# Technical Potential of Agricultural Carbon Sequestration in the Texas High Plains

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## Introduction

Soil represents the largest pool of carbon in the terrestrial biosphere. The amount of carbon stored in soils around the globe is more than twice the amount of total carbon in the atmosphere and vegetation combined (Ciais et al., 2013; Lehmann & Kleber, 2015). As such, variations in soil carbon stores may lead to significant changes in the concentration of atmospheric carbon (Ciais et al., 2013). Soil organic carbon (SOC) has been used by researchers as a measure for indications of soil health. SOC and soil organic matter are two of the most widely used indicators of soil health, and the quality, quantity, and related dynamics or turnover of SOC are essential to overall soil health (Bünemann et al., 2018; Lal, 2014). Maintaining adequate levels of SOC is critical for soil structure which contributes to aeration and tilth, water use efficiency and retention which govern tolerance to deviations in normal climate conditions (e.g., drought and heat waves), nutrient retention and effective use of retained nutrients, and gas emissions that manage atmospheric concentrations of individual gases and regulate changes in climate (Lal, 2014).

Through land use changes over time, agricultural soils that historically possessed sizable stocks of carbon now have the potential to directly sequester atmospheric carbon due to depletions in original carbon levels. Rising concerns over changes in global climate have increased the need for mitigation strategies to limit related impacts of greenhouse gas emissions. Moreover, the potential of agricultural soils to sequester carbon depends largely upon environmental conditions such as precipitation and temperature, soil texture, the types of practices implemented, and additional site-specific conditions (Bell et al., 2023; Potter et al., 1998; Zhu et al., 2011). Lands currently in production agriculture that were once native grasslands likely have great potential for carbon sequestration (Hutchinson, et al., 2007). As such, the Great Plains in the central U.S. may have great potential as a carbon sink given the area was primarily native grasslands prior to westward expansion.

The Texas High Plains (THP) consists of 39 counties in the Texas panhandle ranging from the northern border with Oklahoma down to the southwest end of the panhandle on the New Mexico border (USDA-NASS, 2020). The region comprises the Northern High Plains (NHP) and the Southern High Plains (SHP) agricultural districts located in the northern part of the panhandle and the southwestern portion of the panhandle, respectively. The THP along with the Texas Rolling Plains (TRP) form the southern end of the Great Plains that span the central U.S. and is separated from the TRP by the Caprock Escarpment. Major crops produced in the region include cotton, wheat, corn, and sorghum with the region producing approximately 25% of the total U.S. cotton crop (Bell et al., 2023; SARE, 2025). Soil surface textures range from clays in the north to sands in the southern section of the region, and the region consists mostly of irrigated agriculture with native vegetation including juniper and mesquite (TPWD, 2024). Average rainfall in the region ranges from 15 to 22 inches annually, and evapotranspiration exceeds precipitation by as much as 3 times in the southern portion of the THP (Gustavson & Holliday, 1999; TPWD, 2024). As such, groundwater resources from the Ogallala aquifer are routinely utilized to sustain crop production in the region. Agriculture supports numerous rural communities and accounts for over 40% of the total economy in the semi-arid region but relies heavily on non-sustainable rates of withdrawal from the Ogallala aquifer (SARE, 2025). Moreover, the total stock of SOC and sequestration potential of agricultural production systems in the region may be significantly influenced by the semi-arid climate of the region.

Previous research from Potter et al. (1998) found a negative relationship between mean annual temperature and SOC in three study sites across Texas, including the THP. Despite this, other research has shown the adoption of specific practices to have a positive influence on SOC levels in the region. For example, the use of cover crops paired with no-till cotton systems increased SOC in the top 15 cm of soil compared to conventional till winter fallow treatments in Lamesa, TX following 17 years of management (Lewis et al., 2018). Similarly, DeLaune et al. (2019) found cover cropping and no-till to increase SOC in soil surface layers after 15 years. However, there was no significant difference in SOC levels in subsurface layers between conventional tillage and no-till. In a long-term study of tillage and cropping practice effects of SOC in dryland systems in Bushland, TX, Schwartz et al. (2015) found decreased tillage intensity to be associated with higher SOC levels in the surface 30 cm of soil for a wheat-fallow rotation in stubble-mulch plots. The absence of fallow periods has also shown to have a positive influence on SOC in the THP where continuous cropping systems had higher levels of SOC compared to systems that incorporate fallow periods (Potter et al., 1998; Schomberg & Jones, 1999).

The management of SOC in the THP is similarly impacted by the economic returns producers experience when adopting sequestering practices. Returns for producers adopting sequestering practices may be affected by resulting yield changes in major cash crops and associated costs of implementing said practices. Net returns for the adoption of cover crops are affected by a variety of factors such as timing of planting and termination, type of cover crop, local soil conditions and climate, and coupled management practices. Research has shown variable yield impacts on subsequent cash crops following cover cropping and the additional opportunity costs producers face when managing an additional crop instead of employing fallow periods may hinder adoption of the practice (Boyer et al., 2018; Deines et al., 2023; Plastina et al., 2020). In the THP, Lewis et al. (2018) found SOC to be twice as high under a no-till rye cover crop compared to conventional tillage for continuous cotton systems in Amarillo Fine Sandy Loam soil. However, the conventional tillage treatment was shown to be more profitable than no-till rye and no-till mixed species cover crop treatments because of higher average revenue from greater cotton lint yield.

In contrast, similar studies in the THP have found either no difference or significantly greater cotton lint yields when utilizing no-till in the region's cotton systems (Baumhardt et al., 2009; Bordovsky et al., 1994).[1] Segarra et al. (1991) similarly found higher net revenues for dryland cotton systems in the THP utilizing

[1] The systems analyzed by Baumhardt et al. (2009) consisted of wheat-cotton-fallow rotations where cotton crops received two levels of deficit irrigation. There were no significant differences observed between the two levels of deficit irrigation. Bordovsky et al. (1994) found cotton lint yield increases from no-till for both dryland and irrigated cotton systems.

no-till and reduced tillage compared to conventional tillage, but an irrigated continuous cotton system under conventional tillage had higher net revenue compared to no-till and an irrigated conservation till system with a wheat-cotton rotation had the highest overall net revenue above total costs. These studies highlight the potential viability of sequestering practices in the THP, and how economic feasibility may be significantly influenced by producers applying irrigation from the diminishing Ogallala aquifer that sustains irrigated crop production in the region.

Incentive-based approaches have been used for environmental regulation and for facilitating ecosystem and environmental services from agriculture. This approach is generally considered more efficient compared to command-and-control regulations where policies that mandate specific management practices and land uses would be largely inefficient given the significant heterogeneity in site-specific biophysical and economic conditions (Antle et al., 2003; Fleming & Adams, 1997). Among incentive-based strategies, voluntary market-based policies such as carbon contracting have begun to emerge as potential tools to encourage agricultural producers to effectively manage and increase levels of soil carbon. However, the development of voluntary soil carbon markets and trading systems remains limited due to challenges such as accurate measurement, verification, additionality, leakage, and concerns about permanence and potential reversals of soil carbon, all of which create uncertainty in carbon accounting (Keenor et al., 2021; Kreibich & Hermwille, 2021; Vermeulen et al., 2019). Currently, there is no market price for sequestered soil carbon in the THP and, therefore, it may be seen as a “free” output of agricultural production processes (Sperow et al., 2016). As economic theory suggests, free outputs will not necessarily influence production decisions, and establishing a price for sequestered soil carbon in the THP would have influences on management and crop production decisions in the region (Kimble et al., 2016). In the absence of interactive market prices for soil carbon, producers in the THP generally rely on federal incentive programs (e.g., the EQIP and CSP) to supply economic benefits for adopting sequestering practices. The EQIP and CSP do not function as true market-based mechanisms and enrolled producers are not necessarily rewarded for their carbon storage efficiency. Instead, they provide incentives to producers based on individual practices and do not account for additional levels of accumulated soil carbon. Inadequate consideration for additionality compared to business-as-usual conditions and the associated measurement difficulty are issues commonly referenced for programs that focus on carbon sequestration (Thamo & Pannell, 2016; Trexler, 2011).

A full accounting of additionality requires comparison against baseline carbon changes expected from business-as-usual conditions. For voluntary programs that issue carbon credits to producers to operate efficiently, credits or incentives should only be provided for sequestered carbon that is 'additional' (Thamo & Pannell, 2016). Effectively accounting for the additionality of sequestered carbon in market-based policies increases transaction costs that may be reduced through policy simplification but would increase the uncertainty and overall efficiency of the program (Cacho et al., 2013; Capon et al., 2013). For example, comprehensive soil sampling in a given project/market region at the farm level such that individual producers are compensated for the amount of carbon they sequestered would entail significant costs. However, leveraging econometric modeling that accounts for the uncertainty inherent in heterogeneous production systems, environmental conditions, and soil types could offer a more cost-effective alternative by estimating soil carbon levels with limited direct sampling, thereby balancing accuracy with feasibility in measurement.

Hierarchical Bayesian (HB) models have been used for a number of environmental applications and the approach allows estimated model inferences to be shared across subunits (e.g., unique sampling locations) resulting in both subunit-specific and global parameter estimates (Agarwal et al., 2005; Borsuk et al., 2001; Yang et al., 2011). Researchers have used plot-scale data to inform policy decisions for both global and regional changes in environment but scaling from the plot level to larger areas remains difficult because of high spatial variability at many scales (Burke, 2000). HB approaches allow the use of diverse data types to evaluate soil properties and researchers can draw predictions for independent variables at points where data is scarce. For example, Kaye et al. (2008) use a HB model of plot-scale pools for soil nutrients to predict storage of various soil nutrients, including SOC, across various ecosystems and find that Bayesian scaling can accommodate varied factors driving soil nutrients across ecosystems. Therefore, the authors claim that Bayesian scaling could represent an important tool for ecological scaling that spans various land use types (Kaye et al., 2008). Similarly, soil texture impacts both water permeability and soil aeration which indirectly contributes to the carbon consumption or production capacity of the soil. As such, Li et al. (2015) used a HB approach to model soil carbon flux across four soil texture classes and found that a hierarchical approach better represented texture-specific observations compared to a nonhierarchical Bayesian model (Bayesian pooled model). The authors also claimed that future research could utilize soil texture as an upscaling factor when extrapolating results to the regional scale.

Fitting hierarchically structured soil sampling data to Bayesian models allows researchers to derive inferences in instances when data is scarce or covers relatively limited geographic regions. The intention of this research is to utilize HB models to estimate the agricultural carbon storage potential of the THP. Specifically, by utilizing soil sampling data from eight counties in the THP the objective of this paper is to evaluate the agricultural production practices, soil textures, and environmental conditions associated with higher levels of SOC in the semi-arid THP, and assess the response of SOC to the stated factors at 30 cm depth increments from the soil surface to 90 cm in the soil profile.

## Methods

### Data

The data for this study comes from soil analyses conducted across eight counties in the THP in 2022. Soil core samples were taken from each location from the soil surface down to a depth of 90cm and analyzed in 15 cm intervals for SOC, bulk density, pH, electrical conductivity, potassium permanganate oxidizable carbon, and soil texture. For the purposes of this study, the six 15 cm depth increments were aggregated into 30 cm measurements for the sake of brevity. The fields sampled span 11 soil series and 10 soil textures in the THP and include both conventional (e.g., conventional tillage) and regenerative/carbon sequestering practices (e.g., cover cropping and no-tillage). Soil textures were determined at each depth increment directly from the percentages of sand, silt, and clay at each soil layer using the soil texture calculator from the USDA (USDA-NRCS, 2024). The sampled fields also comprised a variety of crops typically planted in the THP (e.g., cotton, corn, sorghum) and crop rotations/treatments commonly used by producers in the region (e.g., continuous cotton, sorghum-cotton, sorghum-corn, etc.). Only a single treatment was utilized in each field, and the majority of fields contained three replications of each treatment. Replications were treated as individual observations for a total of 67 observations across the THP. In addition to the soil sampling data described above, county-level environmental data from the PRISM Climate Group and 2022 Census of Agriculture were utilized for estimating county and regional SOC stocks (PCG, 2024).[2]

Model

The purpose of this study is to evaluate the agricultural production practices, soil textures, and environmental conditions that are associated with greater levels of SOC in the semi-arid THP, assess the response of SOC to various factors throughout the soil profile, and calculate the total SOC stock of the region. Previous studies have used variations of a hierarchical Bayesian (HB) model in a number of environmental applications, including evaluations of SOC fluxes and estimates of stocks of diverse soil nutrients. The HB model has been reported to be effective in sharing model inferences across sites, deriving sub-unit specific inferences, estimating global parameter estimates, and accurately representing natural variability and related uncertainty. As such, a HB model was employed to analyze soil characteristics of samples collected from across the THP, estimate the association between specific agricultural practices and SOC levels, calculate total SOC stocks in the agricultural

[2] The PRISM Climate Group is part of the Northwest Alliance for Computational Science and Engineering and is based at Oregon State University (PCG, 2024).

soils of the region, and account for inherent variability and uncertainty regarding SOC levels.

Malve and Qian (2006) maintain that hierarchical modeling can reduce model uncertainty and improve parameter estimates by pooling data from different sources, and hierarchical models may be used to form realistic models without overfitting the data. The main focus of this study is to estimate the association of SOC and various agricultural practices across different soil textures in the THP. Soil texture classes were determined by the observed percentages of clay, sand, and silt at individual depths. By characterizing soil texture at each depth interval, the model is better able to capture the heterogeneity between soil texture and SOC in different soil horizons. Specifically, the 10 soil texture classes in the analysis are clay (C), clay loam (CL), loam (L), loamy sand (LS), sandy clay (SC), sandy clay loam (SCL), sandy loam (SL), silt (S), silt loam (StL), and silty clay loam (StCL). Therefore, following adaptation from Li et al. (2015) the HB model can be defined as follows:

$$ln(SOC_{ij}) = N(\mu_{\ln(SOC_{ij})}, \sigma^2_{SOC}) \quad (1)$$

$$\mu_{\ln(SOCij)} = \beta_1 + U_j + \beta_2 NoTill_i + \beta_3 CoverCrop_i + \beta_4 Irrigated_i \quad (2)$$

$$+\beta_5 \log(Precipitation_i) + \beta_6 \log(MeanTemp) + \beta_7 PriorCrop_i$$

$$U_j \sim N(0, \sigma^2_U). \quad (3)$$

where $SOC$ represents the $i$-th observation of SOC for the $j$-th soil texture, $i$ is the data point (i.e., plot) ranging from 1 to N, and $j$ is the soil texture class ($j$=1, C; $j$=2, CL; $j$=3, L; $j$=4, LS; $j$=5, SC; $j$=6, SCL; $j$=7, SL; $j$=8, S; $j$=9 StL; $j$=10, StCL). It is important to note that the above specification represents a single permutation of the model, and separate iterations of the model were estimated for the three soil depths analyzed. The texture specific model parameter is denoted by $U_j$ and represents the random intercept for each of the $j$ soil texture classes. That is, the random intercept assumes common partial effects from the included explanatory variables across soil texture but assumes different initial stocks of SOC across soil texture classes. The prior distribution of the random intercepts is defined as normal with mean 0 and variance $\sigma_U^2$, where $\sigma_U^2$ captures the variability in baseline SOC levels across soil textures.

The explanatory variables *NoTill, CoverCrop,* and *Irrigated* are dummy variables indicating whether the plot was under no-till, a cover crop was grown on the plot, and if the plot was irrigated, respectively. *Precipitation* is the average county-level annual precipitation level (inches) in which the plot is located and *MeanTemp* is the average county-level annual mean temperature (Fahrenheit) in which the plot is located. *PriorCrop* is a categorical variable indicating the crop grown on the plot prior to the soil samples being taken. The variance of the model error is denoted by $\sigma_{SOC}^2$. Equations 1-3 above denoting the hierarchical structure of the model include distributions where ln $(SOC_{ij})$ is normally distributed with mean $\mu_{\ln(SOC_{ij})}$ and variance $\sigma_{SOC}^2$. The hyper parameters and other parameters also need to have a prior distribution. Relatively uninformative or diffuse priors have shown favorable outcomes and are widely used in HB modeling (Haque et al., 2010; Huang & Abdel-Aty, 2010; Lacombe & Flores, 2017). Therefore, relatively uninformative or vague priors were used in this specification and are as follows:

$$\beta_k \sim N(0, 10000) \tag{4}$$

$$\sigma_{SOC}, \sigma_U \sim igamma(0.01, 0.01). \tag{5}$$

The number of the parameter is denoted by $k$ where $k = 1, \ldots 7$, and is denoted as $\beta_1, \ldots, \beta_7$, respectively. The distributions of the $\beta_k$'s are normal with mean 0 and variance 10000, and an inverse gamma distribution is specified for $\sigma_{SOC}$ and $\sigma_U$ with the shape and scale parameters specified as 0.01.

When utilizing Bayesian econometrics, all inference is deduced from the posterior distribution of the relevant parameters. The following equation characterizes the posterior distribution:

$$p(\theta|y) \propto p(y|\theta)\, p(\theta). \tag{6}$$

From the equation, the posterior distribution of the parameters is proportional to the product of the likelihood function and the individual priors for all parameters (Hall et al., 2022). Independent priors are used in this study for all of the parameters, meaning that the elements of $p(\theta)$ are multiplicatively separable. $p(\theta|y)$ denotes the posterior distribution and, given the observed data ($y$), represents the probability of the model parameter ($\theta$) values (Li et al., 2015). $\theta$ contains $\beta_1 \sim \beta_7, U_1 \sim U_{10}$ , $\sigma_U$, and $\sigma_{SOC}$ for the HB model used in this study. The prior distribution is represented by $p(\theta)$ and the likelihood function is denoted by $p(y|\theta)$. The following expression defines the likelihood function:

$$p(y|\theta) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_{SOC}^2}} \exp\left(-\frac{\left(\ln(SOC_i) - (\mu_{\ln(SOC)})_i\right)^2}{2\sigma_{SOC}^2}\right). \quad (7)$$

$\ln(SOC_i)$ is the measured value of SOC log-transformed and $\left(\mu_{\ln(SOC)}\right)_i$ denotes the predicted value of the HB model in equation 2. $N$ is equal to 67 and represents the total number of observations, and $\sigma_{SOC}$ is the standard deviation corresponding to equation 5. The Markov Chain Monte Carlo (MCMC) method was used to estimate a representative sample of parameters from the posterior distribution. 35,000 iterations of sampling from the prior distribution were conducted to obtain posterior probability distributions. To avoid the influence of the initial values, the initial 5,000 iterations were discarded as a "burn-in" period and the remaining 30,000 iterations were used to evaluate the posterior parameter distributions.

Evaluating SOC Stocks in the THP

The HB models are used to predict SOC at the county level by applying the posterior draws from the fitted models. The procedure iteratively computes predictions for each of the 30,000 posterior draws, accounting for both fixed effects and random effects (e.g., soil texture) and then back-transforms predictions from the log scale to the natural scale (tons/acre). The process involved five main steps: (1) defining the linear predictor for the natural logarithm of SOC; (2) back transforming the prediction natural logarithm of SOC to the natural scale; (3) estimating individual county SOC stocks; (4) aggregating for regional SOC stocks; and (5) summarizing the predictions. The steps were repeated for each of the three soil depths considered. Therefore, predictions of SOC stocks were made for each soil layer and aggregating results from each soil layer gave SOC stock for the entire 0-90 cm soil profile. Below is a detailed breakdown of the procedure and associated formulas for each step:

**(1)** Prediction Structure:

$$\log\left(SOC_i^k\right) = \widehat{\beta_1} + \widehat{U_J} DominantTexture + \widehat{\beta_2} NoTillProportion_i + \widehat{\beta_3} CoverCropProportion_i + \widehat{\beta_4} IrrigatedProportion_i + \widehat{\beta_5} \log(Precipitation_i) + \widehat{\beta_6} \log(MeanTemp) + \widehat{\beta_7} PriorCropProportions_i. \quad (8)$$

Where $SOC$ represents the predicted natural log of SOC per acre in county *i* for posterior draw *k,* $\widehat{\beta_1} \sim \widehat{\beta_7}$ are the mean values for management practices and environmental covariates from the posterior draw, and $\widehat{U_J}$ is the random intercept for soil texture *j* from the posterior draw. *DominantTexture* is the dominant soil texture at each depth increment as determined by county-level data from the Web Soil Survey.[3] *NoTillProportion, CoverCropProportion, IrrigatedPropotion,* and *PriorCropProportions* represent the proportion of total cropland in each county utilizing no-till, cover cropping, irrigation, and planted to cotton and sorghum. The proportions of total cropland dedicated to each practice were determined from the 2022 Census of Agriculture county-level data (USDA-NASS, 2024). *Precipitation* and *MeanTemp* are the average county-level precipitation and mean temperatures in each county obtained from the PRISM database.

**(2)** Back Transformation:

Following the first step defined above, the linear predictor on the log scale is then back-transformed with a bias correction to the natural scale using the following equation:

[3] Percentages of sand, silt, and clay were used to determine soil texture, and the dominant texture was defined as the soil texture covering the largest percentage of total acreage in county *i* at depth *j*.

$$SOC_i^k = \exp\left(log\left(SOC_i^k\right) + \frac{1}{2}\sigma_{SOC}^2\right). \quad (9)$$

$SOC$ represents the predicted tons per acre value of SOC, $log(SOC)$ is the predicted log SOC value from county *i* for posterior draw *k*, and $\sigma_{SOC}^2$ is the residual variance from the posterior draw. The transformation helps ensure that predictions are unbiased when converting from the log scale to the natural scale (Baskerville, 1972).

**(3)** Individual County SOC Stocks

The prior step provides predictions of SOC levels in tons per acre. Because the linear predictor defined in step (1) above uses total cropland in each county to determine proportions of individual practices, the following equation is used to determine the total stock of SOC in the cropland of each county in the THP:

$$Stock_i^k = SOC_i^k \times Total\ Cropland_i. \quad (10)$$

$Stock$ is the total stock of SOC in county *i'*s cropland and *Total Cropland* simply represents the total acres of cropland in county *i.*

**(4)** Regional SOC Stock

After obtaining predictions for the total stock of SOC in each county, estimating the total stock of SOC in the entire THP involves summing the county-level SOC stocks for each posterior draw:

$$THPStock^k = \sum_{i=1}^{I} Stock_i^k. \quad (11)$$

Where $THPStock^k$ represents the total stock of SOC in the entire THP for each posterior draw *k, I* is equal to 29 and represents the total number of counties in the region for which data were available for predictions.

**(5)** Post-processing and Summarizing Predictions:

The predicted values of SOC across all posterior draws were averaged to provide point estimates for each county using the following equation:

$$\overline{SOC_i} = \frac{1}{K}\sum_{k=1}^{K} \widehat{SOC_i^k}. \quad (12)$$

$\overline{SOC_i}$ is the mean value of SOC in county *i* across all posterior draws *K*. This process was used to obtain point estimates of both SOC in tons per acre and total SOC stock for each county, and to obtain summary statistics of the regional (i.e., THP) and sub regional (i.e., NHP and SHP) measurements of SOC.

Following the estimates of county-level SOC stocks, sensitivity analyses were conducted to evaluate how changes in cropland allocation to individual practices in the region would affect the stocks of SOC across each soil depth. Using county-level acreage data from the 2022 Census of Agriculture, total acreage dedicated to individual practices were increased by 5%, 10%, 25%, and 50%. These adjustments allowed for an evaluation of both the net changes in SOC stock at each soil depth and the average increase in SOC per acre of cropland in each county. Calculating the average increase in SOC per acre across soil layers provided a foundation for further economic analysis. To estimate potential revenues for producers under various SOC crediting schemes, SOC prices ranging from $5 to $50 per ton were applied. A report from the World Bank on carbon pricing found the average monthly world price of nature-based carbon credits to range from a high of just under $18/ton in 2022 to below $5/ton in 2024 (World Bank, 2024). Therefore, the prices used for the sensitivity analyses cover both the low and high end of potential prices for SOC. Similarly, because existing protocols for crediting soil carbon use a wide range of recommended soil depths, three crediting depths (0-3 0cm, 0-60 cm, and 0-90 cm) were considered, enabling an assessment of the financial incentives associated with carbon sequestration at different soil depths (Dupla et al., 2024).

**Results**

Summary statistics for the management practices, county-level environmental characteristics, and aggregated SOC data are presented in Table 1. Of the 67 total observations, approximately 86% and 40% utilize no-till and cover cropping, respectively. Over half of the observations (68.6%) are irrigated and cotton is the most common crop on the field prior to the soil samples being collected. Average annual precipitation and mean temperature were obtained from the PRISM Climate Group for the eight counties in the THP in which soil samples were collected. The observed counties include Dawson, Swisher, Dallam, Sherman, Moore, Lamb, Crosby, and Howard. The average precipitation for the observed counties is 12.78 inches annually, and the average annual mean temperature is just under 60 degrees Fahrenheit.

As noted previously, the six depth measurements for each observation were aggregated into three 30 cm measurements for concision. Average levels of SOC are approximately 10.97 ton/acre in the surface 30 cm, 10.71 ton/acre in the 30-60 cm layer, and 12.34 ton/acre in the bottom 60-90cm layer. While these measurements are consistent with previous studies finding higher levels of SOC in subsurface soil layers beneath the plow depth, the standard deviation of the SOC measurements increases with depth and nearly doubles from the surface 30 cm of the soil to the lower 60-90 cm layer indicating larger variations in observed SOC values at deeper soil horizons.

Table 1: Summary Statistics of Observed Locations

| **Variable** | **Percentage of Occurrence** | **Mean** | **Std. Dev.** |
|---|---|---|---|
| Tillage | | 0.866 | 0.344 |
| 1 = No-till | 86.6% | | |
| 0 = Conventional | 13.4% | | |
| Cover Crop | | 0.403 | 0.494 |
| 1 = Cover | 40.3% | | |
| 0 = No Cover | 59.7% | | |
| Irrigation | | 0.686 | 0.465 |
| 1 = Irrigated | 68.6% | | |
| 0 = Dryland | 31.4% | | |
| Prior Crop | | 1.913 | 0.728 |
| 1 = Corn | 31.3% | | |
| 2 = Cotton | 46.3% | | |
| 3 = Sorghum | 22.4% | | |
| Precipitation (in.) | | 12.778 | 1.301 |
| Mean Temperature (°F) | | 58.890 | 1.917 |
| SOC (ton/acre) | | | |

| | | |
|---|---|---|
| 0 – 30 cm | 10.972 | 4.580 |
| 30 – 60 cm | 10.709 | 6.208 |
| 60 – 90 cm | 12.335 | 8.667 |

The distributions of soil texture by each soil depth are presented in Table 2. At the 0-30 cm layer, the majority of observed samples are classified as *Silt Loam* (52.24%), followed by *Loam* (13.43%) and *Sandy Loam* (13.43%). At 30-60 cm, *Silt Loam* remained prevalent in 38.81% of observed samples, with *Clay Loam* (16.42%) and *Clay* (13.43%) becoming more common. At 60-90 cm, *Silt Loam* was again dominant, observed in 40.91% of samples, followed by *Clay Loam* in 28.79%, 18.18% of samples were *Silt*, and 7.58% of the samples were *Loam*. The observed distribution suggests a trend of increasing clay content with depth, as indicated by the rising presence of *Clay Loam* and *Clay* in deeper layers. Conversely, the dominance of *Silt Loam* across all depths suggests a relatively consistent silt component throughout the profile.

Table 2: Soil Texture Distribution by Depth

| | **Texture** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Depth (cm)** | **Clay** | **Clay Loam** | **Loam** | **Loamy Sand** | **Sandy Clay** | **Sandy Clay Loam** | **Sandy Loam** | **Silt** | **Silt Loam** | **Silty Clay Loam** |
| **0-30** | 0% | 10.45% | 13.43% | 2.99% | 0% | 2.99% | 13.43% | 4.48% | 52.24% | 0% |
| **30-60** | 13.43% | 16.42% | 7.46% | 0% | 0% | 4.48% | 4.48% | 13.43% | 38.81% | 1.49% |
| **60-90** | 1.52% | 28.79% | 7.58% | 0% | 1.52% | 1.52% | 0% | 18.18% | 40.91% | 0% |

<u>HB Models</u>

The mean, standard deviation, and Monte Carlo standard error (MCSE) values in addition to the 95% credible intervals of the posterior distributions of the parameters for the HB model are presented in Table 3. All of the values for SOC are in short tons (i.e., U.S. tons) per acre and because the raw SOC data were not normally distributed, all the following HB analyses were performed on the natural logarithm of SOC. The values presented in Table 3 are for the 0-30 cm soil layer, and the observations were sorted into seven soil textures (i.e., groups) for the purpose of the HB model. Given the dependent variable is log transformed levels of SOC, the mean posterior distribution estimates for *No-till, Cover Crop, Irrigated,* and *Prior Crop* can be interpreted as percentage changes (e.g., $100 \times (\exp(\widehat{\beta_k}) - 1)$), and parameter estimates for *Precipitation* and *Mean Temperature* are interpreted as elasticities. It is important to note that SOC measurements are in tons per acre; therefore, the following interpretations can be characterized as higher or lower percentages in tons of SOC per acre in the 0-30 cm soil layer. Because much of the disturbances from agricultural practices occur in the surface layers of the soil (e.g., tillage and root growth) much of the positive impacts of sequestering practices are likely to take place in the 0-30 cm layer of the soil. The is the case for both *No-till* and *Cover Crop* which are associated with approximately 92.7% and 12.6% higher levels of SOC in the top 30 cm of the soil, respectively. In contrast, irrigated fields are associated with approximately 5.91% less SOC. A *Prior Crop* of corn was used as the base for comparison, and both *Cotton* and *Sorghum* are associated with higher levels of SOC compared to corn. Specifically, crops of *Cotton* and *Sorghum* directly preceding the collection of soil samples are associated with approximately 16% and 3.4% higher levels of SOC compared to corn, respectively.

Table 3: HB Model Posterior Distributions – 0-30 cm Soil Layer

| **Parameter** | **Mean** | **Std. Dev.** | **MCSE** | **Median** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| **No-till** | 0.656 | 0.148 | 0.001 | 0.657 | [0.366, | 0.946] |
| **Cover Crop** | 0.119 | 0.173 | 0.001 | 0.120 | [-0.222, | 0.461] |
| **Irrigated** | -0.061 | 0.113 | 0.001 | -0.061 | [-0.281, | 0.164] |
| **Prior Crop (base=corn)** | | | | | | |
| **Cotton** | 0.148 | 0.126 | 0.001 | 0.149 | [-0.102, | 0.396] |
| **Sorghum** | 0.038 | 0.168 | 0.001 | 0.039 | [-0.293, | 0.368] |
| **ln(Precipitation)** | 0.093 | 0.585 | 0.005 | 0.088 | [-1.048, | 1.237] |
| **ln(Mean Temperature)** | -8.018 | 2.576 | 0.019 | -8.020 | [-13.097, | -2.951] |
| **Constant** | 34.093 | 10.720 | 0.083 | 34.063 | [13.119, | 55.234] |

| | | | | | | |
|---|---|---|---|---|---|---|
| $U_2$ (*Clay Loam*) | -0.024 | 0.112 | 0.002 | -0.022 | [-0.268 | 0.195] |
| $U_3$ (*Loam*) | 0.007 | 0.112 | 0.002 | 0.007 | [-0.221 | 0.236] |
| $U_4$ (*Loamy Sand*) | -0.025 | 0.133 | 0.002 | -0.020 | [-0.311 | 0.234] |
| $U_6$ (*Sandy Clay Loam*) | -0.034 | 0.131 | 0.002 | -0.029 | [-0.313 | 0.218] |
| $U_7$ (*Sandy Loam*) | -0.014 | 0.109 | 0.002 | -0.015 | [-0.234 | 0.207] |
| $U_8$ (*Silt*) | 0.089 | 0.138 | 0.003 | 0.074 | [-0.139 | 0.416] |
| $U_9$ (*Silt Loam*) | 0.022 | 0.113 | 0.003 | 0.017 | [-0.197 | 0.263] |
| $\sigma_U^2$ | 0.027 | 0.039 | 0.001 | 0.016 | [0.003, | 0.119] |
| $\sigma_{SOC}^2$ | 0.118 | 0.029 | 0.000 | 0.114 | [0.079, | 0.183] |

Regarding county-level environmental characteristics, higher levels of precipitation have a negligible, positive association with SOC, and higher mean temperatures have a negative association. An additional inch increase in annual precipitation and degree Fahrenheit increase in annual mean temperatures are associated with .093% higher and 8.02% lower levels of SOC, respectively. It is important to note the data for these variables are recorded at the county level and are not field-specific. That is, the effect of these variables can be interpreted as general trends for environmental characteristics at the county level and their relationships to SOC storage.

When considering the 95% credible intervals of the explanatory variables, *No-till* and *Mean Temperature are* the only parameters for which the 95% credible interval does not contain 0. Therefore, there is strong statistical evidence for the absence of conventional tillage in the surface 30 cm of the soil contributing to higher levels of SOC while higher county-level annual mean temperatures are associated with lower levels of SOC. The credible intervals of the remaining explanatory variables contain 0 and, thus, indicate a potential lack of strong evidence for explanatory power and the associated effects may be small. However, the Bayesian approach allows for probabilistic interpretations and both the directions and magnitude of the estimated means for the posterior distributions of parameters can provide valuable insights into the dynamics of SOC in the surface layers of the soil. Similarly, the variance component $\sigma_U^2$ represents the heterogeneity between soil textures and the credible interval suggests significant variation between groups.

In contrast to the frequentist approach, the Bayesian approach used here does not integrate out the random effects when estimating the model. Instead, the Bayesian approach predicts the random effects as model parameters in conjunction with the individual explanatory variables. The random effects in Table 3 are denoted as $U_j(Texture)$ and represent random intercepts for each texture class and can be characterized as deviations in baseline SOC stocks between each texture class. For example, the random effects in Table 3 show *Loam, Silt,* and *Silt Loam* texture classes to be associated with higher baseline values of SOC in the surface 30 cm of soil. This finding indicates that soil textures with relatively high percentages of silt, are associated with higher levels of SOC in soil surface layers.

Table 4: HB Model Posterior Distributions – 30-60 cm Soil Layer

| **Parameter** | **Mean** | **Std. Dev.** | **MCSE** | **Median** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| **No-till** | 0.225 | 0.157 | 0.001 | 0.225 | [-0.086, | 0.536] |
| **Cover Crop** | -0.371 | 0.191 | 0.002 | -0.373 | [-0.746, | 0.009] |
| **Irrigated** | -0.173 | 0.126 | 0.001 | -0.173 | [-0.421, | 0.074] |
| **Prior Crop (base=corn)** | | | | | | |
| **Cotton** | 0.215 | 0.129 | 0.001 | 0.215 | [-0.039, | 0.468] |
| **Sorghum** | 0.280 | 0.179 | 0.002 | 0.280 | [-0.070, | 0.631] |
| **ln(Precipitation)** | 0.959 | 0.659 | 0.009 | 0.958 | [-0.331, | 2.256] |
| **ln(Mean Temperature)** | -0.461 | 3.198 | 0.052 | -0.430 | [-6.800, | 5.722] |
| **Constant** | 1.538 | 13.581 | 0.233 | 1.476 | [-24.681, | 28.373] |
| $\boldsymbol{U_1\ (Clay)}$ | -0.068 | 0.151 | 0.005 | -0.063 | [-0.380 | 0.216] |
| $\boldsymbol{U_2\ (Clay\ Loam)}$ | -0.039 | 0.148 | 0.005 | -0.038 | [-0.340 | 0.259] |
| $\boldsymbol{U_3\ (Loam)}$ | 0.044 | 0.161 | 0.005 | 0.033 | [-0.242 | 0.392] |
| $\boldsymbol{U_6\ (Sandy\ Clay\ Loam)}$ | -0.064 | 0.183 | 0.005 | -0.057 | [-0.445 | 0.303] |
| $\boldsymbol{U_7\ (Sandy\ Loam)}$ | -0.164 | 0.194 | 0.005 | -0.140 | [-0.589 | 0.167] |
| $\boldsymbol{U_8\ (Silt)}$ | 0.055 | 0.156 | 0.006 | 0.044 | [-0.227 | 0.381] |
| $\boldsymbol{U_9\ (Silt\ Loam)}$ | 0.262 | 0.164 | 0.007 | 0.250 | [-0.011 | 0.602] |
| $\boldsymbol{U_{10}\ (Silty\ Clay\ Loam)}$ | -0.010 | 0.193 | 0.004 | -0.008 | [-0.406 | 0.378] |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\sigma_U^2$ | 0.060 | 0.094 | 0.003 | 0.038 | [0.007, | 0.240] |
| $\sigma_{SOC}^2$ | 0.119 | 0.033 | 0.000 | 0.113 | [0.078, | 0.192] |

The posterior distributions of the HB models for SOC in the 30-60 cm and 60-90 cm soil layers are shown in Tables 4 and 5, respectively. The HB model for the two successive soil layers were estimated in a similar manner to the model for the surface 30 cm layer. However, given soil texture was assigned based on percentages of sand, silt, and clay at each soil layer, the number of groups and specific groupings are not the same as presented in Table 2. For the 30-60 cm soil layer, there are eight groups of soil texture and seven groupings of soil texture in the lower 60-90 cm soil layer.

Table 5: HB Model Posterior Distributions – 60-90 cm Soil Layer

| **Parameter** | **Mean** | **Std. Dev.** | **MCSE** | **Median** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| **No-till** | 0.282 | 0.254 | 0.002 | 0.282 | [-0.218, | 0.783] |
| **Cover Crop** | -0.193 | 0.311 | 0.002 | -0.192 | [-0.803, | 0.424] |
| **Irrigated** | -0.304 | 0.205 | 0.001 | -0.304 | [-0.706, | 0.101] |
| **Prior Crop (base=corn)** | | | | | | |
| **Cotton** | 0.070 | 0.235 | 0.001 | 0.070 | [-0.395, | 0.529] |
| **Sorghum** | 0.040 | 0.307 | 0.002 | 0.043 | [-0.565, | 0.641] |
| **ln(Precipitation)** | 0.785 | 0.970 | 0.007 | 0.775 | [-1.104, | 2.673] |
| **ln(Mean Temperature)** | -1.359 | 5.059 | 0.057 | -1.303 | [-11.399, | 8.463] |
| **Constant** | 5.808 | 21.119 | 0.243 | 5.588 | [-35.123, | 47.753] |
| $\boldsymbol{U_1}$ $(\boldsymbol{Clay})$ | -0.048 | 0.237 | 0.004 | -0.028 | -0.578 | 0.406 |
| $\boldsymbol{U_2}$ $(\boldsymbol{Clay\ Loam})$ | -0.096 | 0.177 | 0.004 | -0.084 | -0.473 | 0.245 |
| $\boldsymbol{U_3}$ $(\boldsymbol{Loam})$ | -0.055 | 0.200 | 0.004 | -0.045 | -0.480 | 0.327 |
| $\boldsymbol{U_5}$ $(\boldsymbol{Sandy\ Clay})$ | 0.002 | 0.238 | 0.004 | -0.002 | -0.488 | 0.499 |
| $\boldsymbol{U_6}$ $(\boldsymbol{Sandy\ Clay\ Loam})$ | -0.016 | 0.239 | 0.003 | -0.015 | -0.523 | 0.478 |
| $\boldsymbol{U_8}$ $(\boldsymbol{Silt})$ | 0.061 | 0.196 | 0.005 | 0.046 | -0.299 | 0.503 |
| $\boldsymbol{U_9}$ $(\boldsymbol{Silt\ Loam})$ | 0.187 | 0.191 | 0.006 | 0.167 | -0.137 | 0.627 |
| $\sigma_U^2$ | 0.078 | 0.132 | 0.003 | 0.042 | [0.006, | 0.378] |
| $\sigma_{SOC}^2$ | 0.378 | 0.088 | 0.001 | 0.364 | [0.254, | 0.578] |

The sign of the mean values for the posterior distribution of every explanatory remained the same in both the 30-60 cm and 60-90 cm layers as they were in the surface 30 cm of the soil; the only exception is the negative mean values for *Cover Crop* in Tables 4 and 5. A possible explanation for this difference could be the limited root penetration of cover crops beyond the surface 30 cm of the soil. The random intercepts for soil texture remain relatively consistent for each of the soil depths, except for *Loam* which has an opposite sign in the 60-90 cm depth compared to the two shallower soil depths. *Loam* soils are associated with higher levels of SOC in the 0-30 cm and 30-60 cm layers and lower levels of SOC in the 60-90 cm layer. However, it is important to note that the prediction accuracy of the HB models decreases for each successive soil layer. For example, the 95% credible intervals for every variable included in the models increase from the surface 30 cm soil layer to the 30-60 cm layer. The credible intervals also expand between the model for the 30-60 cm layer and the subsequent model for the 60-90 cm layer.

**Model Evaluation**

The deviance information criteria (DIC) are used to compare the HB models for each depth to non-hierarchical Bayesian (i.e., Bayesian pooled) models. The DIC is an evaluation method designed specifically to evaluate both pooled and HB models. Goodness of fit and a penalty for model complexity are both considered in calculating DIC, and the model with a lower DIC is the model expected to best predict a replicated dataset sharing the same structure as the observed data (Li et al., 2015). The pooled models are estimated using the same explanatory variables as the HB models, but the pooled models assume no explicit grouping or hierarchical structure to the data. That is, the pooled model assumes that all data points belong to a single, homogeneous population, meaning that the relationships between variables remain constant across observations. The DIC for each of the HB models along with the Bayesian pooled models for each soil depth are presented in Table 6.

The DIC values indicate that the pooled model performs better in the soil surface layer (0-30 cm), where the Bayesian pooled model has the lowest estimated

DIC (50.899). A key reason for this is that management practices strongly influence SOC accumulation and decomposition in soil surface layers, which may contribute to relatively consistent patterns across sites. At shallow depths management effects are likely dominate over inherent soil properties and the inclusion of random intercepts (i.e., the hierarchical structure) may not add significant value, potentially leading to a higher DIC for the HB model.

Table 6: DIC values for the HB and Bayesian Pooled Models

| | **DIC** | |
|---|---|---|
| **Depth** | **HB** | **Bayesian Pooled** |
| **0-30 cm** | 57.442 | 50.899 |
| **30-60 cm** | 59.182 | 61.494 |
| **60-90 cm** | 133.061 | 133.193 |

In contrast, the HB models perform better than the Bayesian pooled models in the two subsequent soil layers as shown by the lower DIC values. This shift is likely because SOC dynamics at deeper depths are less influenced by direct management and, instead, more controlled by soil texture, water retention, and microbial activity. The random intercepts for soil texture in the HB model allow for texture-specific baseline differences in SOC levels, which become increasingly important with depth. This suggests increasing variability with depth, where a model that allows for different effects across groups provides a better fit. A hierarchical model is better suited to handle this variability because it allows different locations or soil types to have distinct relationships while still borrowing strength from the overall dataset. This flexibility makes the HB model better suited for capturing the complex and site-dependent nature of subsoil SOC processes, where environmental and microbial factors play a greater role than direct human intervention.

Figure 1 shows the posterior density intervals of the parameters at each soil layer. The solid dots indicate mean posterior estimates, and the error bars indicate 95% posterior credible intervals. The depiction makes it possible to visualize the differences between parameter estimates across each soil layer and the shape of the intervals shows the dispersion of the estimates. A key observation from the figure is that the credible intervals for each variable generally widen as soil depth increases.

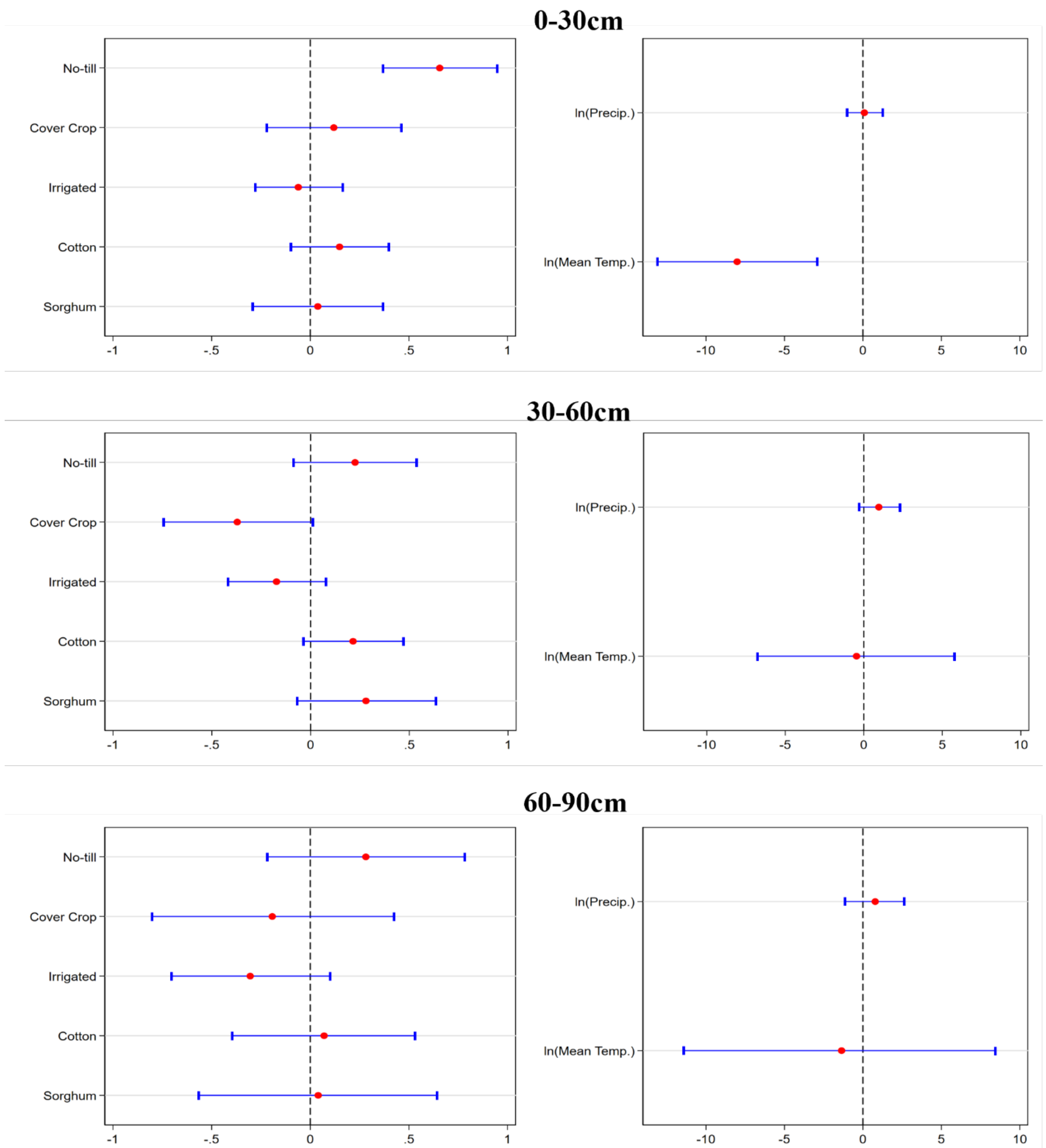


Figure 1: Posterior Density Intervals

This indicates greater uncertainty in the estimated effects of various management practices and environmental factors on SOC at deeper depths. This figure underscores the importance of considering depth when assessing the impact of land management and environmental factors on soil carbon storage. The widening credible intervals at greater depths and increasing uncertainty emphasize the need for deeper soil measurements in future studies to improve model precision. The posterior distributions of the random intercepts across depth for each soil texture are shown Figure 2.

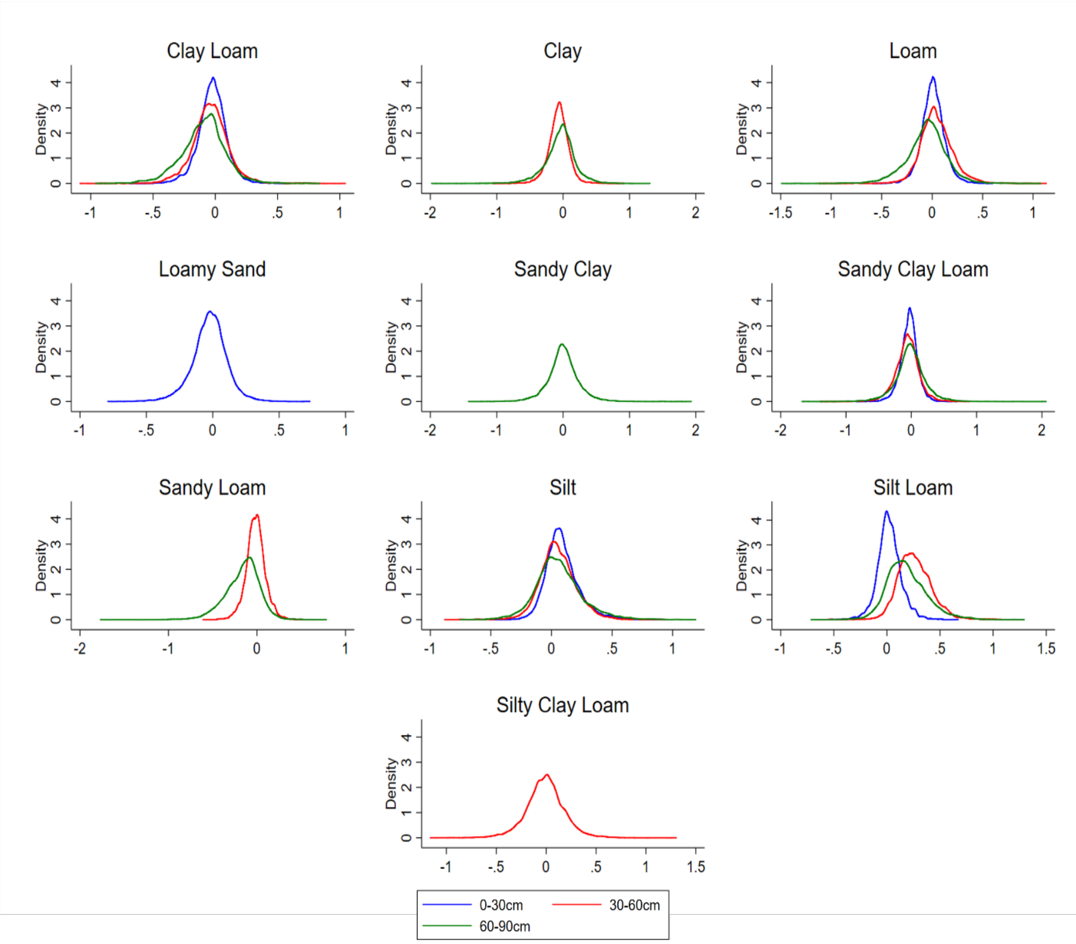


Figure 2: Posterior Distributions of the Random Intercepts

The y-axis represents the density, illustrating the relative probability of different values occurring within the posterior samples. The key pattern that emerges across all textures is that the surface layer (0–30 cm) consistently exhibits the narrowest and tallest distribution, while the distributions at deeper depths become progressively wider and more dispersed. The tighter distributions in the soil surface suggest that estimates of the random intercepts are more precise at the 0-30 cm depth. In contrast, the widening of distributions at deeper soil layers indicates greater variability in the posterior estimates, meaning the effect of soil texture on the random intercepts becomes less certain as depth increases. This could be due to more heterogeneous environmental influences at deeper depths, such as variability in root penetration, water movement, and organic matter accumulation.

SOC Predictions

Table 7 shows the predictions of average levels of SOC in tons per acre and total SOC stock in the entire 0-90 cm soil profile and additional summary statistics for individual counties in the THP.[4] The predictions were made using equations 8-12 and the results from the HB models presented in Tables 3, 4, and 5. Additionally, county-level data on agricultural practices from the 2022 Census of Agriculture, precipitation and mean temperature from the PRISM Climate Group, and dominant soil texture for each soil layer from the USDA Web Soil Survey were obtained for SOC predictions. Acreage totals for each of the individual practices were not reported for 10 counties the THP.[5] Therefore, Table 7 presents results for 29 of the 39 counties in the THP, average values for the Northern High Plains (NHP) and Southern High Plains (SHP) sub regions, and average values for the entire THP. Instead of simply using the mean values presented in Tables 3, 4, and 5, the full set of 30,000 MCMC posterior iterations were used to generate predictive distributions of SOC levels across individual counties. This approach helps account for the uncertainty and variability in the parameter estimates and should provide a more comprehensive picture of potential levels of SOC rather than levels estimated from a single deterministic prediction.

Table 7: SOC Predictions: 0-90 cm

| County | SOC (tons/acre) | | | | SOC Stock (million tons) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev. | Min | Max | Mean | St.Dev. | Min | Max |
| **NHP** | 29.97 | 10.95 | 9.22 | 693.03 | 8.780 | 5.793 | .795 | 245.000 |

[4] The predictions were made for each of the three soil layers independently and aggregated to find the values presented in Table 7.
[5] The data are often withheld to avoid disclosing information on individual farms (USDA, 2024).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Briscoe | 30.87 | 7.76 | 13.32 | 174.00 | 2.928 | .736 | 1.263 | 16.500 |
| Carson | 41.09 | 14.82 | 11.52 | 450.49 | 14.100 | 5.076 | 3.946 | 154.000 |
| Castro | 26.04 | 4.89 | 13.04 | 84.39 | 10.200 | 1.909 | 5.090 | 32.900 |
| Dallam | 31.79 | 7.67 | 12.96 | 151.09 | 13.100 | 3.155 | 5.328 | 62.100 |
| Deaf Smith | 24.95 | 5.08 | 12.16 | 99.28 | 13.500 | 2.747 | 6.571 | 53.600 |
| Floyd | 22.76 | 5.04 | 9.22 | 86.00 | 7.433 | 1.647 | 3.011 | 28.100 |
| Gray | 40.73 | 19.36 | 10.30 | 693.03 | 5.903 | 2.805 | 1.492 | 100.000 |
| Hale | 43.28 | 19.22 | 9.42 | 515.55 | 20.600 | 9.150 | 4.484 | 245.000 |
| Hansford | 24.03 | 6.23 | 9.51 | 126.94 | 7.799 | 2.021 | 3.086 | 41.200 |
| Hartley | 26.24 | 6.66 | 11.01 | 134.15 | 9.406 | 2.388 | 3.947 | 48.100 |
| Hutchinson | 30.39 | 7.25 | 13.33 | 164.38 | 2.877 | .686 | 1.261 | 15.600 |
| Lipscomb | 30.77 | 6.88 | 14.74 | 129.54 | 3.462 | .773 | 1.658 | 14.600 |
| Oldham | 28.76 | 5.89 | 14.78 | 118.45 | 3.390 | .694 | 1.742 | 14.000 |
| Parmer | 26.09 | 5.17 | 13.13 | 88.26 | 11.600 | 2.301 | 5.849 | 39.300 |
| Potter | 25.07 | 5.48 | 11.78 | 89.27 | 1.692 | .369 | .795 | 6.025 |
| Randall | 29.16 | 6.52 | 13.20 | 151.94 | 6.450 | 1.443 | 2.920 | 33.600 |
| Sherman | 28.34 | 6.41 | 12.61 | 128.42 | 11.400 | 2.589 | 5.092 | 51.900 |
| Swisher | 29.14 | 5.84 | 14.17 | 109.01 | 12.200 | 2.451 | 5.948 | 45.800 |
| **SHP** | 27.76 | 12.49 | 6.14 | 834.71 | 10.700 | 6.069 | 2.205 | 414.000 |
| Bailey | 31.14 | 6.80 | 14.89 | 135.13 | 6.893 | 1.504 | 3.296 | 29.900 |
| Cochran | 25.92 | 5.74 | 11.62 | 98.99 | 7.477 | 1.656 | 3.351 | 28.600 |
| Crosby | 27.40 | 8.24 | 9.34 | 196.13 | 8.259 | 2.485 | 2.816 | 59.100 |
| Dawson | 26.43 | 12.60 | 6.14 | 297.77 | 11.900 | 5.678 | 2.767 | 134.000 |
| Gaines | 19.36 | 6.06 | 6.19 | 102.46 | 12.500 | 3.925 | 4.008 | 66.400 |
| Hockley | 27.67 | 7.28 | 10.45 | 158.27 | 12.200 | 3.218 | 4.620 | 70.000 |
| Lamb | 28.99 | 7.79 | 11.76 | 176.91 | 12.000 | 3.221 | 4.860 | 73.100 |
| Lubbock | 35.75 | 19.54 | 7.15 | 695.05 | 12.900 | 7.059 | 2.584 | 251.000 |
| Lynn | 22.37 | 7.02 | 7.78 | 107.97 | 9.784 | 3.070 | 3.404 | 47.200 |
| Terry | 37.02 | 22.69 | 6.46 | 834.71 | 18.400 | 11.300 | 3.208 | 414.000 |
| Yoakum | 23.38 | 5.07 | 10.60 | 73.73 | 4.865 | 1.054 | 2.205 | 15.300 |
| **THP** | 29.13 | 11.61 | 6.14 | 834.71 | 9.492 | 5.969 | .795 | 414.000 |

The counties with the highest and lowest average level of SOC in the 0-90 cm soil profile are Hale County with 43.28 tons/acre and Gaines County with 19.36 tons/acre, respectively. The higher average SOC level in Hale County can be mostly attributed to the number of acres under no-till and acres planted to cotton in the county given the use of no-till and fields planted to cotton were associated with higher levels of SOC in the HB models for each soil depth. Of the counties presented in Table 7, Hale County has the third highest total acres under no-till and the highest total acres planted to cotton in the THP. Conversely, the low predicted average value of SOC in Gaines County can be attributed mostly to the higher number of irrigated acres and total acres planted to a cover crop in the county. Gaines county has the fifth highest total number of irrigated acres, and the highest total acres planted to a cover crop in the THP. While the results of the HB models showed irrigated fields to be associated with lower levels of SOC in each of the three soil depths, cover cropping was associated with higher levels in the surface 30 cm of the soil. However, cover cropping was associated with lowers levels of SOC in both the 30-60 cm and 60-90 cm soil layers and the negative association in the lower two layers is enough to outweigh the positive association in the surface 30 cm when considering the entire 0-90 cm soil profile.

Regarding the total stock of SOC, Hale County also has the highest total stock of SOC at 20.6 million tons (MT) and Potter County has the lowest at 1.69 MT. It is important to note that the stock of SOC in each county represents the total stock of SOC in the cropland of the county and not the entirety of the county. That is, the stock values in Table 7 are calculated by directly multiplying the average level of SOC per acre by the total number of cropland acres in each county. Therefore, because Hale County has the overall highest average level of SOC per acre and the fourth highest total cropland acres it is reasonable that the highest total stock of SOC is in Hale County as well. However, while Gaines County has the lowest average level of SOC per acre it is also the county with the highest total acres of cropland in the THP. The high number of cropland acres in Gaines County results in the total stock of SOC in the county to be above the average for the entire THP. The low total stock of SOC in Potter County is a result of the county having the lowest total cropland acres in the THP

Sensitivity Analyses

Because the use of no-till and cover cropping have been routinely promoted to producers as practices to increase levels of SOC in their fields and cotton is an important commodity grown in the THP, sensitivity analyses were conducted to evaluate how increasing total acreage in the THP under each practice and planted to cotton affected the stock of SOC in the region's cropland. Specifically, the total acres under no-till, cover cropping, and planted to cotton in each county were independently increased by 5%, 10%, 25%, and 50%, and the predicted stock of SOC was recalculated for each county and compared to the stock values in Table 7.[6] This comparison allowed assessment of the total changes in SOC stock from increasing the total number of acres allocated to no-till, cover cropping, and planted to cotton in the THP. Table 8 shows the net increase or decrease in total stock of SOC resulting from a 5%, 10%, 25%, and 50% increase in total acres under no-till, cover cropping, and planted to cotton for the NHP, SHP, and entire THP.

[6] The mean stock values in Table 7 represent the total stock in the entire 0-90 cm soil profile. The values used in Table 8 are the total stock values in each soil layer.

Table 8: Net Changes in SOC Stock due to Changes in Acre Allocations

| | | No-Till Acreage | | | | Cover Cropping Acreage | | | | Cotton Acreage | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0-30 cm | | | | 0-30 cm | | | | 0-30 cm | | | |
| | **Base** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** |
| **NHP** | 40847533 | 247992 | 497869 | 1259019 | 2567068 | 20563 | 41181 | 103366 | 208131 | 22790 | 45608 | 114281 | 229437 |
| **SHP** | 21424183 | 111342 | 223393 | 563883 | 1146148 | 14525 | 29097 | 73092 | 147380 | 20419 | 40876 | 102495 | 206014 |
| **THP** | 62271716 | 359334 | 721262 | 1822902 | 3713216 | 35088 | 70278 | 176458 | 355511 | 43209 | 86484 | 216776 | 435451 |
| | | **30-60 cm** | | | | **30-60 cm** | | | | **30-60 cm** | | | |
| | **Base** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** |
| **NHP** | 50295370 | 102058 | 204486 | 514034 | 1037590 | -93816 | -187310 | -465876 | -923811 | 47617 | 95322 | 238991 | 480315 |
| **SHP** | 36561106 | 62727 | 125648 | 315607 | 636229 | -103109 | -205830 | -511660 | -1013711 | 47700 | 95500 | 239517 | 481611 |
| **THP** | 86856476 | 164785 | 330134 | 829641 | 1673819 | -196925 | -393140 | -977536 | -1937522 | 95317 | 190822 | 478508 | 961926 |
| | | **60-90 cm** | | | | **60-90 cm** | | | | **60-90 cm** | | | |
| | **Base** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** | **+5%** | **+10%** | **+25%** | **+50%** |
| **NHP** | 66899479 | 152295 | 305449 | 770183 | 1562592 | -69466 | -138585 | -343871 | -679171 | 6005 | 12127 | 31237 | 65536 |
| **SHP** | 59257272 | 91161 | 282751 | 560154 | 1231394 | -92804 | -185133 | -559280 | -1128886 | 4014 | 8186 | 21680 | 47436 |
| **THP** | 1.26E+08 | 243456 | 588200 | 1330337 | 2793986 | -162270 | -323718 | -903151 | -1808057 | 10019 | 20313 | 52917 | 112972 |

The results in Table 8 show that increasing the total acreage under no-till causes the stock of SOC to increase at each depth level in both the NHP and SHP with the largest increases in the surface 30 cm in the NHP. Increasing the total number of acres planted to cotton also results in net increases to SOC stocks in both the NHP and SHP in every soil layer. In contrast, the largest increases in SOC stocks from increasing cotton acreage are in the 30-60 cm soil layer compared to the surface layer with no-till. Similarly, increasing the total acreage of cropland utilizing cover crops results in net increases in the SOC stocks of both the NHP and SHP in the surface 30 cm of the soil. However, increased cover cropping results in net decreases in the SOC stocks of both the NHP and SHP in both the 30-60 cm soil layer and 60-90 cm layer. The net decreases in SOC stocks in the subsurface soil layers are also large enough to offset all the net increases in SOC stocks in the surface 30 cm of the soil resulting from increases in the total acreage of cover cropping in the region.

While the results in Table 8 show net increases or decreases in SOC stocks across the THP and offer critical insights into the environmental impacts of shifting land management practices, they do not fully capture the economic implications for producers of increasing SOC stocks. To contextualize the above changes in SOC stocks within a potential soil carbon market framework, average per acre potential revenues that producers may earn were calculated based on varying prices of SOC credits and various depths of SOC credit recognition. These revenues reflect how changes in acreage under no-till practices, cover cropping, and cotton cultivation could translate into tangible financial returns to producers in the THP, depending on the potential market structure and the specific crediting protocols employed. The potential revenue estimates from no-till adoption across the THP highlight both the opportunities and limitations for producers participating in voluntary carbon markets and are presented in Table 9.

Table 9: Potential Revenue from Increased No-Till Adoption Across Depths and Payment Levels

| | No-Till Acreage | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0-30 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.23 | 0.47 | 0.94 | 2.34 | 0.47 | 0.94 | 1.88 | 4.70 | 1.19 | 2.38 | 4.76 | 11.89 | 2.43 | 4.85 | 9.70 | 24.25 |
| SHP | 0.13 | 0.26 | 0.52 | 1.30 | 0.26 | 0.52 | 1.05 | 2.62 | 0.66 | 1.32 | 2.64 | 6.60 | 1.34 | 2.69 | 5.37 | 13.43 |
| THP | 0.19 | 0.38 | 0.75 | 1.88 | 0.38 | 0.75 | 1.51 | 3.77 | 0.95 | 1.91 | 3.81 | 9.53 | 1.94 | 3.88 | 7.77 | 19.42 |
| | 0-60 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.33 | 0.66 | 1.32 | 3.31 | 0.66 | 1.33 | 2.65 | 6.63 | 1.67 | 3.35 | 6.70 | 16.75 | 3.41 | 6.81 | 13.62 | 34.05 |
| SHP | 0.20 | 0.41 | 0.82 | 2.04 | 0.41 | 0.82 | 1.64 | 4.09 | 1.03 | 2.06 | 4.12 | 10.30 | 2.09 | 4.18 | 8.35 | 20.88 |
| THP | 0.27 | 0.55 | 1.10 | 2.74 | 0.55 | 1.10 | 2.20 | 5.50 | 1.39 | 2.77 | 5.55 | 13.87 | 2.82 | 5.63 | 11.27 | 28.17 |
| | 0-90 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.47 | 0.95 | 1.90 | 4.75 | 0.95 | 1.90 | 3.81 | 9.52 | 2.40 | 4.81 | 9.61 | 24.03 | 4.88 | 9.76 | 19.53 | 48.81 |
| SHP | 0.31 | 0.62 | 1.24 | 3.11 | 0.74 | 1.48 | 2.96 | 7.40 | 1.69 | 3.37 | 6.75 | 16.86 | 3.53 | 7.06 | 14.12 | 35.30 |
| THP | 0.40 | 0.80 | 1.61 | 4.01 | 0.86 | 1.71 | 3.43 | 8.57 | 2.08 | 4.17 | 8.33 | 20.83 | 4.28 | 8.56 | 17.11 | 42.78 |

The results in Table 9 indicate that while adopting no-till practices can generate additional income through carbon credits, the financial incentives under lower credit prices and modest acreage increases are relatively limited. For instance, at a carbon credit price of $5 per ton and a 5% increase in no-till acreage, average per-acre revenues remain minimal, ranging from $0.13 in the SHP to $0.23 in the NHP for the 0-30 cm crediting depth. Even when increasing the crediting depth to 90 cm, revenues under these conditions only rise to $0.31 and $0.47 per acre for SHP and NHP, respectively. These small returns may be insufficient to motivate producers to adopt no-till solely for carbon market participation, especially when considering the potential costs of implementation, measurement, and verification.

However, the revenue potential improves significantly with larger acreage expansions and higher carbon credit prices. At $50/ton and a 50% increase in no-till acreage, revenues reach $24.25 per acre in the NHP and $13.43 in the SHP for the 0-30 cm depth, with even higher returns at deeper crediting depths—up to $48.81 per acre in the NHP and $35.30 in the SHP at 90 cm. These higher revenues could provide a more compelling economic incentive, particularly for larger-scale operations capable of implementing no-till practices across substantial portions of their land. Regional differences are also evident in the results, with the NHP consistently generating higher revenues compared to the SHP across all scenarios. This variation likely reflects differences in soil characteristics, baseline SOC levels, and local environmental conditions that influence sequestration rates. Moreover, the HB model results indicated that cover cropping is associated with higher levels of SOC in the surface 30 cm of the soil. This is reflected in the positive potential revenues observed across the THP at the 0–30 cm depth presented in Table 10.

Table 10: Potential Revenue from Increased Cover Crop Adoption Across Depths and Payment Levels

| | Cover Cropping Acreage | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0-30 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.02 | 0.04 | 0.08 | 0.19 | 0.04 | 0.08 | 0.16 | 0.39 | 0.10 | 0.20 | 0.39 | 0.98 | 0.20 | 0.39 | 0.79 | 1.97 |
| SHP | 0.02 | 0.03 | 0.07 | 0.17 | 0.03 | 0.07 | 0.14 | 0.34 | 0.09 | 0.17 | 0.34 | 0.86 | 0.17 | 0.35 | 0.69 | 1.73 |
| THP | 0.02 | 0.04 | 0.07 | 0.18 | 0.04 | 0.07 | 0.15 | 0.37 | 0.09 | 0.18 | 0.37 | 0.92 | 0.19 | 0.37 | 0.74 | 1.86 |
| | 0-60 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | -0.07 | -0.14 | -0.28 | -0.69 | -0.14 | -0.28 | -0.55 | -1.38 | -0.34 | -0.68 | -1.37 | -3.42 | -0.68 | -1.35 | -2.70 | -6.76 |
| SHP | -0.10 | -0.21 | -0.42 | -1.04 | -0.21 | -0.41 | -0.83 | -2.07 | -0.51 | -1.03 | -2.05 | -5.14 | -1.01 | -2.03 | -4.06 | -10.15 |
| THP | -0.08 | -0.17 | -0.34 | -0.85 | -0.17 | -0.34 | -0.68 | -1.69 | -0.42 | -0.84 | -1.68 | -4.19 | -0.83 | -1.65 | -3.31 | -8.27 |
| | 0-90 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | -0.13 | -0.27 | -0.54 | -1.35 | -0.27 | -0.54 | -1.08 | -2.69 | -0.67 | -1.33 | -2.67 | -6.67 | -1.32 | -2.64 | -5.27 | -13.18 |
| SHP | -0.21 | -0.42 | -0.85 | -2.12 | -0.42 | -0.85 | -1.7 | -4.24 | -1.17 | -2.34 | -4.68 | -11.69 | -2.34 | -4.67 | -9.35 | -23.37 |
| THP | -0.17 | -0.34 | -0.68 | -1.69 | -0.34 | -0.68 | -1.35 | -3.38 | -0.89 | -1.78 | -3.56 | -8.91 | -1.77 | -3.55 | -7.09 | -17.73 |

For instance, in the entire THP, with a 50% increase in cover cropping acreage and a carbon price of $50/ton, potential revenue reaches only $1.97/acre. While these revenues are relatively modest compared to those from no-till adoption, they suggest that cover cropping can generate economic returns when surface SOC accumulations are credited. The positive association between cover cropping and SOC in the surface soil aligns with expectations, given that cover crops contribute to organic matter inputs primarily near the surface through root biomass and residue deposition. Payments tied to SOC sequestration would therefore be most substantial when focusing on the 0–30 cm depth, where SOC gains are evident across all regions. However, the results for deeper soil layers revealed SOC under cover cropping to be lower, and this is similarly indicated by negative values in Table 10. These negative values reflect potential decreases in SOC, suggesting that cover cropping may not consistently enhance carbon storage at greater depths. From a carbon market perspective, these losses would not result in negative payments; rather, they would translate to zero payments, as credits are awarded only for positive SOC sequestration. This highlights the importance of depth-specific monitoring in carbon programs to ensure accurate assessments of carbon gains.

The HB model results similarly showed positive associations between levels of SOC and fields planted to cotton across all measured depths. In the surface 0-30 cm layer, positive revenues for SOC payments were observed across all regions, with higher payments leading to greater potential revenues as shown in Table 11. For example, a 50% increase in cotton acreage in the NHP was associated with potential revenues ranging from $0.22 to $2.17 per acre, depending on the payment rate. Similar trends were seen in the SHP and entire THP where 50% acreage increases yielded revenues up to $2.41 and $2.28 per acre, respectively. These results highlight that expanding cotton acreage may be able to enhance SOC in the surface soils of the THP, particularly under higher payment scenarios.

The HB models for deeper soil layers (30-60 cm and 60-90 cm) also showed positive SOC associations when cotton was planted prior to sampling, and increasing crediting depth for potential market transactions would thereby increase the potential revenue for producers. When the crediting depth includes the top 60 cm, potential revenues ranged from \$0.67 to \$6.70 per acre in the NHP under a 50% acreage increase, while SHP and THP exhibited similar patterns, with maximum revenues reaching \$8.05 and \$7.31 per acre, respectively. At the 0-90 cm crediting depth, the results remained consistent, with SOC increases translating to higher potential revenues across both the NHP and SHP. The NHP showed potential revenues up to \$7.32 per acre under the highest payment and acreage increase scenarios. The SHP and entire THP followed similar trends, with revenues reaching \$8.61 and \$7.90 per acre, respectively. Overall, the results indicate that increasing cotton acreage is positively associated with SOC gains at multiple soil depths. Unlike the mixed results observed with other practices, such as cover cropping, cotton expansion consistently led to SOC increases across all measured depths and regions. Therefore, increasing cotton acreage could benefit producers from carbon payments in a potential SOC market, though average returns may be marginal at low prices for soil carbon.

Table 11: Potential Revenue from Increased Cotton Acreage Across Depths and Payment Levels

| | Cotton Acreage | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0-30 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.02 | 0.04 | 0.09 | 0.22 | 0.04 | 0.09 | 0.17 | 0.43 | 0.11 | 0.22 | 0.43 | 1.08 | 0.22 | 0.43 | 0.87 | 2.17 |
| SHP | 0.02 | 0.05 | 0.10 | 0.24 | 0.05 | 0.10 | 0.19 | 0.48 | 0.12 | 0.24 | 0.48 | 1.20 | 0.24 | 0.48 | 0.97 | 2.41 |
| THP | 0.02 | 0.05 | 0.09 | 0.23 | 0.05 | 0.09 | 0.18 | 0.45 | 0.11 | 0.23 | 0.45 | 1.13 | 0.23 | 0.46 | 0.91 | 2.28 |
| | 0-60 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.06 | 0.13 | 0.27 | 0.67 | 0.13 | 0.27 | 0.53 | 1.33 | 0.33 | 0.67 | 1.33 | 3.34 | 0.67 | 1.34 | 2.68 | 6.70 |
| SHP | 0.08 | 0.16 | 0.32 | 0.80 | 0.16 | 0.32 | 0.64 | 1.60 | 0.40 | 0.80 | 1.60 | 4.01 | 0.81 | 1.61 | 3.22 | 8.05 |
| THP | 0.07 | 0.14 | 0.29 | 0.72 | 0.15 | 0.29 | 0.58 | 1.45 | 0.36 | 0.73 | 1.45 | 3.64 | 0.73 | 1.46 | 2.92 | 7.31 |
| | 0-90 cm | | | | | | | | | | | | | | | |
| | +5% | | | | +10% | | | | +25% | | | | +50% | | | |
| | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 | $5 | $10 | $20 | $50 |
| NHP | 0.07 | 0.14 | 0.29 | 0.72 | 0.14 | 0.29 | 0.58 | 1.45 | 0.36 | 0.73 | 1.45 | 3.63 | 0.73 | 1.46 | 2.93 | 7.32 |
| SHP | 0.09 | 0.17 | 0.34 | 0.84 | 0.17 | 0.34 | 0.68 | 1.69 | 0.43 | 0.85 | 1.70 | 4.26 | 0.86 | 1.72 | 3.44 | 8.61 |
| THP | 0.08 | 0.16 | 0.31 | 0.78 | 0.16 | 0.31 | 0.62 | 1.56 | 0.39 | 0.78 | 1.57 | 3.91 | 0.79 | 1.58 | 3.16 | 7.90 |

**Discussion & Conclusion**

The purpose of this paper was to evaluate the agricultural production practices, soil textures, and environmental conditions that are associated with higher levels of SOC in the semi-arid THP and estimate both the potential SOC storage and revenue for producers with increasing SOC levels in the region. The results of the HB models give insights into the drivers of SOC levels across the THP at individual soil horizons. The posterior distributions revealed nuanced effects of management practices, crop choices, environmental factors, and soil types on SOC accumulation. The estimates of SOC stock and resulting changes in stock from increasing total acreage allocated to individual production practices showed that producers in the region may be able to marginally increase SOC levels. However, substantial increases in land dedicated to sequestering practices, along with relatively high prices for soil carbon, may be necessary to create strong enough economic incentives for producers to actively manage soil carbon in a potential regional SOC market.

Regarding specific management practices, no-till practices had a positive mean effect on SOC in each soil layer and cover cropping was associated with higher levels of SOC in only the surface 30 cm of the soil. Specifically, no-till and cover cropping were associated with 92.7% and 12.6% higher levels of SOC in the top 30 cm of the soil, respectively. The mean effect of no-till generally decreased with soil depth with less certain and weaker effects in the 30-60 cm and 60-90 cm soil layers, and the mean effect of cover cropping is negative in subsurface soil layers which may suggest a tradeoff between subsurface and surface soil carbon dynamics. These findings are similar with previous research in the THP that found higher SOC levels in soil surface layers with no-till and cover cropping (Lewis et al., 2018; Schwartz et al., 2015). However, the HB models showed no-till to have a positive association with SOC throughout the entire 0-90 cm profile which differs from Lewis et al. (2018) who found no significant difference in SOC between no-till and conventional tillage below the surface 15 cm of the soil.

Irrigation showed a consistent negative mean effect on SOC that increased at each subsequent depth, implying that irrigation may limit SOC accumulation due possibly to leaching effects or enhanced decomposition. Alternatively, it may suggest that water availability alone doesn't drive deeper SOC accumulation without complementary management practices. A notable point for consideration when interpreting the results of the HB models is the residual variance ($\sigma^2_{SOC}$) which increases notably with depth. This highlights the greater unexplained variability in SOC at deeper soil layer and indicates that surface SOC may be more strongly influenced by management and environmental conditions while deeper SOC may be affected by unmeasured or more complex processes. The crop grown prior to soil sampling also impacted SOC levels. Compared to corn, a prior crop of both cotton and sorghum were associated with higher levels of SOC in each soil layer, particularly in the 30-60 cm layer. Environmental variables similarly played critical roles, with precipitation positively influencing SOC, especially in the subsoil layers, though with wide uncertainty. In contrast, higher mean temperatures were consistently associated with lower SOC, particularly in the topsoil where the negative effect is strongest, possibly reflecting the role of temperature in accelerating organic matter decomposition.

Soil texture exhibited varying influences across each of the soil depths. Throughout the entire soil profile considered, soils with a higher percentage of silt (e.g., Loam, Silt, and Silt Loam) were associated with higher levels of SOC, apart from Loam in the 60-90 cm layer of the soil. In contrast, soils with a higher percentage of clay (e.g., Sandy Clay Loam, Clay Loam, Silty Clay Loam, and Clay) were generally associated with lower levels of SOC throughout the entire soil profile considered. Additionally, the variance of soil type effects (i.e., $\sigma^2_U$) increases with depth, from 0.027 in the surface layer to 0.078 in the deepest layer, indicating greater heterogeneity in SOC levels among soil types at deeper depths. The higher SOC in soils such as silt loam aligns with literature finding a positive association between percentage silt and SOC in regions where soil water may be a limiting production factor (Augustin & Cihacek, 2016). Similarly, as agricultural production is limited by water availability in semi-arid regions, soil textural components with high water holding capacities such as silt may improve plant productivity and carbon inputs into the soil (Burke et al., 1989; Hanks et al., 1969).

Because soil texture impacts both plant available water and water holding capacity, well drained more coarse soils may result in elevated oxidation of soil organic matter (Augustin & Cihacek, 2016). However, the generally wide credible intervals from the HB models suggest significant variability within soil types, reinforcing the importance of localized studies when scaling carbon estimates. Moreover, the DIC values indicated that a Bayesian pooled model performed better than the hierarchical model at the soil surface, where management effects are likely stronger and more uniform. The hierarchical models performed better in the deeper soil layers, where increased uncertainty and weaker management effects may necessitate a more flexible modeling approach.

SOC stock predictions across counties show notable heterogeneity. Counties like Hale (43.28 tons/acre) and Lubbock (35.75 tons/acre) exhibited higher mean SOC stocks, while Gaines (19.36 tons/acre) and Lynn (22.37 tons/acre) had lower values. High standard deviations in counties like Terry (22.69) and Lubbock (19.54) highlight the spatial variability and uncertainties in SOC stocks, likely driven by diverse management practices, soil types, and climatic variations. The large predicted range in total SOC stock (e.g., Hale's 20.6 MT vs. Potter's 1.7 MT) underscores the potential for targeted carbon sequestration strategies focusing on high-potential areas.

Average revenues producers may reasonably expect from payments in a potential market for SOC were also estimated. Overall, the findings suggested that while voluntary carbon markets can offer economic benefits for no-till and cover crop adoption, the magnitude of those benefits is highly sensitive to credit prices, acreage changes, and crediting depths. Under market conditions with relatively low credit prices, the financial incentives may be insufficient for widespread adoption. However, if carbon markets mature and prices rise, or if policies begin to credit SOC below surface layers, the economic feasibility of no-till adoption could improve, potentially encouraging broader participation among producers in the THP. The varying SOC responses across depths underscore the complexity of soil carbon dynamics under cover cropping. While surface SOC improvements are promising for carbon sequestration incentives, the potential for SOC losses at deeper depths with cover cropping calls for further investigation into management practices that promote carbon stability throughout the soil profile. This understanding is crucial for designing effective carbon programs that maximize sequestration benefits while minimizing unintended outcomes. The results also showed the potential for cotton acreage expansion to contribute to carbon sequestration efforts in the THP, offering meaningful revenue opportunities under carbon payment programs. Additionally, these findings suggest that by crediting producers for SOC gains beyond surface soils, they would have more of an economic incentive to maintain and/or increase their SOC stocks which could potentially enhance long-term carbon storage in the region.

This study provides a comprehensive assessment of the factors influencing SOC sequestration across the THP using a HB framework. The findings suggest that management practices, environmental factors, and soil types jointly shape SOC dynamics, though substantial variability and uncertainty persist. Additionally, the results give insight into the spatial distribution of the SOC stocks of cropland in the region, and how producers in the region may induce increases in SOC stocks while obtaining additional revenue through selling SOC credits in a potential voluntary market. Future research should focus on refining estimates by incorporating longer-term datasets, especially for management practices like cover cropping, and integrating more precise spatial data to improve model accuracy. Additionally, exploring the economic feasibility of deep SOC sequestration, given the observed spatial variability, could guide policy development and incentive structures in the THP. Understanding these dynamics will be critical for designing effective carbon sequestration strategies that maximize both environmental and economic benefits.

This study contributes to the growing body of literature on SOC in semi-arid agricultural systems by providing the first Bayesian analysis of SOC levels across multiple soil depths in the THP. By explicitly modeling the relationships between management practices, environmental conditions, and soil texture with SOC at different depths, this study enhances understanding of the factors driving SOC variability at both spatial and soil profile scales. A key contribution of this study is its depth-specific evaluation of SOC levels under different agricultural management practices. While previous research has extensively examined surface SOC responses to conservation practices like no-till and cover cropping, this study extends the analysis to subsurface layers, revealing key differences in SOC distribution across depths. The finding that no-till practices are associated with consistently higher SOC levels at all depths, while cover cropping primarily increases SOC in surface soils but may reduce it in deeper layers, refines existing knowledge on the long-term effects of these practices. This depth-dependent response highlights the need for more nuanced evaluations of SOC dynamics when assessing management impacts.

Another important contribution is the use of a HB modeling framework, which provides a probabilistic approach to understanding SOC variation across the region. Unlike traditional regression-based methods, the HB approach better accounts for the uncertainty in SOC estimates. The results demonstrate that deeper soil layers exhibit greater unexplained variability, suggesting that while surface SOC is more strongly influenced by management and environmental conditions, deeper SOC levels may be governed by more complex or unmeasured processes. This insight is valuable for refining future studies on SOC distribution and variability, particularly in semi-arid regions. Moreover, the results of the HB models presented in this study may serve to prime the prior distributions of future Bayesian analyses looking at the impact of agricultural practices and environmental characteristics on SOC concentrations.

This study also advances the literature on the economic implications of SOC management by linking SOC estimates with potential revenue from voluntary carbon markets. While previous studies have explored the financial feasibility of conservation practices, this study integrates regional SOC estimates with economic considerations, demonstrating that revenue potential is highly dependent on carbon prices, crediting depth, and the scale of adoption. These findings contribute to discussions on market-based incentives for soil carbon management and the role of policy in shaping economic opportunities for producers in the THP.

Finally, this research provides new insights into spatial patterns of SOC across the THP, identifying counties with higher SOC stocks and those with greater variability. The substantial differences in SOC levels between counties underscore the importance of localized studies when evaluating soil carbon dynamics. Future research should incorporate spatial effects to help inform targeted soil management strategies, helping policymakers and producers identify areas where SOC-enhancing practices may be most effective. Together, these contributions provide a more detailed and regionally specific understanding of SOC dynamics in the THP, offering a potential modeling strategy for larger-scale estimates of SOC for future market developments and practical implications for soil management, economic incentives, and regional agricultural policy. Future research should build upon these findings by incorporating long-term datasets and higher-resolution spatial data to refine SOC estimates and better understand the drivers of SOC variability across different agricultural landscapes.

Limitations

This study provides insights into the relationships between SOC levels and key management and environmental factors in the THP. However, several limitations must be acknowledged. First, the analysis relies on cross-sectional data with only 67 observations for a single year which prevents the identification of SOC sequestration rates over time. A longitudinal dataset with repeated soil sampling would be necessary to assess the actual sequestration potential of different practices. Second, the HB models reveal substantial uncertainty. Many of the posterior mean values have credible intervals that contain zero, indicating a lack of statistical certainty about the direction or magnitude of some effects. Additionally, this uncertainty increases with soil depth, where SOC measurements exhibit greater variability and fewer strong predictors. Future studies could incorporate higher-resolution soil carbon measurements, longer-term data, or alternative modeling approaches that account for measurement error and spatial dependence.

Third, data constraints related to soil surveys and county-level Census of Agriculture data present additional challenges. Soil survey data often rely on broad-scale classifications that may not fully capture site-specific variations in soil properties and management history. Similarly, the use of county-level agricultural data limits the precision of economic and agronomic inferences at the farm level. Incorporating farm-level management records or remotely sensed data could improve the granularity and accuracy of future analyses. Fourth, the economic analysis focuses solely on potential revenues from carbon sequestration and does not account for the costs of implementation. The feasibility of adopting climate-smart agricultural practices depends not only on carbon payments but also on costs associated with changes in tillage, cover cropping, irrigation management, and potential yield impacts. Future research should develop a full cost-benefit analysis, incorporating both direct costs and opportunity costs, to better assess the net economic viability of SOC sequestration for producers in the region.

Beyond these limitations, this study raises several directions for future research. First, a time-series or panel dataset would allow for an assessment of SOC sequestration dynamics over time, rather than just current SOC levels. Integrating spatial econometric techniques could help account for spatial dependencies in SOC levels that arise from environmental and management similarities across locations. Third, exploring alternative Bayesian priors or incorporating additional hierarchical levels (e.g., field-level or regional effects) could improve the robustness of the Bayesian inference and reduce uncertainty in model estimates. Lastly, future work should expand the economic assessment to include carbon market dynamics, transaction costs, and producer decision-making under risk and uncertainty. By addressing these limitations and pursuing these research avenues, future studies can provide a more comprehensive understanding of the biophysical and economic feasibility of SOC sequestration in the THP and similar agricultural regions.

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