Final Technical Report

FCEB Project #12

FINAL REPORT AWD15832

1. Project Title and principal investigator contact information:

Digital soil carbon storage and sequestration mapping in Florida grazinglands through spatial sampling and machine learning methods

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Project Summary:

This project will assess the soil organic carbon (SOC) stocks in 15 beef cattle operations in Florida. Within each farm, we will determine the average SOC stock under different land use types. We will collect samples from the following land uses in each site: cropping fields, hay and/or baleage fields with perennial grasses, intensive grazing areas, pine tree areas, rangelands, and/or low-input areas. Additionally, we will predict the spatial variability of SOC stocks in grazing lands in Florida using earth observations, spatial covariates, and geospatial artificial intelligence methods. Project goals are to quantify the impact of different land uses on SOC stocks across the state and determine the most critical factors in controlling SOC stocks in Florida beef cattle operations. The project contributes to the spatially explicit ecosystem service assessments for grazing lands in Florida. These goals are aligned with the FCA research priorities Ecosystem Services of Grazing lands and are also aligned with the specific appropriation language. Mapping the SOC stocked in different land uses and locations can help to assess ecosystem services in beef cattle production systems in Florida, strengthening the market position of Florida's Cattle Industry by the aggregated value to the final product (beef). In this progress report we present our sampling design and preliminary information on the soil assessment across FL ranches.

Specific aims:

Our objective with this project is to: 1) assess soil organic carbon (SOC) stocks under different land use types in beef cattle farms; 2) assess and predict the spatial variability of SOC stocks in grazing lands in Florida using earth observations, spatial covariates, and geospatial artificial intelligence methods; 3) determine the most critical factors in controlling SOC stocks in Florida grazing lands. The project contributes to the spatially explicit ecosystem service assessments for grazing lands in Florida by measuring, modeling and spatially predicting soil carbon storage services, addressing the first program area priority about ecosystem services of grazing lands, and are also aligned with the specific appropriation language.

2. Significance

Almost one-half of all Florida agricultural land is involved in cattle production. Beef cattle operations in Florida are an important component of the State economy, producing high- quality food and generating income for producers and allied industries. Beef production systems in Florida are predominantly cow-calf operations, typically producing forages locally to reduce transportation costs. Most common forages include perennial C4 grasses such as bahiagrass (*Paspalum notatum* Flüggé) and bermudagrass [*Cynodon dactylon* (L.) Pers.]. Florida beef cattle systems are typically extensive, based on grazing forages. Diets based on forages produce a greater proportion of total volatile fatty acids as acetate, generating more hydrogen, which is substrate for methanogenesis (Janssen, 2010). Therefore, it is expected that forage- based systems used in the cow-calf phase will generate more methane per unit of carcass weight (CW) than feedlot systems with high-grain diets. Rotz et al. (2019) estimated that the cow-calf phase is responsible for almost 70% of the GHG emissions in US beef systems.

Although livestock has been the focus on greenhouse gas (GHG) emissions, especially methane released from enteric fermentation, the beef cattle operations based on grazing systems have high potential to sequester carbon. Less focus has been given to the potential to offset the livestock emissions by sequestering carbon. Soil in grazing lands contains significant quantities of carbon and presents opportunities for climate change mitigation through increased carbon storage (Adhikari and Hartemink, 2016). Mapping SOC stocks and associated uncertainties are fundamental to detect trends of gains or losses in SOC linked to recent and future regional and national policy decisions on carbon management strategies. To achieve appropriate soil carbon management, it is critical to know where the carbon-rich soil is, and how much carbon they hold. Nonetheless, information on SOC stocks distributions on regional grazing lands is largely available as discrete point observations, continuous spatial information of SOC stocks is still lacking. A key challenge in accurately mapping SOC stocks is the inherent spatial variability of soil carbon driving factors.

Assessing carbon stocks in beef cattle production fields would provide an estimate of the potential ecosystem service FL beef cattle systems are providing by accumulating soil organic carbon, promoting the Florida beef cattle industry. The more sustainable beef production can leverage the meat consumption and aggregate market value to the final product in Florida.

3. Approach

3.1. Soil organic carbon survey data

We will collect soil samples from 15 Florida beef cattle farms across the State. Farm selection will be based on geographical location and the willingness of the beef producer to participate in the project. We will try to select farms representing North, Central, and South Florida. We will keep the sites as uniform as possible regarding soil type using a web soil survey from USDA. Within each farm, we will collect samples from the following land uses: cropping fields, hay and/or baleage fields with perennial grasses, grazing areas on pastureland, pine tree areas, rangelands, and/or low-input areas. Each farm will be considered a block.

Soil samples will be collected using the Wintex® 3000 soil probe adapted to a RTV vehicle. On each land use type, we will collect a composite sample formed by 20 subsamples using a random transect in a representative area of the field. Soil samples will be collected down to 3 ft. depth, at the following soil layers: 0- to 6-, 6- to 12-, 12- to 36-inch layers. Soil cores will also be used to determine soil bulk density to estimate soil organic carbon stock. In addition, soil texture of each site will be determined within each layer. Soil organic C will be determined after acid fumigation to remove carbonates prior to total organic carbon analyzes (Harris et al., 2001). Soil samples from each layer will be ball milled in a Mixer Mill MM 400 (Retsch) for 9 min at 25 Hz and analyzed for total carbon using a CHNS analyzer (Vario Micro Cube) and the Dumas combustion method. Soil carbon stock of each land-use type within each farm will be estimated by using soil bulk density and soil organic C concentration within each soil layer.

Statistical analyses will be performed using proc mixed from SAS where land use type will be considered a fixed effect and farm site will be random effect. Soil layers will be considered repeated measures in space. We will analyze SOC stocks down to the entire soil profile and by layer.

3.2. Soil organic carbon spatial prediction

For the spatial prediction of SOC, several legacy soil data will be evaluated, harmonized, and integrated into a spatial database to provide data for model training, and for mapping SOC stocks once the model is developed. These include soil sample data from the World Soil Information Service (WoSIS) (Batjes et al., 2017), the Florida Soils Characterization Database, and the Florida Carbon Project by the Environmental Pedology Laboratory of the Soil Science Department, University of Florida.

Based on the SCORPAN (S: Soil, C: Climate, O: Organism, R: Relief, P: Parent material, A: Age, and T: time) framework in digital soil mapping (McBratney et al., 2003), five major factors have been identified to represent the controls on SOC stocks, including vegetation, topography, climate, land use and soil properties. The spatial covariates used in the study include Sentinel 2 surface reflectance and spectral indices, topographic variables such as digital elevation model (DEM) derivatives - slope, aspects, terrain roughness; climatic variables including temperature, precipitation; land use and land cover types; and soil properties including texture and soil type. We will select the most effective spatial covariates for modeling based on the recursive feature elimination (RFE) analysis.

We will use the Random Forest with Residuals Kriging (RFRK), a hybrid machine learning and geostatistical model for spatial prediction of SOC stocks (Figure 1). Random forest (RF) is a machine learning method that works well with high-dimensional problems and allows for nonlinear relationships between predictors. Kriging is a classical geostatistical model used to estimate the residuals so that the local error variance is minimized. Studies have shown that a hybrid model that combines the two models can increase the accuracy of SOC spatial predictivity, because it considers spatial autocorrelation between soil sampling points compared to non-spatial predictive model (Rostaminia et al., 2021). We will assess map accuracy using the coefficient of determination (R^2) and root mean squared error (RMSE) and create an uncertainty map of SOC stocks distribution by the Quantile Regression Forests method (Meinshausen and Ridgeway, 2006).

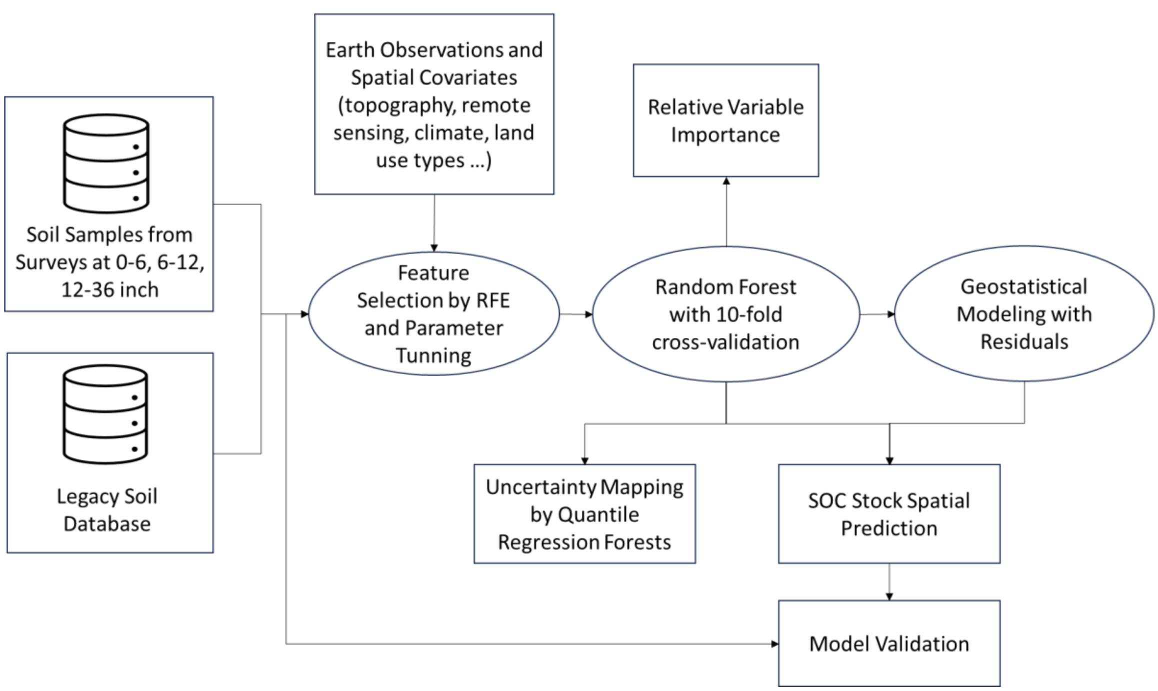

Figure 1. Methodological flowchart for modeling and mapping SOC stocks in Florida grazing lands

4. Results

5.1 Sampling design

Conditional Latin Hypercube Sampling

The Conditional Latin Hypercube Sampling (cLHS) is considered as a robust data-driven sampling strategy for selecting a statistically representative sample of a landscape based on environmental variables and their multivariate distribution. This stratified sampling procedure yields samples from multivariate feature space such that the multivariate distribution and correlation among auxiliary features are preserved. The algorithm is described in detail by McBratney et al., 2003. In this study, we used cLHS to select 15 georeferenced cattle farm locations for soil sampling across potential grazing lands in Florida, considering the spatial variability of topographical, climatic and land use patterns across the state. Due to practical operational restrictions of this sampling method in digital soil mapping, some selected points by cLHS may not be accessible in the field, we therefore also considered nearby geolocations to obtain alternative samples with a lower cost in time and labor.

We define potential grazing lands as any vegetated land areas, such as grasses and grass-like plants, forbs or shrubs that are grazed or has the potential to be grazed by livestock and wildlife (Allen et al., 2011). We reclassified land use and land covers from the Multi-Resolution Land Characteristics National Land Cover Database (MRLC NLCD) and the USDA NASS Cropland Data Layer, by which we assigned shrub/scrub, grassland/herbaceous, pasture/hay, and various areas of crops, such as sorghum, barley, wheat, and other small grains as potential grazing land use and land cover.

We excluded non-grazing lands in the cLHS sample selection process. Furthermore, a Digital Elevation Model (DEM) was produced for Florida from the USGS 3D Elevation Program (3DEP) which provides high-quality elevation data derived from LiDAR point clouds. Specifically, the USGS 3DEP 10m National Map Seamless (1/3 Arc-Second) was retrieved from Google Earth Engine (GEE). The DEM forms the basis for the calculation of four terrain attributes: (1) Slope; (2) Aspect; (3) Roughness; and (4) Topographic Position Index. Additional climatic and soil variables were extracted, including 30-year average of annual total precipitation and monthly mean temperature obtained from the PRISM Long-Term Average Climate Dataset Norm91m on GEE, and Hydrologic Soil Groups based on estimates of runoff potential from the USGS NRCS Gridded National Soil Survey Geographic Database (gNATSGO). All environmental data were resampled to 30-meter based on bilinear interpolation. The cLHS algorithm was performed in R using the clhs package.

Figure 1 shows the spatial distribution of the 15 selected georeferenced points for soil sampling by cLHS. It is notable that the points are spatially distributed throughout the state, covering northern, central, and southern Florida. Figures 2 and 3 show the distribution of environmental data among the population (the entire state of Florida) and sampled locations (selected points by cLHS). The shape of the histograms and boxplots are similar, with minor difference in mean and median. It is therefore suggested that the cLHS method can select statistically representative points in both geographical space and feature space, while preserving multivariate data distribution.

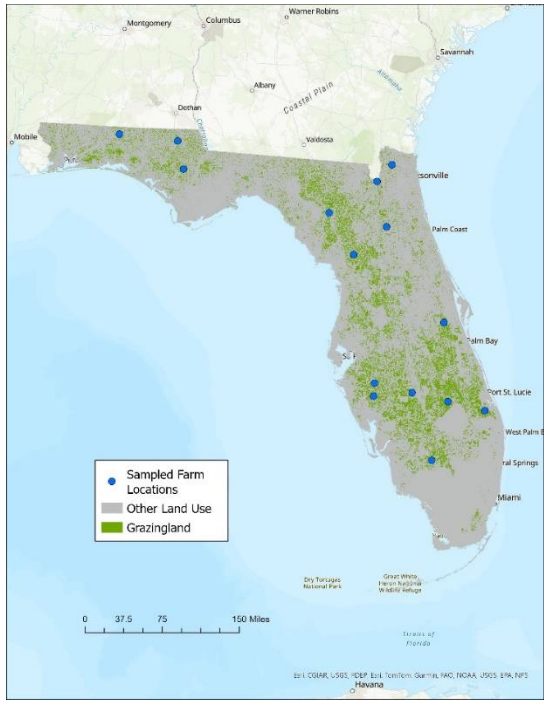

Fig 2. Spatial distribution of the selected soil sampling points by cLHS.

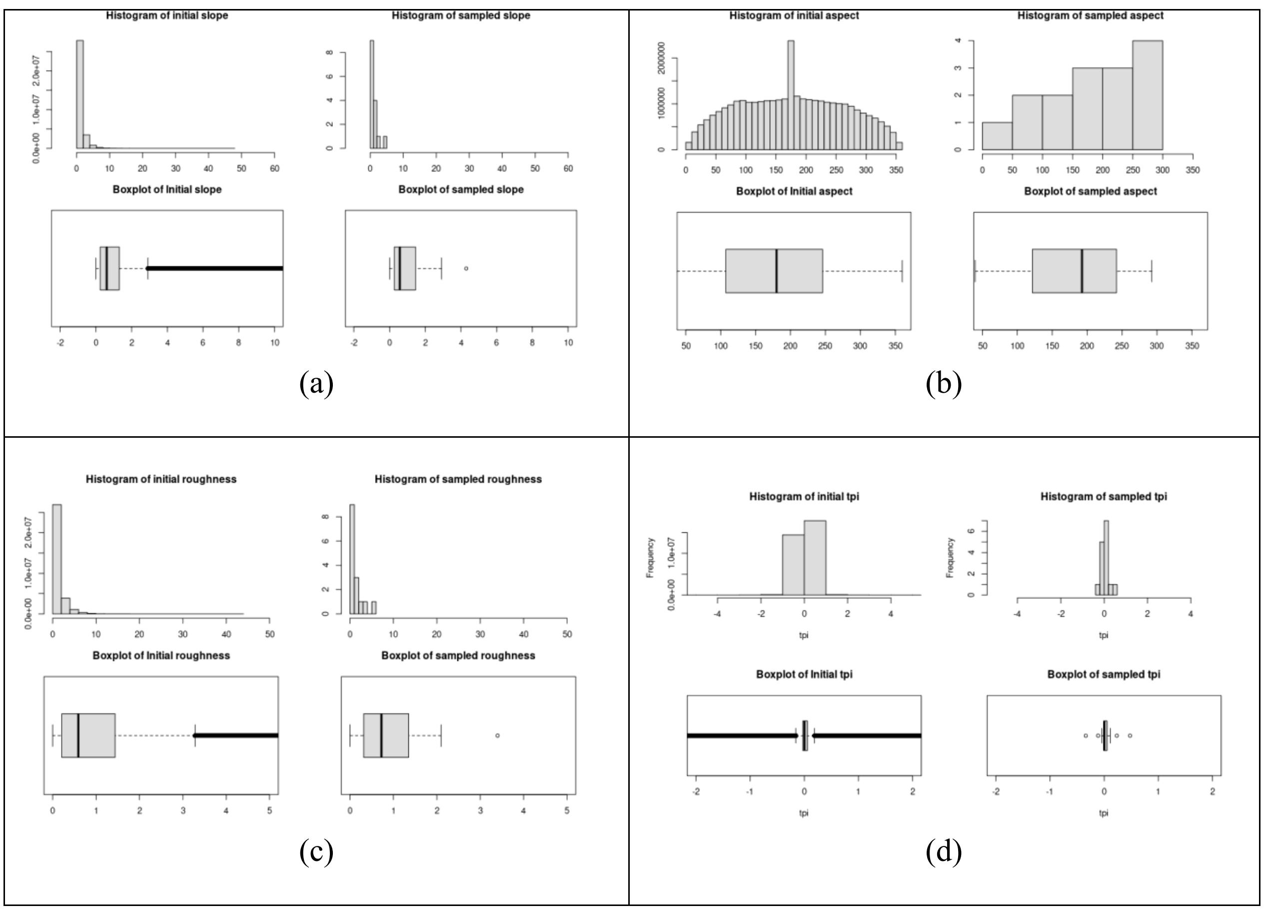

Fig 3. Distribution of DEM-derived variables among the population (the entire state of Florida) and sample (selected points by cLHS). (a) slope; (b) aspect; (c) roughness; (d) topographic position index.

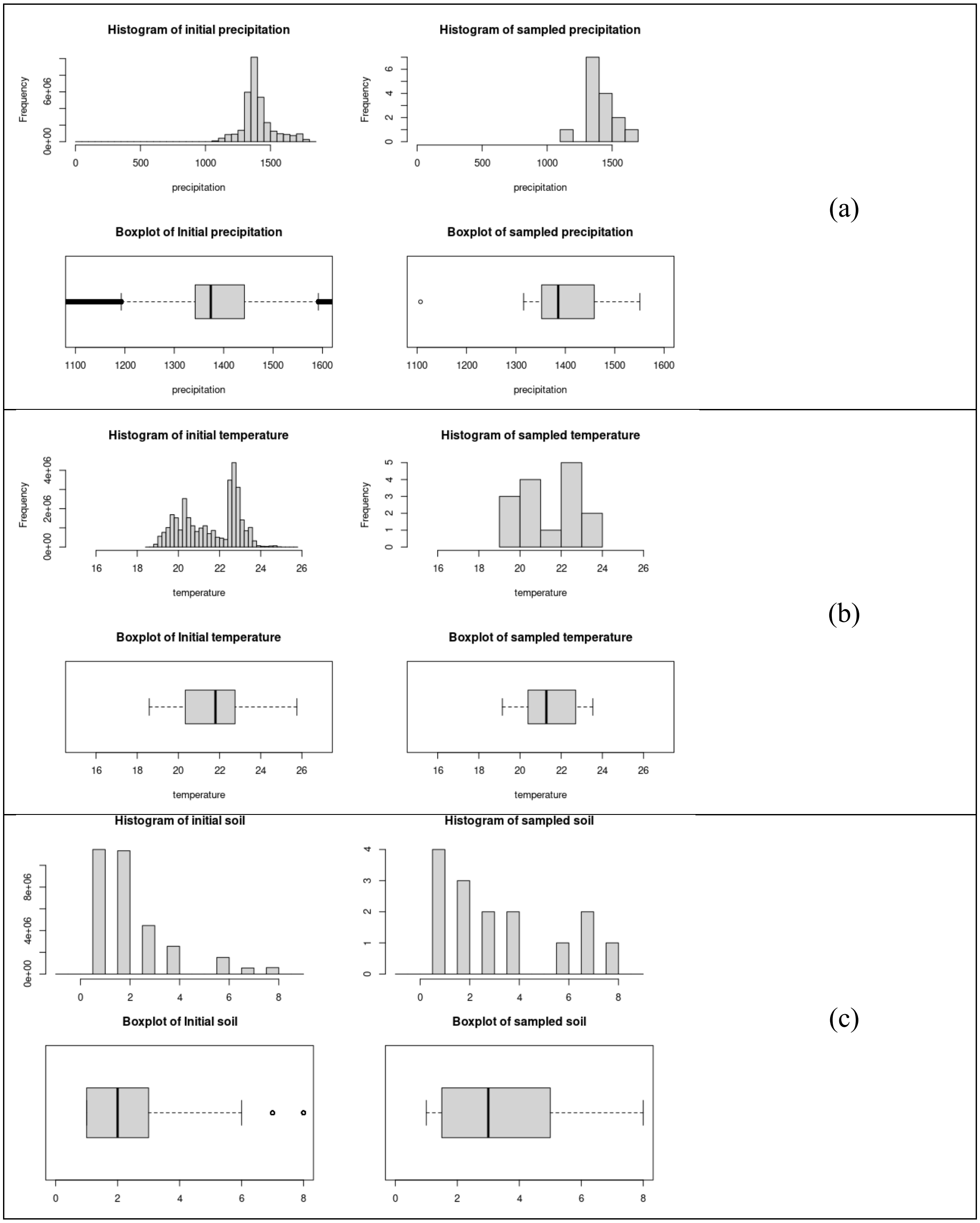

Fig 4. Distribution of climate and soil attributes among the population (the entire state of Florida) and sample (selected points by cLHS). (a) annual total precipitation; (b) monthly mean temperature; (c) soil hydrological groups.

5.2 Soil organic carbon and nitrogen stocks

Twenty farms near the previously defined locations were sampled, including up to five different land uses within each farm (Figure 4).

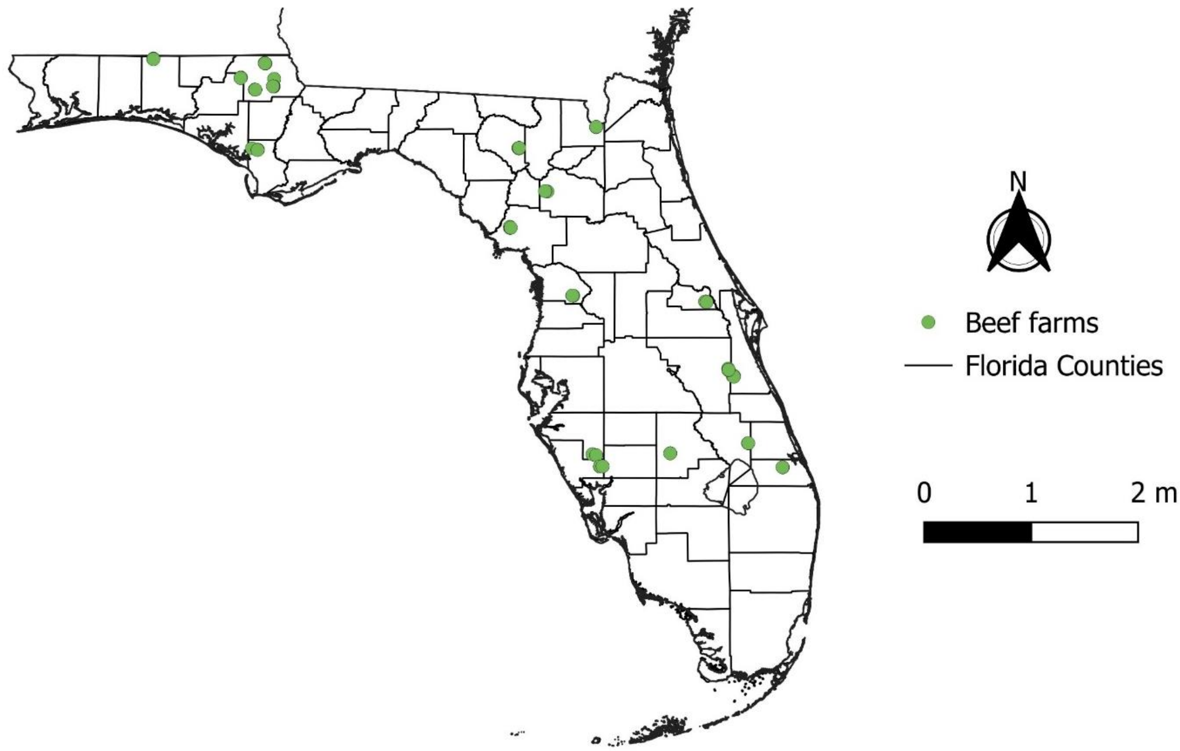

Figure 4– Soil sampling map to access soil organic carbon in beef cattle operations across Florida.

The total soil organic carbon and nitrogen stocks across Florida beef cattle farms are presented in Table 1.

Table 1 – Cumulative soil organic carbon and nitrogen stocks across Florida beef cattle farms by soil depth.

	Crop	Grazing	Hay/Baleage	Low-Input	Native/Rangeland	Pine-tree	P-value
SOC stock (Mg ha^{-1})							
0-6 in	9.87	12.28	12.74	13.31	16.12	10.30	0.450
0-12 in	18.82	26.99	24.59	23.56	26.93	22.34	0.851
0-36 in	35.5	46.0	47.2	36.8	40.6	40.3	0.768
N stock (Mg ha^{-1})							
0-6 in	4.19	4.24	4.23	4.08	4.22	4.29	0.659
0-12 in	8.06	8.13	8.09	8.00	8.29	8.38	0.442
0-36 in	15.6	15.7	15.5	15.7	16.1	16.3	0.457

Soils of Florida beef cattle farms are storing, on average, 41 Mg ha^{-1} of SOC and 16 Mg ha^{-1} of N with no statistical difference among land uses. Deep soil layers (12-36 in) are storing 42 and 48% of the total SOC and N, respectively. The spatial distribution of SOC in Florida is currently under analysis for further reporting.

5. Outcomes and their potential benefits

A comprehensive assessment comparing different land uses in Florida beef cattle farms will provide information on how much carbon is potentially stored, as well as the potential of beef cattle operations to mitigate greenhouse gas emissions, promoting the Florida beef cattle industry. Additionally, the project will generate baseline SOC stocks and uncertainty maps for grazing lands in Florida. The maps generated in this study will provide a deeper understanding of the spatial distribution and uncertainty of SOC stocks estimates. By pinpointing potential areas with hotspots and coldspots of soil carbon storage services, these maps will enable policy makers and land managers to target critical locations requiring in-depth soil carbon assessments and prioritization to restore, preserve, and, where necessary, enhance soil carbon storage, a critical ecosystem service provided by grazing lands.

The maps could also be used as extension materials that support agricultural and environmental applications at farm, county, and regional levels. We foresee that the maps could be updated with data from future soil sampling and be made interactive to meet stakeholder demands in the future. Furthermore, our replicable and spatially explicit methodology improves rapid SOC stocks mapping over large areas, given the nearly global availability of earth observation data and spatial covariates. The presented geospatial artificial intelligence-based methodology has great potential to be used in future soil-related ecosystem service accounting and inventories, providing the necessary spatial information for economic valuation of ecosystem services.

Results of this proposal will be disseminated in field days organized at each location. We will also deliver the results in extension reports and scientific articles in peer-reviewed journals and present at the FCA Annual Convention in 2024.

6. References

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Invoice Period:	03/01/2024 - 07/31/2024
Principal Investigator:	Batista Dubeux Jr.,Jose Carlos
Award Begin Date:	10/30/2023
Award End Date:	07/31/2024
UF FEIN:	59-6002052

Sponsor Award ID:	12
Award Title:	Digital soil carbon storage and sequestration mapping in Florida grazinglands through spatial sampling and machine learning methods
Award Amount:	$65,685.00

Invoice #	I000130456
UF Award #	AWD15832
Primary Project #	P0325272
Primary Department:	60770000
Current Invoice Amount:	$51,447.88

Description	Current	Cumulative
Personnel - Salary	$14,088.88	$23,998.23
Personnel - Fringe Benefits	$2,884.75	$4,437.32
Materials and Supplies	$7,453.33	$7,476.32
Contractual Services	$17,044.50	$17,044.50
Other Expenses	$443.91	$534.81
Domestic Travel	$4,020.21	$4,020.21
Direct Cost	$45,935.58	$57,511.39
Facilities and Administrative Costs	$5,512.30	$6,901.41
Total	$51,447.88	$64,412.80

For billing questions, please call 352.392.1235
Peterson,Nathan Kyle npeterson82@ufl.edu
Please reference the UF Award Number and Invoice Number in all correspondence

By signing this report, I certify to the best of my knowledge and belief that the report is true, complete, and accurate, and the expenditures, disbursements and cash receipts are for the purposes and objectives set forth in the terms and conditions of the federal award. I am aware that any false, fictitious, or fraudulent information, or the omission of any material fact, may subject me to criminal, civil, or administrative penalties for fraud, false statements, false claims or otherwise. (U.S Code Title 18, Section 1001 and Title 31, Sections 3729-3730 and 3801-3812).

Payment History	
Cumulative Invoices:	$64,412.80
Payments Received:	$12,964.92
Outstanding Balance:	$51,447.88
Note: Outstanding balance includes current invoice amount	

Nathan Peterson

Certifying Official

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Project ID	Deptid	Department Name	Current	Cumulative
P0325272	60770000	AG-NFREC-QUINCY	$39,760.16	$47,030.91