gap-filling step, e.g. save component table after the *hydgrp* parameter is filled and just before the gap-filling procedure of all other component parameters is executed. This option could be useful to not completely loose intermediate database compilation steps should a crash occur during execution.

7. References

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8. Appendix A: Table Schemas

8.1. Mapunit_model Table

Column Name	**Type**	**Description**	**Units**	**Derivation Method**
musym	TEXT	Mapunit symbol		*musym* in gNATSGO mapunit table
mukey	TEXT	Mapunit key		*mukey* in gNATSGO mapunit table
muname	TEXT	Mapunit name		*muname* in gNATSGO mapunit table
mukind	TEXT	Mapunit		*mukind* in gNATSGO mapunit table
muacres_orig	FLOAT	Mapunit area	acres	*muacres* in gNATSGO mapunit table
lkey	TEXT	Legend key		*lkey* in gNATSGO mapunit table
muacres	FLOAT	Mapunit area	acres	Processing of *count* in conus_mukeys table based on raster cell size
ncomp	INTEGER	Number of components		Processing of gNATSGO component table
source	TEXT	Data source		Processing of gNATSGO sapolygon table
areasymbol	TEXT	Soil Survey Area identifier		Processing of gNATSGO legend table

8.2. Component_model and Component_model_filled Tables

Column Name	Type	Description	Units	Derivation Method
compname	TEXT	Component Name		*compname* in gNATSGO component table
comppct_r	FLOAT	Percentage of Map Unit, representative value	%	Processing of *comppct_r* in gNATSGO component table
mukey	TEXT	Mapunit Key		*mukey* in mapunit_model table
hydgrp	TEXT	Hydrologic Group		*hydgr*p in gNATSGO component table
cokey	TEXT	gNATSGO Component Key		*cokey* in gNATSGO component table
taxclname	TEXT	Taxonomic Class		*taxclname* in gNATSGO component table
taxsubgrp	TEXT	Subgroup		*taxsubgrp* in gNATSGO component table
taxgrtgroup	TEXT	Great group		*taxgrtgroup* in gNATSGO component table
taxpartsize	TEXT	Particle Size		*taxpartsize* in gNATSGO component table
taxsuborder	TEXT	Suborder		*taxsuborder* in gNATSGO component table
taxorder	TEXT	Order		*taxsuborder* in gNATSGO component table
albedodry_r	FLOAT	Albedo Dry, representative value		*albedodry_r* in gNATSGO component table
muacres	FLOAT	Mapunit Area	acres	*muacres* in mapunit_model table
areasymbol	TEXT	Soil Survey Area Identifier		*areasymbol* in mapunit_model table
xids	INTEGER	APEX Soil Weathering Code		Processing soil taxonomy groups in gNATSGO component table

Column Name	Type	Description	Units	Derivation Method
xidk	INTEGER	APEX Soil Grouping		Processing soil taxonomy groups in gNATSGO component table
compnum	INTEGER	Component Number for Respective Map Unit (highest to lowest area)		Processing of gNATSGO component table
cokey_custom	TEXT	Customized Component Key		Concatenation of *mukey* and *compnum*
nhorizons	INTEGER	Number of Soil Horizons		Processing of the gNATSGO horizon table
wtdepannmin	FLOAT	Minimum Depth to Water Table	m	*wtdepannmin* in gNATSGO muaggatt table
coacres	FLOAT	Component Area	acres	*muacres* x *comppct_r* / 100
state	TEXT	Two-letter State Abbreviation		Extracted from *areasymbol*
fill_flag	TEXT	Data Gap-filling Flag		Gap_filling procedure
horizons_cokey_custom	TEXT	Customized Component Key identifying Soil Horizons		*cokey_custom* or from component table gap-filling process
compname_custom	TEXT	Simplified Component Name		Gap_filling procedure

8.3. Horizon_model and Horizon_model_filled Tables

Column Name	Type	Description	Units	Derivation Method	Conversion from gNATSGO Value
hzname	TEXT	Designation		*hzname* in gNATSGO chorizon table	
hzdepb_r	FLOAT	Bottom Depth, rv*	m	Converting *hzdebp_r* from gNATSGO chorizon table	hzdebp_r x 0.01

Column Name	Type	Description	Units	Derivation Method	Conversion from gNATSGO Value
wfifteenbar_r	FLOAT	Wilting Point, rv	%	*wfifteenbar_r* in gNATSGO chorizon table	
wthirdbar_r	FLOAT	Field Capacity, rv	%	*wthirdbar_r* in gNATSGO chorizon table	
sandtotal_r	FLOAT	Total Sand, rv	%	*sandtotal_r* in gNATSGO chorizon table	
silttotal_r	FLOAT	Total Silt, rv	%	*silttotal_r* in gNATSGO chorizon table	
claytotal_r	FLOAT	Total Clay, rv	%	*claytotal_r* in gNATSGO chorizon table	
ph1to1h2o_r	FLOAT	Soil pH, rv		*ph1to1h2o_r* in gNATSGO chorizon table	
oc_r	FLOAT	Organic Carbon Content, rv	%	Processing *om_r* from gNATSGO chorizon table	om_r / 1.724
dbthirdbar_r	FLOAT	Bulk Density, rv	g/cm^3	*dbthirdbar_r* in gNATSGO chorizon table	
ksat_r	FLOAT	Saturated Conductivity, rv	mm/hr	Converting *ksat_r* from gNATSGO chorizon table	ksat_r x 3.6
cokey	TEXT	gNATSGO Component Key		*cokey* in gNATSGO chorizon table	
chkey	TEXT	gNATSGO Horizon Key		*chkey* in gNATSGO chorizon table	
sumbases_r	FLOAT	Sum of Bases, rv	cmol/kg	*sumbases_r* in gNATSGO chorizon table	

Column Name	Type	Description	Units	Derivation Method	Conversion from gNATSGO Value
caco3_r	FLOAT	Calcium Carbonate Content of Soil, rv	%	*caco3_r* in gNATSGO chorizon table	
cec7_r	FLOAT	Cation Exchange Capacity, rv	cmol/kg	*cec7_r* in gNATSGO chorizon table	
dbovendry_r	FLOAT	Dry Bulk Density, rv	g/cm3	*dbovendry_r* in gNATSGO chorizon table	
ec_r	FLOAT	Electrical Conductivity, rv	g/t	*ec_r* in gNATSGO chorizon table	
texture	TEXT	Soil texture description		Processing *texture* from gNATSGO chtexturegrp table	
horizon_cokey_custom	TEXT	Customized Component Key Identifying Soil Horizons		Renaming *cokey_custom* in horizon_model table**	
rock_r	FLOAT	Rock content, rv	%	Processing *sieveno10_r* from gNATSGO chorizon table	100 - sieveno10_r
horizonnum	INTEGER	Horizon number (top to bottom order) for the respective component		Processing of the gNATSGO chorizon table	
chkey_custom	TEXT	Customized Horizon Key		Concatenation of *cokey_custom* and *horizonnum*	
fill_flag	TEXT	Data Gap-filling Flag		Gap_filling procedure	

(*) rv = representative value

(**) Initial horizon_model table compilation imports *cokey_custom* from the component table. This column is then renamed to be able to identify any soil component and its horizons by *horizon_cokey_custom* values.

8.4. Tex_Attr Table

Column Name	**Type**	**Description**	**Derivation Method**
texture	TEXT	Texture Modifier and Class	*texture* from gNATSGO chtexturegrp table
texdesc	TEXT	Texture Description	*texdesc* from gNATSGO chtexturegrp table

Appendix B

Table 18. Observed Data From GHG Field Sites.

Time period	Site ID	YLDF_sum t/ha/a	NEP_mean kgC/ha/d	CO2_mean kgC/ha/d	N2O_mean kgN/ha/d	absC_mean kgC/ha	absN_mean kgN/ha	RSPC_mean kg/ha-mo	OCPD_mean %
01/01/2000-12/31/2022	GHG_01		-4.7758		0.00296				
01/01/2000-12/31/2022	GHG_02		-4.7362		0.00697				
01/01/2000-12/31/2022	GHG_03		-13.2500		0.00714				
01/01/2000-12/31/2022	GHG_04		-6.6254		0.00714				
05/01/2016-12/31/2016	GHG_05			196.80283	0.04747				
05/01/2017-12/31/2017	GHG_05			266.88401	0.08006				
12/31/2017	GHG_05					159386.3	155136.0		
05/01/2016-12/31/2016	GHG_06			195.58319	0.04747				
05/01/2017-12/31/2017	GHG_06			252.36212	0.04398				
12/31/2017	GHG_06					137184.1	127945.6		
05/01/2016-12/31/2016	GHG_07			250.27900	0.09776				
05/01/2017-12/31/2017	GHG_07			204.70583	0.11867				
12/31/2017	GHG_07					114440.4	122960.7		
05/01/2016-12/31/2016	GHG_08			240.61658	0.07374				
05/01/2017-12/31/2017	GHG_08			230.84833	0.06004				
12/31/2017	GHG_08					106859.2	112084.6		
05/01/2016-12/31/2016	GHG_09			122.44612	0.10367				
05/01/2017-12/31/2017	GHG_09			137.22769	0.08196				
12/31/2017	GHG_09					101444.0	103021.1		
05/01/2016-12/31/2016	GHG_10			122.70012	0.10995				

05/01/2017-12/31/2017	GHG_10			172.71701	0.05830				
12/31/2017	GHG_10					106859.2	95317.2		
04/01/2016-11/30/2016	GHG_11			23.58000	0.02073				
04/01/2017-11/30/2017	GHG_11			32.72000	0.05407				
04/01/2018-06/30/2018,10/01/2018-11/30/2018	GHG_11			20.24000	0.03522				
04/01/2016-11/30/2016	GHG_12			31.39000	0.02868				
04/01/2017-11/30/2017	GHG_12			30.49000	0.02787				
04/01/2018-11/30/2018	GHG_12			23.64000	0.01697				
01/01/2016-12/31/2016	GHG_11								1.972
01/01/2018-12/31/2018	GHG_11								2.378
04/01/2016-04/30/2016	GHG_11							8437.5	
11/1/2018-11/30/2018	GHG_11							9843.75	
01/01/2016-12/31/2016	GHG_12	4.505817							2.726
01/01/2017-12/31/2017	GHG_12	4.93174							
01/01/2018-12/31/2018	GHG_12	3.967809							4.118
04/01/2016-04/30/2016	GHG_12							10237.5	
11/1/2018-11/30/2018	GHG_12							16087.5	

Table 19. Observed Data from Monitoring Sites.

Year	Number of events	siteid	Q_sum mm	MUSS_sum T/ha/a	QP_sum kg/ha	YP_sum kg/ha	TP_sum kg/ha	QN_sum kg/ha	YN_sum kg/ha	TN_sum hg/ha	QDR_sum mm	QDRP_sum kg/ha	QDRN_sum kg/ha
2015	6	CHA_01	60.24818										
2015	16	CHA_01	138.6354										
2017	29	CHA_01	364.4756										
2018	23	CHA_01	286.5921										
2012	7	FER_01	28.05357										
2013	16	FER_01	145.1225										
2014	4	FER_01	28.39296										
2015	15	FER_01	96.7203										

2012	10	PAW_01	59.8278	
2013	30	PAW_01	272.1202	
2014	7	PAW_01	76.71436	
2015	17	PAW_01	52.34812	
2012	7	SHE_01	21.96457	
2013	17	SHE_01	248.7452	
2014	7	SHE_01	44.44249	
2015	15	SHE_01	135.433	
2016	7	SHE_01	76.95939	
2017	20	SHE_01	254.7908	
2018	6	SHE_01	108.5758	
2012	6	SHO_01	35.67426	
2013	18	SHO_01	89.96475	
2014	5	SHO_01	39.43098	
2015	21	SHO_01	77.73671	
2015	5	CHA_01		0.015148
2015	10	CHA_01		0.083910
2017	14	CHA_01		0.423186
2018	14	CHA_01		0.307063
2012	2	FER_01		0.001489
2013	15	FER_01		0.188732
2014	4	FER_01		0.006669
2015	11	FER_01		0.019097
2012	6	PAW_01		0.135487
2013	23	PAW_01		1.362056
2014	3	PAW_01		0.010159
2015	11	PAW_01		0.057753
2012	5	SHE_01		0.003115
2013	15	SHE_01		0.062277
2014	4	SHE_01		0.001969
2015	14	SHE_01		0.014264
2016	5	SHE_01		0.007545
2017	14	SHE_01		0.063525
2018	6	SHE_01		0.023330

2012	2	SHO_01	0.002587			
2013	7	SHO_01	0.011460			
2014	2	SHO_01	0.003199			
2015	8	SHO_01	0.003606			
2015	6	CHA_01		0.993243	0.051972	
2015	12	CHA_01		0.833224	0.113627	
2017	14	CHA_01		1.151979	0.586372	
2018	13	CHA_01		0.739481	0.412225	
2012	2	FER_01		0.006468	0.004229	
2013	12	FER_01		0.602023	0.08945	
2014	3	FER_01		0.335776	0.006079	
2015	9	FER_01		0.537886	0.066012	
2012	6	PAW_01		0.013908	0.19907	
2013	22	PAW_01		0.442078	1.393265	
2014	3	PAW_01		0.062702	0.02317	
2015	10	PAW_01		0.085694	0.100222	
2012	5	SHE_01		0.089888	0.011607	
2013	15	SHE_01		0.280014	0.12896	
2014	4	SHE_01		0.175706	0.024332	
2015	14	SHE_01		0.616139	0.079631	
2016	6	SHE_01		0.122359	0.026789	
2017	14	SHE_01		0.220783	0.163165	
2018	6	SHE_01		0.245983	0.081908	
2012	2	SHO_01		0.216945	0.024213	
2013	6	SHO_01		0.124161	0.012298	
2014	1	SHO_01		0.283203	0	
2015	6	SHO_01		0.080122	0.00374	
2015	5	CHA_01				1.048888
2015	11	CHA_01				0.946852
2017	14	CHA_01				1.738351
2018	14	CHA_01				2.078123
2012	2	FER_01				0.010697
2013	15	FER_01				0.754087
2014	4	FER_01				0.342739

2015	11	FER_01	0.695604		
2012	6	PAW_01	0.212978		
2013	23	PAW_01	1.835676		
2014	3	PAW_01	0.085871		
2015	10	PAW_01	0.185916		
2012	5	SHE_01	0.101494		
2013	15	SHE_01	0.408974		
2014	4	SHE_01	0.200038		
2015	14	SHE_01	0.69577		
2016	7	SHE_01	0.367832		
2017	14	SHE_01	0.383948		
2018	6	SHE_01	0.327891		
2012	2	SHO_01	0.181641		
2013	7	SHO_01	0.170857		
2014	2	SHO_01	0.305193		
2015	8	SHO_01	0.15672		
2015	3	CHA_01		4.680929	0.388826
2015	9	CHA_01		2.827744	0.31115
2017	14	CHA_01		6.108799	1.716905
2018	13	CHA_01		8.935775	1.296706
2012	2	FER_01		0.03035	0.012348
2013	11	FER_01		2.224346	1.491848
2014	1	FER_01		0.014238	0.00115
2015	6	FER_01		2.641212	0.198426
2012	6	PAW_01		1.142932	0.513132
2013	21	PAW_01		6.407644	4.068406
2014	2	PAW_01		1.287392	0.088287
2015	9	PAW_01		0.456306	0.244829
2012	5	SHE_01		0.224625	0.07124
2013	15	SHE_01		1.868876	2.556306
2014	4	SHE_01		7.732922	0.140569
2015	14	SHE_01		1.801938	0.576563
2016	7	SHE_01		0.800937	0.272677
2017	14	SHE_01		1.489701	0.709739

2018	8	SHE_01	2.005508	0.206939		
2012	2	SHO_01	0.144648	0.147581		
2013	4	SHO_01	0.778538	0.007082		
2015	3	SHO_01	0.219704	0.025969		
2015	4	CHA_01			5.12347	
2015	11	CHA_01			3.405298	
2017	14	CHA_01			7.825703	
2018	13	CHA_01			10.23248	
2012	2	FER_01			0.042699	
2013	15	FER_01			4.045625	
2014	4	FER_01			2.011579	
2015	10	FER_01			3.528269	
2012	6	PAW_01			1.656064	
2013	23	PAW_01			10.68245	
2014	3	PAW_01			1.396266	
2015	11	PAW_01			1.151738	
2012	5	SHE_01			0.295865	
2013	15	SHE_01			4.425182	
2014	4	SHE_01			0.970579	
2015	14	SHE_01			2.378501	
2016	7	SHE_01			1.073613	
2017	14	SHE_01			2.19944	
2018	6	SHE_01			2.333971	
2012	2	SHO_01			0.292229	
2013	7	SHO_01			1.379257	
2014	2	SHO_01			0.742419	
2015	8	SHO_01			1.352799	
2017	1	JBT_01				157.4506
2018	1	JBT_01				268.3996
2017	1	JBT_04				127.6666
2018	1	JBT_04				139.1007
2017	1	JBT_05				108.5141
2018	1	JBT_05				138.1509
2017	1	JBT_07				79.015

2018	2	JBT_07	94.41773		
2017	1	JBT_11	97.79252		
2018	1	JBT_11	203.6145		
2017	1	JBT_18	81.15976		
2018	2	JBT_18	164.176		
2017	1	JBT_01		0.253076	
2018	1	JBT_01		0.847668	
2017	1	JBT_04		0.323517	
2018	1	JBT_04		0.235365	
2017	1	JBT_05		0.221661	
2018	1	JBT_05		0.250686	
2017	1	JBT_07		0.158776	
2018	2	JBT_07		0.209338	
2017	1	JBT_11		0.045263	
2018	1	JBT_11		0.118324	
2017	1	JBT_18		0.104573	
2018	2	JBT_18		0.320111	
2017	1	JBT_01			8.843578
2018	1	JBT_01			0.468485
2017	1	JBT_04			7.527707
2018	1	JBT_04			0.005413
2017	1	JBT_05			15.7384
2018	1	JBT_05			0.011246
2017	1	JBT_07			7.505279
2018	1	JBT_07			0.006194
2017	1	JBT_11			0.7727
2018	1	JBT_11			0.002791
2017	1	JBT_18			0.462502
2018	1	JBT_18			0.001705
2015	12	M_01	20.14246		
2015	60	M_01	77.06951		
2016	109	M_01	162.3867		
2018	77	M_01	217.134		
2018	35	M_01	110.5203		

2015	8	M_01	19.0771			
2016	21	M_01	65.13042			
2017	20	M_01	118.5795			
2018	11	M_01	22.86753			
2019	8	M_01	6.939853			
2015	11	M_01				0.007569
2015	40	M_01				0.036076
2016	92	M_01				0.027249
2017	66	M_01				0.090082
2018	33	M_01				0.094889
2015	5	M_01			0.138095	
2016	14	M_01			0.331264	
2017	13	M_01			0.320087	
2018	4	M_01			0.012973	
2019	4	M_01			0.008443	
2015	8	M_01		0.022382		
2016	13	M_01		0.064715		
2017	13	M_01		0.24768		
2018	4	M_01		0.00283		
2019	4	M_01		0.000603		

Table 20. Observed Data from SH and KV Sites.

Time period	Site ID	Q_sum mm	MUSS_sum T/ha/a	TP_sum kg/ha	TN_sum hg/ha	QDR_sum mm	QDRP_sum kg/ha	QDRN_sum kg/ha	YLDF_sum t/ha/a	NEP_mean kgC/ha/d	RSPC_mean kg/ha-mo	OCPD_mean %
10/01/2018-10/1/2019	KV_01	151.8	0.0262	0.156	3.1							
10/01/2018-10/1/2019	KV_02	92.7	0.0278	0.0628		29.7	0.0059	2.4				
10/01/2019-10/1/2020	KV_01	164.9	0.0921	0.1326	9.8							
10/01/2019-10/1/2020	KV_02	72.4	0.1014	0.1346		146.4	0.0667	17.4				
1/1/2014-12/31/2014	SH_01								13.31232			2.535

1/1/2015-12/31/2015	SH_01	21.0896		2.34
1/1/2016-12/31/2016	SH_01	21.7952		2.262
1/1/2017-12/31/2017	SH_01	17.64		2.262
1/1/2018-12/31/2018	SH_01	11.8384		2.6455
1/1/2019-12/31/2019	SH_01	15.7584		2.1905
1/1/2020-12/31/2020	SH_01	14.896		2.15
1/1/2021-12/31/2021	SH_01	15.7584		2.07
4/1/2014-4/30/2014	SH_01		5625	
4/1/2015-4/30/2015	SH_01		5625	
4/1/2016-4/30/2016	SH_01		5976.563	
4/1/2017-4/30/2017	SH_01		6384.375	
4/1/2018-4/30/2018	SH_01		6159.375	
4/1/2019-4/30/2019	SH_01		6117.188	
4/1/2020-4/30/2020	SH_01		7551.563	
4/1/2021-4/30/2021	SH_01		6679.688	
1/1/2014-12/31/2014	SH_02	17.81248		2.925
1/1/2015-12/31/2015	SH_02	21.8736		2.6
1/1/2016-12/31/2016	SH_02	21.2464		2.47
1/1/2017-12/31/2017	SH_02	17.248		2.4505

1/1/2018-12/31/2018	SH_02	12.7792		2.743
1/1/2019-12/31/2019	SH_02	18.3456		2.314
1/1/2020-12/31/2020	SH_02	1.58368		2.3
1/1/2021-12/31/2021	SH_02	4.12384		2.25
4/1/2014-4/30/2014	SH_02		9843.75	
4/1/2015-4/30/2015	SH_02		8437.5	
4/1/2016-4/30/2016	SH_02		7734.375	
4/1/2017-4/30/2017	SH_02		8170.313	
4/1/2018-4/30/2018	SH_02		7143.75	
4/1/2019-4/30/2019	SH_02		5765.625	
4/1/2020-4/30/2020	SH_02		9435.938	
4/1/2021-4/30/2021	SH_02		8704.688	
1/1/2014-12/31/2014	SH_03	12.96736		2.795
1/1/2015-12/31/2015	SH_03	18.7376		2.6
1/1/2016-12/31/2016	SH_03	18.1104		2.405
1/1/2017-12/31/2017	SH_03	16.7776		2.3595
1/1/2018-12/31/2018	SH_03	10.192		2.821
1/1/2019-12/31/2019	SH_03	16.2288		2.353
1/1/2020-12/31/2020	SH_03	13.6416		2.49

1/1/2021-12/31/2021	SH_03	17.7968		2.42
4/1/2014-4/30/2014	SH_03		8437.5	
4/1/2015-4/30/2015	SH_03		8437.5	
4/1/2016-4/30/2016	SH_03		7031.25	
4/1/2017-4/30/2017	SH_03		7087.5	
4/1/2018-4/30/2018	SH_03		8001.563	
4/1/2019-4/30/2019	SH_03		6623.438	
4/1/2020-4/30/2020	SH_03		9365.625	
4/1/2021-4/30/2021	SH_03		7804.688	
1/1/2014-12/31/2014	SH_04	12.96736		2.795
1/1/2015-12/31/2015	SH_04	18.7376		2.405
1/1/2016-12/31/2016	SH_04	18.1104		2.405
1/1/2017-12/31/2017	SH_04	16.7776		2.3595
1/1/2018-12/31/2018	SH_04	10.192		2.821
1/1/2019-12/31/2019	SH_04	16.2288		2.353
1/1/2020-12/31/2020	SH_04	13.6416		2.49
1/1/2021-12/31/2021	SH_04	16.856		2.21
4/1/2014-4/30/2014	SH_04		7031.25	
4/1/2015-4/30/2015	SH_04		8437.5	

4/1/2016-4/30/2016	SH_04		7031.25	
4/1/2017-4/30/2017	SH_04		7087.5	
4/1/2018-4/30/2018	SH_04		8001.563	
4/1/2019-4/30/2019	SH_04		6623.438	
4/1/2020-4/30/2020	SH_04		9365.625	
4/1/2021-4/30/2021	SH_04		8901.563	
1/1/2014-12/31/2014	SH_05	15.9936		2.6
1/1/2015-12/31/2015	SH_05	21.6384		2.21
1/1/2016-12/31/2016	SH_05	22.0304		2.275
1/1/2017-12/31/2017	SH_05	18.7376		2.249
1/1/2018-12/31/2018	SH_05	11.76		2.6585
1/1/2019-12/31/2019	SH_05	15.1312		2.1645
1/1/2020-12/31/2020	SH_05	14.9744		2.23
1/1/2021-12/31/2021	SH_05	17.4048		2.04
4/1/2014-4/30/2014	SH_05		7031.25	
4/1/2015-4/30/2015	SH_05		7031.25	
4/1/2016-4/30/2016	SH_05		7031.25	
4/1/2017-4/30/2017	SH_05		7256.25	
4/1/2018-4/30/2018	SH_05		7298.438	

4/1/2019-4/30/2019	SH_05		5892.188	
4/1/2020-4/30/2020	SH_05		8915.625	
4/1/2021-4/30/2021	SH_05		7228.125	
1/1/2014-12/31/2014	SH_06	4.13952		3.055
1/1/2015-12/31/2015	SH_06	29.61952		2.73
1/1/2016-12/31/2016	SH_06	18.80032		2.7495
1/1/2017-12/31/2017	SH_06	3.8808		2.743
1/1/2018-12/31/2018	SH_06	3.521728		3.172
1/1/2019-12/31/2019	SH_06	3.188136		2.821
1/1/2020-12/31/2020	SH_06	13.8768		3.02
1/1/2021-12/31/2021	SH_06	13.9552		2.77
4/1/2014-4/30/2014	SH_06		8437.5	
4/1/2015-4/30/2015	SH_06		11250	
4/1/2016-4/30/2016	SH_06		11953.13	
4/1/2017-4/30/2017	SH_06		11896.88	
4/1/2018-4/30/2018	SH_06		12234.38	
4/1/2019-4/30/2019	SH_06		11010.94	
4/1/2020-4/30/2020	SH_06		16312.5	
4/1/2021-4/30/2021	SH_06		12164.06	

Appendix C

Table 21. Modeled bulk density to 30 cm from APEX and measured bulk density 30 cm from SSHVT cropland fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	1.26	1.26	1.25	1.25	1.35	1.42	0.92	1.09	0.06	0.12	1368	6
loam	1.22	1.34	1.19	1.36	1.54	2.17	0.60	0.98	0.11	0.20	3420	80
loamy sand	1.15	1.47	1.24	1.47	1.70	1.49	0.98	1.44	0.17	0.03	3708	2
organic soil	0.63	*NA*	0.62	*NA*	0.72	*NA*	0.51	*NA*	0.04	*NA*	324	*NA*
sand	0.95	*NA*	0.94	*NA*	1.40	*NA*	0.68	*NA*	0.19	*NA*	324	*NA*
sandy loam	1.23	1.38	1.24	1.38	1.58	1.83	0.80	0.93	0.15	0.15	6948	36
silt loam	1.22	1.33	1.18	1.32	1.42	1.57	0.73	1.13	0.13	0.10	6480	21
silty clay	1.26	1.30	1.24	1.26	1.35	1.42	1.01	1.00	0.07	0.15	468	9
silty clay lo am	1.18	1.34	1.19	1.36	1.35	1.48	0.94	1.28	0.09	0.08	432	6

Table 22. Modeled bulk density to 30 cm from APEX and measured bulk density 30 cm from VLTHS pasture fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	**VLTHS**	**APEX**	**VLTHS**	**APEX**	**VLTHS**	**APEX**	**VLTHS**	**APEX**	**VLTHS**	**APEX**	**VLTHS**
clay	1.31	1.25	1.31	1.25	1.36	1.25	1.21	1.25	0.03	*NA*	896	1
loam	1.15	1.05	1.16	1.02	5.93	1.33	0.64	0.66	0.34	0.17	3388	19
loamy sand	1.15	*NA*	1.23	*NA*	1.70	*NA*	1.05	*NA*	0.17	*NA*	1750	*NA*
organic soil	0.64	*NA*	0.64	*NA*	0.65	*NA*	0.64	*NA*	0.00	*NA*	238	*NA*
sand	0.76	*NA*	0.84	*NA*	1.40	*NA*	0.74	*NA*	0.13	*NA*	588	*NA*
sandy loam	1.20	1.27	1.22	1.27	1.58	1.27	0.81	1.27	0.17	*NA*	7042	1

silt loam	1.17	1.15	1.16	1.10	1.42	1.37	0.90	0.74	0.14	0.18	4214	15
silty clay	1.30	1.29	1.30	1.26	1.35	1.32	1.30	1.17	0.01	0.07	252	4
silty clay loam	1.30	1.24	1.28	1.22	1.35	1.31	1.18	1.07	0.08	0.09	154	5

Table 23. Modeled organic matter (%) in plow depth (to 15 cm) from APEX and measured organic matter (%) to 30 cm from SSHVT cropland fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	2.37	5.61	2.63	5.41	6.27	5.98	1.01	3.96	0.98	0.73	1368	6
loam	2.23	3.97	2.44	4.22	12.61	7.23	0.66	2.23	1.27	1.05	3420	89
loamy sand	2.03	1.78	2.05	1.78	3.55	2.11	0.69	1.45	0.47	0.47	3708	2
organic soil	10.05	NA	9.95	NA	13.31	NA	3.43	NA	2.00	NA	324	NA
sand	2.86	NA	3.00	NA	6.27	NA	0.75	NA	1.21	NA	324	NA
sandy loam	2.24	3.59	2.36	3.59	5.62	7.51	0.93	1.57	0.72	1.36	6948	39
silt loam	2.30	4.03	2.53	4.33	10.69	7.30	0.53	2.68	1.11	1.28	6480	24
silty clay	3.92	5.19	4.25	5.00	7.09	6.34	2.52	3.26	1.18	1.05	468	10
silty clay loam	3.23	5.84	3.51	5.99	6.89	8.68	1.64	4.12	1.14	1.32	432	10

Table 24. Modeled organic matter (%) in plow depth (to 15 cm) from APEX and measured organic matter (%) to 30 cm from VLTHS pasture fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	3.82	5.59	4.80	5.59	14.11	5.59	3.10	5.59	2.29	NA	896	1
loam	5.23	5.73	5.83	5.89	24.68	12.51	1.76	2.82	2.80	2.23	3374	19
loamy sand	4.42	NA	4.55	NA	9.56	NA	2.13	NA	1.29	NA	1750	NA
organic soil	16.87	NA	17.46	NA	26.35	NA	12.77	NA	2.54	NA	238	NA
sand	6.96	NA	7.46	NA	16.48	NA	2.22	NA	2.23	NA	588	NA
sandy loam	5.30	3.64	5.55	3.64	15.52	3.64	2.73	3.64	1.64	NA	7042	1

silt loam	5.62	4.78	6.08	5.41	19.32	10.41	1.91	4.16	2.42	1.63	4214	15
silty clay	7.80	4.94	8.16	5.05	13.66	6.21	6.98	4.10	1.48	0.87	252	4
silty clay loam	7.16	5.03	7.27	5.32	13.48	6.32	5.31	4.71	1.68	0.64	154	5

Table 25. Modeled total carbon stocks from APEX and measured total carbon stocks from SSHVT cropland fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	3.42	2.87	3.62	2.85	8.61	3.70	1.51	1.90	1.38	0.58	2052	6
loam	2.76	2.74	3.07	2.89	10.58	4.90	0.82	1.59	1.36	0.77	5130	93
loamy sand	2.46	1.54	2.65	1.54	5.21	2.14	1.04	0.94	0.78	0.85	5562	2
organic soil	6.14	*NA*	6.31	*NA*	9.50	*NA*	2.69	*NA*	1.41	*NA*	486	*NA*
sand	2.90	*NA*	3.09	*NA*	6.16	*NA*	0.94	*NA*	1.12	*NA*	486	*NA*
sandy loam	2.88	2.27	3.07	2.50	7.84	4.40	1.06	1.01	1.04	0.89	10422	40
silt loam	2.99	3.05	3.25	3.03	11.03	5.38	0.78	1.55	1.31	0.96	9720	26
silty clay	5.27	2.81	5.54	2.87	9.57	3.69	2.81	2.25	1.68	0.45	702	15
silty clay loam	4.18	3.60	4.50	3.70	9.01	5.75	1.84	2.02	1.66	0.86	648	19

Table 26. Modeled total carbon stocks from APEX and measured total carbon stocks from VLTHS pasture fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	4.36	3.14	5.50	3.14	15.92	3.14	3.54	3.14	2.66	*NA*	896	1
loam	5.26	3.60	5.58	4.05	16.45	9.23	2.35	1.61	1.90	1.72	3374	19
loamy sand	4.58	*NA*	4.84	*NA*	9.89	*NA*	2.41	*NA*	1.32	*NA*	1750	*NA*
organic soil	9.41	*NA*	9.76	*NA*	14.67	*NA*	7.24	*NA*	1.40	*NA*	238	*NA*
sand	5.34	*NA*	5.82	*NA*	12.93	*NA*	2.71	*NA*	1.86	*NA*	588	*NA*
sandy loam	5.39	2.42	5.85	2.42	13.39	2.42	2.74	2.42	1.79	*NA*	7042	1

silt loam	5.76	3.13	6.02	3.53	16.84	7.05	2.15	2.32	2.07	1.17	4214	15
silty clay	8.84	2.41	9.27	2.57	16.08	3.66	7.92	1.81	1.69	0.78	252	4

Table 27. Modeled soil nitrogen (%) from APEX and measured soil nitrogen (%) from SSHVT cropland fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	0.08	0.27	0.08	0.27	0.17	0.36	0.04	0.19	0.03	0.06	1368	6
loam	0.07	0.26	0.07	0.26	0.38	0.44	0.02	0.13	0.04	0.06	3420	93
loamy sand	0.06	0.11	0.06	0.11	0.09	0.15	0.02	0.07	0.01	0.06	3708	2
organic soil	0.32	NA	0.32	NA	0.41	NA	0.14	NA	0.05	NA	324	NA
sand	0.10	NA	0.10	NA	0.21	NA	0.03	NA	0.04	NA	324	NA
sandy loam	0.07	0.20	0.07	0.21	0.16	0.34	0.03	0.08	0.02	0.07	6948	40
silt loam	0.07	0.25	0.08	0.27	0.31	0.47	0.02	0.14	0.03	0.08	6480	26
silty clay	0.12	0.26	0.13	0.27	0.19	0.35	0.09	0.22	0.03	0.04	468	15
silty clay loam	0.10	0.32	0.11	0.33	0.18	0.53	0.06	0.00	0.03	0.11	432	19

Table 28. Modeled soil nitrogen (%) from APEX and measured soil nitrogen (%) from VLTHS pasture fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	0.08	0.30	0.10	0.30	0.22	0.30	0.07	0.30	0.04	NA	896	1
loam	0.11	0.31	0.12	0.32	0.50	0.67	0.04	0.10	0.07	0.14	3374	19
loamy sand	0.09	NA	0.09	NA	0.14	NA	0.04	NA	0.02	NA	1750	NA
organic soil	0.43	NA	0.43	NA	0.55	NA	0.32	NA	0.04	NA	238	NA
sand	0.16	NA	0.17	NA	0.32	NA	0.04	NA	0.05	NA	588	NA
sandy loam	0.11	0.18	0.11	0.18	0.22	0.18	0.06	0.18	0.03	NA	7042	1
silt loam	0.11	0.28	0.12	0.29	0.39	0.46	0.04	0.21	0.05	0.07	4214	15
silty clay	0.18	0.25	0.19	0.26	0.25	0.36	0.17	0.18	0.02	0.07	252	4
silty clay loam	0.17	0.28	0.16	0.31	0.24	0.39	0.12	0.25	0.03	0.06	154	5

Table 29. Modeled soil respiration from Apex and measured soil respiration from SSHVT cropland fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	0.21	0.76	0.22	0.76	0.43	1.07	0.05	0.46	0.07	0.20	1368	6
loam	0.24	0.73	0.26	0.79	0.96	1.85	0.07	0.40	0.10	0.29	3420	94
loamy sand	0.22	0.37	0.22	0.37	0.36	0.48	0.08	0.26	0.05	0.16	3708	2
organic soil	1.28	*NA*	1.24	*NA*	1.78	*NA*	0.43	*NA*	0.32	*NA*	324	*NA*
sand	0.34	*NA*	0.34	*NA*	0.60	*NA*	0.08	*NA*	0.11	*NA*	324	*NA*
sandy loam	0.25	0.61	0.26	0.63	0.49	1.14	0.10	0.32	0.06	0.19	6948	40
silt loam	0.28	0.73	0.29	0.84	0.78	1.70	0.06	0.29	0.09	0.34	6480	26
silty clay	0.34	0.87	0.32	0.86	0.50	1.16	0.18	0.52	0.08	0.21	468	15
silty clay loam	0.30	1.07	0.30	1.07	0.51	1.51	0.18	0.54	0.08	0.25	432	19

Table 30. Modeled soil respiration from Apex and measured soil respiration from VLTHS pasture fields in Vermont.

Soil Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	0.36	0.77	0.48	0.77	2.24	0.77	0.08	0.77	0.36	*NA*	896	1
loam	1.24	0.99	1.40	1.17	6.92	2.66	0.00	0.33	0.81	0.62	3388	19
loamy sand	1.28	*NA*	1.42	*NA*	4.27	*NA*	0.18	*NA*	0.72	*NA*	1750	*NA*
organic soil	3.94	*NA*	4.06	*NA*	8.12	*NA*	1.80	*NA*	1.10	*NA*	238	*NA*
sand	1.78	*NA*	1.98	*NA*	5.98	*NA*	0.15	*NA*	1.01	*NA*	588	*NA*
sandy loam	1.37	0.51	1.51	0.51	5.41	0.51	0.37	0.51	0.71	*NA*	7042	1
silt loam	1.18	0.82	1.34	0.91	4.62	1.85	0.09	0.46	0.70	0.34	4214	15
silty clay	0.72	0.71	0.78	0.71	1.90	0.96	0.33	0.46	0.33	0.20	252	4
silty clay loam	0.78	0.89	0.84	0.84	2.36	0.99	0.34	0.62	0.38	0.15	154	5

Table 31. Modeled active carbon from apex and measured active carbon from SSHVT cropland fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	**SSHVT**	**APEX**	**SSHVT**	**APEX**	**SSHVT**	**APEX**	**SSHVT**	**APEX**	**SSHVT**	**APEX**	**SSHVT**

clay	382.12	740.99	417.22	696.58	990.03	803.44	80.96	457.19	199.89	129.74	2052	6
loam	238.12	723.04	261.51	741.62	1549.60	1102.80	35.09	420.00	151.44	136.83	5130	94
loamy sand	183.37	472.26	209.12	472.26	588.04	695.24	23.27	249.28	108.85	315.34	5562	2
organic soil	566.07	*NA*	615.30	*NA*	1686.67	*NA*	130.14	*NA*	294.84	*NA*	486	*NA*
sand	241.07	*NA*	267.20	*NA*	815.28	*NA*	41.85	*NA*	149.11	*NA*	486	*NA*
sandy loam	201.06	662.96	224.06	661.30	642.21	1029.70	29.29	336.53	122.88	160.61	10422	40
silt loam	270.82	717.74	304.37	731.24	1147.20	1018.53	40.33	436.33	186.68	147.68	9720	26
silty clay	460.16	797.28	511.89	808.96	1139.11	970.50	101.92	648.57	290.56	93.03	702	15
silty clay loam	367.74	940.61	399.47	933.35	984.47	1096.49	69.12	567.77	233.89	129.55	648	19

Table 32. Modeled active carbon from apex and measured active carbon from VLTHS pasture fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	589.47	704.01	778.96	704.01	3316.61	704.01	363.80	704.01	548.03	*NA*	896	1
loam	604.37	620.39	690.54	651.79	3326.25	1096.86	214.73	236.33	360.80	243.05	3374	19
loamy sand	515.83	*NA*	569.66	*NA*	1571.63	*NA*	225.69	*NA*	253.50	*NA*	1750	*NA*
organic soil	1238.79	*NA*	1381.77	*NA*	3419.35	*NA*	569.05	*NA*	541.43	*NA*	238	*NA*
sand	630.88	*NA*	729.23	*NA*	2446.43	*NA*	330.19	*NA*	352.29	*NA*	588	*NA*
sandy loam	547.42	347.86	608.04	347.86	2018.48	347.86	193.52	347.86	270.59	*NA*	7042	1
silt loam	739.25	659.33	825.21	678.17	3163.37	1041.24	242.23	451.68	402.25	161.28	4214	15
silty clay	1178.98	539.23	1322.36	577.90	3546.70	797.24	762.69	435.89	592.53	160.35	252	4
silty clay loam	956.38	756.49	1062.33	716.67	3128.68	845.45	654.45	586.00	513.74	105.74	154	5

Table 33. Modeled available water capacity from apex and measured available water capacity from SSHVT cropland fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT	APEX	SSHVT
clay	0.23	0.24	0.24	0.25	0.30	0.27	0.21	0.24	0.03	0.01	2052	6
loam	0.21	0.23	0.21	0.23	0.52	0.31	0.14	0.19	0.04	0.02	5130	94
loamy sand	0.13	0.10	0.13	0.10	0.17	0.10	0.07	0.10	0.01	0.00	5562	2
organic soil	0.42	NA	0.39	NA	0.50	NA	0.32	NA	0.05	NA	486	NA
sand	0.24	NA	0.23	NA	0.32	NA	0.07	NA	0.07	NA	486	NA
sandy loam	0.17	0.18	0.17	0.19	0.32	0.24	0.09	0.14	0.03	0.02	10422	40
silt loam	0.30	0.27	0.29	0.27	0.50	0.31	0.11	0.23	0.05	0.02	9720	26
silty clay	0.34	0.25	0.34	0.25	0.36	0.30	0.33	0.21	0.00	0.02	702	15
silty clay loam	0.32	0.26	0.31	0.27	0.38	0.32	0.28	0.19	0.02	0.03	648	19

Table 34. Modeled available water capacity from apex and measured available water capacity from VLTHS pasture fields in Vermont.

Texture	Median		Mean		Maximum		Minimum		Standard Dev.		Count	
	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS	APEX	VLTHS
clay	0.22	0.24	0.23	0.24	0.30	0.24	0.21	0.24	0.03	NA	896	1
loam	0.22	0.24	0.21	0.24	0.41	0.28	-0.21	0.21	0.05	0.02	3388	19
loamy sand	0.13	NA	0.12	NA	0.14	NA	0.08	NA	0.01	NA	1750	NA
organic soil	0.33	NA	0.37	NA	0.43	NA	0.33	NA	0.05	NA	238	NA
sand	0.25	NA	0.25	NA	0.35	NA	0.07	NA	0.05	NA	588	NA
sandy loam	0.18	0.24	0.18	0.24	0.26	0.24	0.09	0.24	0.04	NA	7042	1
silt loam	0.29	0.25	0.27	0.25	0.45	0.34	0.12	0.22	0.06	0.03	4214	15
silty clay	0.34	0.25	0.34	0.25	0.35	0.25	0.34	0.24	0.00	0.01	252	4
silty clay loam	0.33	0.25	0.32	0.25	0.35	0.29	0.29	0.22	0.03	0.03	154	5