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Farming shallow soils: Impacts of soil depth on crop growth in the Everglades Agricultural Area of Florida, USA

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A R T I C L E I N F O

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Food safety

A B S T R A C T

Context: Over half of the US's sugarcane production comes from the Everglades Agricultural Area (EAA) in Florida (USA). However, the loss of organic soils due to oxidation, which results in the gradual reduction of soil depth, poses a significant concern for the future of agriculture throughout the EAA. Understanding the relationship between soil depth and crop production in the EAA is critical to developing sustainable and profitable farming practices in the region.
Objective: This study aimed to assess the depths of organic soils in the EAA and monitor the growth of sugarcane to elucidate the relationship between crop growth and soil depths.
Methods: The soil depth of five locations spanning a total area of 90 ha were surveyed. The sugarcane yield was estimated using the Normalized Difference Vegetation Index (NDVI) derived from publicly available Landsat 8 satellite images.
Results: The soil survey revealed considerable spatial variation in soil depths, ranging from 10 to 105 cm with an average of 51 cm. Over half of the study area had soil depths below 50 cm, while only 11.9 % of the area had soil depths exceeding 80 cm. Multiple linear regression analysis indicated sugarcane variety and age significantly impacts the yield. However, no significant relationship was found between soil depth and sugarcane yields, which can be attributed to the ample availability of nutrients and water in the region, coupled with advancements in agricultural technologies such as stringent soil testing for nutrient recommendations and effective plant breeding that address the constraints posed by shallow soils.
Conclusions: The undetectable threshold for soil depth where crop yields decline may be due to numerous reasons including dataset constraints, and modelling limitations. For sugarcane production to be sustainable and profitable in the region soil loss of Histosols in the region warrants further research. Proactive interventions and conservation farming practices are imperative to mitigate soil loss within the region.
Implications: The outcomes of this study furnish valuable data to support decision-makers in policy formulation, with significant implications for food security and environmental sustainability.

1. Introduction

Over half of the United States' sugarcane is produced in the Everglades Agricultural Area (EAA) (NASS-USDA, 2023). However, the EAA is predominantly covered by Histosol soil, which is prone to soil loss and land subsidence due to oxidation after drainage (Rodriguez et al., 2020). As a result, soil depletion is an ongoing threat to crop production across the region. For example, soil depth in the EAA has been lost at a rate of 0.66 cm per year and is estimated to decrease another 36 cm through 2068 (Rodriguez et al., 2021). In some areas of the EAA, the soil has

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already been depleted to bedrock, revealing a visual reminder of how soil loss shapes the future of EAA agriculture, food security, and local farmer income.

The connection between deeper soils (i.e., increased depth to bedrock) and improved crop production has been documented worldwide (e.g., (Mbagwu et al., 1984; Liu et al., 2013; Kopittke et al., 2019). Soil depth defines plants' available root space and soil volume from where plants meet their water and nutrient demands. Shallow soil depth and subsequently inadequate nutrients and water, can restrict crop yields (Gardner et al., 1999). Even with sufficient water and nutrient availability in shallow soils, the physical restriction of root elongation can limit plant growth (McConnaughay and Bazzaz, 1991; Passioura, 2002). Furthermore, soils with greater depth generally provide more mechanical support to crops, especially for tall field commodities such as sugarcane, so they are less susceptible to damage from windstorms or drought (Rajakaruna and Boyd, 2008). It is usually understood that deeper soils are more hospitable to healthy crops, whereas shallow soils generate more tremendous plant stress due to growth-limiting factors (De la Rosa et al., 2000; Narayan and Lal, 2006).

Most studies have observed the relationship between soil depth and crop productivity using traditional methods (e.g., in-situ sampling and laboratory analyses), which are time-consuming (i.e., require at least one growing cycle) and spatially limited (i.e., specific to localized sampling). However, remote sensing has offered a rapid and efficient way to provide crop growth information across broader spatial scales using ground-based sensors, drones, and satellites (Berger et al., 2019), allowing agricultural research to be conducted in greater temporal and spatial scales (Launay and Guerif, 2005). The Normalized Difference Vegetation Index (NDVI) derived from satellite images is most commonly used as a major indicator to measure the status and biomass of cultivated crops (Li and Chen, 2011; Huang and Han, 2014; Wójtowicz et al., 2016; Li et al., 2019; Shammi and Meng, 2021). Numerous comparative studies have consistently demonstrated that the NDVI exhibited the strongest correlation with ultimate crop yields (Moulin et al., 1998; Bolton and Friedl, 2013; Hu et al., 2022). Yet, few studies have applied remote sensing indicators such as NDVI to investigate the effect of soil depth on crop growth status, leaving a critical knowledge gap in understanding the broad-scale impacts of soil depth on crop production.

85.4 % of the 280,000 ha of EAA's farmland is used to grow sugarcane cultivars and the remaining was grown in rotation with winter vegetables and rice (USDA, 2022). Understanding the relationship between soil depth and sugarcane production in the EAA is critical to developing sustainable and profitable farming practices for the region, as well as other locations with exposed Histosols. Here, we leverage a long-term study at the University of Florida - Everglades Research and Education Center (EREC) to provide unique insights into the impacts of soil depth on sugarcane production across 90 ha from 2014 to 2021. We observed sugarcane established across different planting and harvest times and used a regression approach to quantify correlations between in-situ soil depth and sugarcane yield estimated from remote sensed NDVI.

2. Method and materials

2.1. Study area

This study was located within the EAA (Fig. 1b, c) on experimental farmland managed at the University of Florida EREC in Belle Glade (80°37′55″W, 26°40′3″N). This region has a tropical climate, with average temperatures ranging from 22 to 24 °C and an average annual rainfall of approximately 1270–1520 mm (PRISM-Climate-Group). The rainy season between May and October accounts for 75 % of the yearly precipitation (Schade-Poole and Möller, 2016). The local landscape is regionally flat and low-lying, with an average elevation of 4.5 m (FDEP, 2017). Soil type is entirely Histosol (Watts and Collins, 2008), with over 85 % organic matter by weight (Daroub et al., 2011), and is underlain by impermeable limestone. Land subsidence due to soil loss at EREC has measured 1.9 m from 1924 to 2019 (Bhadha et al., 2020).

Five fields from the experimental farmlands were selected due to their data availability and harvested condition at the time of in-situ soil depth sampling (i.e., fields were accessible without plant cover). Each plot had a length of 900 m and a width of 200 m, totaling 18 ha (Fig. 1d). Historically, the 90-hectare study fields were documented as being covered by Pahokee muck in 1978, with average soil depths ranging from 91.4 to 129.5 cm; they ultimately evolved to Lauderhill muck (50.8–91.4 cm depth) by 1988 (Cox et al., 1988).

Sugarcane has consistently grown across the five fields (A, B, C, D, and E) with two growing seasons: plant cane (planted in November and harvested after 15 months) and ratoon cane (grown from the remaining plant material after plant cane harvest; harvested after a 10–12 month growing season starting in March). Typically, 3–5 ratoon cane succeed the plant cane, followed by a summer fallow period (Jan-Oct), where rotation crops of corn, and rice were planted with a 120-day growing season (Figure S1 in supplemental information). The Sugarcane varieties cultivated from January 2014 to October 2021 include CPCL02–0926, CP96–1252, CP88–1762, MIXED-999, MIXED-1000. Fertilizer (phosphorus and potassium) was applied before each sugarcane planting, and the amount varies based on the soil test result each year. Fields were irrigated using sub-irrigation practices, accomplished by raising lateral ditch water levels to allow the sub-surface seepage of water into the field soil profile. Conversely, fields were drained by lowering ditch water levels.

Daily solar radiation (SR) data was collected from the Florida

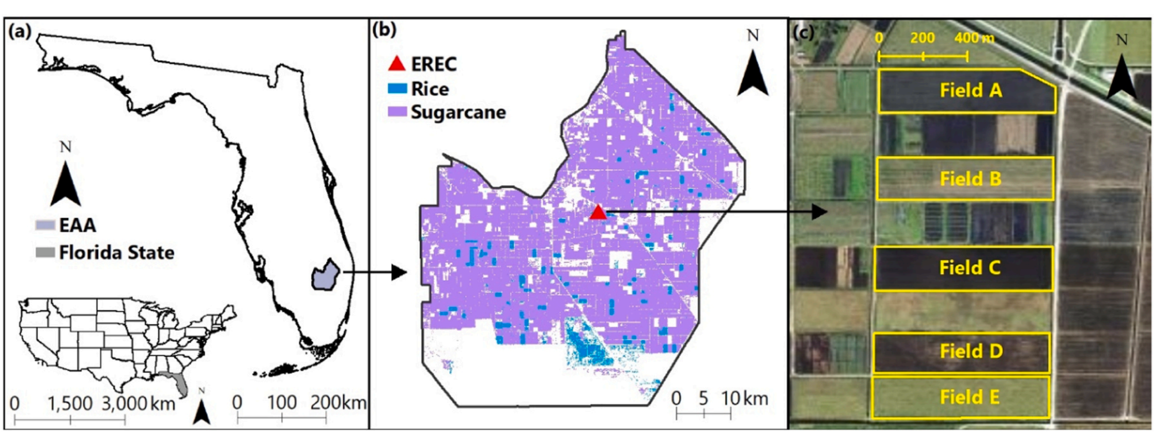

Fig. 1. Geographic location of (a) Florida, site map, and the Everglades Agricultural Area (EAA); (b) the study site (triangle) within the boundary of the EAA; and (c) Fields A to E at the study site. The cultivation distribution of sugarcane is based on the cropland data from the 2016 (NASS-USDA, 2023) cropland data layer.

Automated Weather Network (FAWN), with the weather station situated between fields B and C. The SR ranged from 10 to 25 MJ/m^2 over the period from January 2014 to October 2021 with an annual cycle (Fig. 2). The highest values typically occurred in the summer months (May to August) each year.

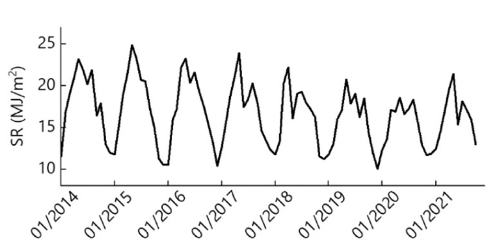

Fig. 2. Temporal variation of daily solar radiation.

2.2. Soil depth sampling and interpolation

Soil depth measurements were collected in 2021 across the five fields using a 30.5 m by 30.5 m grid. Measurements were collected using a 1.5 m sharpened steel rod inserted vertically into the soil down to the bedrock, so the total soil depth was measured and recorded. A total of 591 measurements were collected across the fields.

The soil depth data obtained from the survey were interpolated using the kriging method within ArcMap 10.8.1 (Esri, US). The most suitable kriging model among ordinary, simple, universal, and disjunctive kriging was determined by comparing their accuracy statistics provided by the Geostatistical Analyst of ArcMap. The root mean square error (RMSE) values for each method ranged from 13.94 to 14.18, demonstrating close similarities in performance. Consequently, ordinary kriging was selected due to its adaptability in parameter adjustments based on data characteristics (Figure S2 in supplemental information) (Cressie, 1990). This method estimates the spatial value of an unmeasured point, x_0, by using the known measured values. The estimated value, $Z(x_0)$, is calculated as the linear sum of the measured values at adjacent positions x_i (Eq. 1):

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{1}$$

Here, $Z(x_0)$ was the estimated value at the unmeasured position x_0, $Z(x_i)$ was the measured value at the position x_i, n was the number of adjacent observations used for the prediction, and λ_i was the weighting coefficient from the measured position x_i to x_0, which is given by (Eq. 2):

$$\lambda_i = \sum [\gamma(h_{0i})/\gamma(h_{ij})] Z_i \tag{2}$$

Where $\gamma(h_{0i})$ was the semivariance between the unsampled location x_0 and the observed location x_i, and $\gamma(h_{ij})$ is the semivariance between the observed location x_i and x_j. In this study, the exponential semivariogram model was used to calculate the semivariance (Eq. 3):

$$\gamma(h) = c_0 + c[1 - \exp(-3\frac{h}{\alpha})] \tag{3}$$

Where c_0 is the y-intercept of variogram, c is the sill variance, h is the distance between the unsampled location and the observed location, α is the range of distance parameter, and 3 is a constant that ensures that the semivariance is positive. Cell size (X, Y) of interpolated rasters was set as 7.09 m, 7.09 m by default. Refer to Wackernagel (1995) for more details about ordinary kriging.

2.3. Normalized difference vegetation index

United States Geological Survey Landsat 8 (Level 2, Collection 2, Tier 1) images from Path 15, Row 42 were collected and processed through Google Earth Engine (GEE) in 170 km by 183 km scenes with a pixel size of 30 m for dates starting in January 2014 through October 2021. These images are considered analysis-ready because they contain atmospherically corrected surface reflectance data, which account and correct for aerosol scattering and thick clouds.

For each month of the time series starting in January 2014 and ending in October 2021, the image sets were filtered, and NDVI bands were added using a normalized difference function with band 5 (near infrared surface reflectance) and band 4 (red surface reflectance). The NDVI was mapped on the image set, and the maximum NDVI was retrieved using the high-quality mosaic function in GEE, for a total of 94 monthly images. NDVI quantified the vegetation density and was defined as (Eq. 4):

$$NDVI = (NIR - Red)/(NIR + Red) \tag{4}$$

Where NIR and Red referred to the reflectance measurements acquired in the Near Infrared and Red light, respectively. NDVI values ranged from −1–1, with higher values relating to a greater density of green vegetation up to full coverage, while −1 indicates the absence of vegetation (Gessesse and Melesse, 2019).

These images were exported from GEE to Google Drive as GeoTiff images and then imported into ArcGIS 10.8.1 (Esri, US). Here, they were screened, and clouds were manually removed to exclude pixels that were not clear or were covered by clouds. This step reduced noise in the data by removing mixed pixels and registration errors. To spatially align the NDVI and soil depth layer, a points layer was created from the soil depth raster using the center location of each cell. NDVI values were then attributed to the points layer for each raster and exported as a readable data table (Fig. 3).

2.4. Sugarcane yield estimation from NDVI

The sugarcane yields from 2014 to 2021 for fields A through E were estimated using the SiPAR model (Hu et al., 2022). This model incorporated an enhanced weighting factor (α) derived from the NDVI to reflect potential stem growth rates and used intercepted photosynthetically active radiation (iPAR) as a constraint factor:

$$\widehat{SY} = \beta \times \sum_{t=1}^{T} \alpha_t \times iPAR_t \tag{6}$$

$$\alpha_t = e^{\lambda \times \omega_t} - 1 \tag{7}$$

$$\omega_t = (NDVI_t - NDVI_{\min})/(NDVI_{\max} - NDVI_{\min}) \tag{8}$$

$$iPAR_t = \varepsilon_b \times (1 - e^{-ki \times LAI_t}) \times SR_t \tag{9}$$

Where β is a calibrated parameter set to 0.41 to minimize the RMSE between the estimated and measured sugarcane yields; λ is the model parameter set to 1.85; ω_t is the normalized NDVI at the t^{th} day; $NDVI_{\min}$ and $NDVI_{\max}$ are the minimum and maximum NDVI and set to 0.11 and 0.99, respectively; ε_b is the ratio of PAR to SR, and it is widely set to 0.5; ki is the light extinction coefficient and is set to 0.65. Note that, except β, the model parameters above were directly taken from the study conducted by Hu et al. (2022) at the EAA without any changes.

Leaf area index (LAI) was calculated from NDVI data using a hyperbolic function (Hu et al., 2021):

$$LAI_t = \sqrt[5]{20 \times \omega_t/(1 - \omega_t)} \tag{10}$$

To validate the SiPAR model performance, the estimated yields at different pixels within each field were averaged and compared with the yield data collected from Sugarcane Growers Cooperative of Florida (Table S1 in supplemental information). Fig. 4 presents the predicted sugarcane yield against measured data at field A-E from 2014 to 2021. The coefficient of determination (R^2) is 0.501, and the Root Mean Square Error (RMSE) is 13.9 Mg/ha.

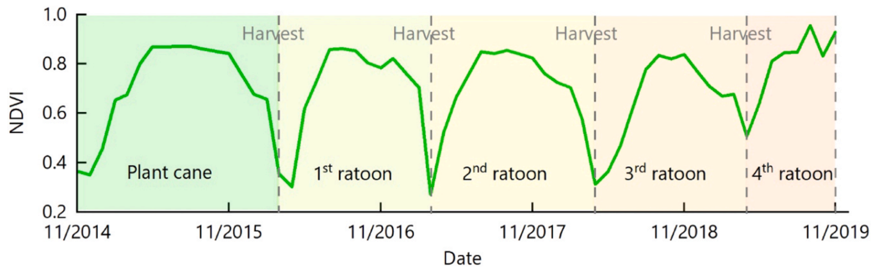

Fig. 3. The temporal variation of NDVI for a representative pixel.

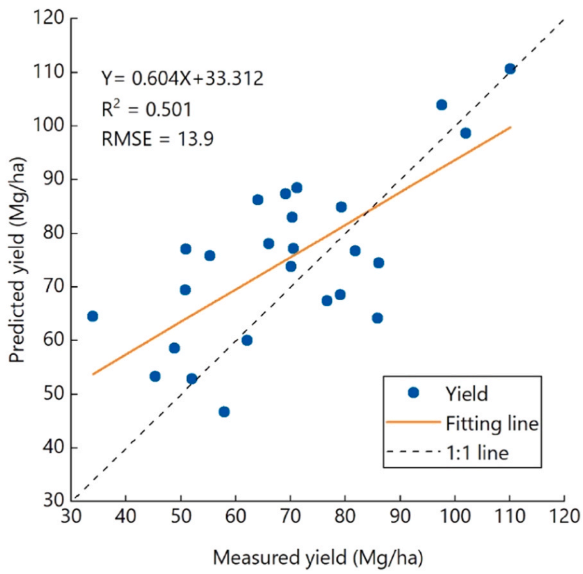

Fig. 4. Comparison of predicted and measured sugarcane yields for fields A-E (2014–2021).

2.5. Statistical analysis

Multilinear regression was used in IBM SPSS Statistics 20 to identify the impact factors of sugarcane yield, the independent variables tested including sugarcane variety, age (plant cane, ratoon cane) and soil depth. In addition, a one-way analysis of variance (ANOVA) was used to determine if there were significant differences in yield performance within sugarcane varieties and cane age categories.

3. Results

3.1. Soil depth distribution in agricultural fields

A total of 903 soil depth cells were extracted from the interpolated map. Soil depth across the five fields (A-E) ranged from 10.2 to 105.0 cm, and the average soil depth for fields A-E was 46.5, 55.9, 43.1, 35.7, and 77.2 cm, respectively (Fig. 5a). Approximately 50.3 % of the study area had soil depths under 50 cm, and 37.8 % had soil depths of 50–80 cm. Only 11.9 % of the area had soil depths above 80 cm (Fig. 5b).

3.2. Sugarcane yield distribution in agricultural fields

Fig. 8 shows the interpolated distribution of sugarcane yield across agricultural fields A to E from 2014 to 2021. The sugarcane yields ranged from 23 Mg/ha to 128 Mg/ha. The highest average yield, 122 Mg/ha, was recorded in 2017 on field C (Fig. 6d), which featured the plant cane of the CP-96–1252 variety. Conversely, the lowest average yield, 51 Mg/ha, was recorded in 2017 on field B (Fig. 6d), which was the 4th ratoon cane of the MIXED-999 variety.

3.3. Impact factors on sugarcane yield

The multiple linear regression analysis indicated that there's no significance between soil depth and sugarcane yield ($p < 0.05$). However, sugarcane variety and age significantly impact yield values, with cane age having a more substantial negative impact (Table 1). The results of one-way ANOVA showed that CPCL02–0926 and CP96–1252 had higher yields averaging 82 mg/ha compared to other varieties (Table 2). The average yield of plant sugarcane was 101.48 mg/ha, which was significantly higher than that of rotated sugarcane, and the yield declined with the age of the sugarcane from the 1st rotation to the

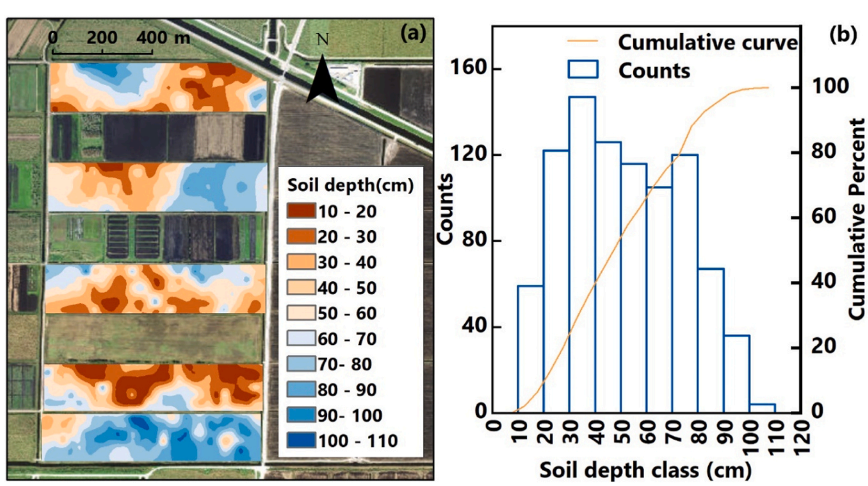

Fig. 5. Kriging interpolation map of soil depth (a) and histogram and cumulative curve of soil depth classes based on soil depth survey for five fields (b).

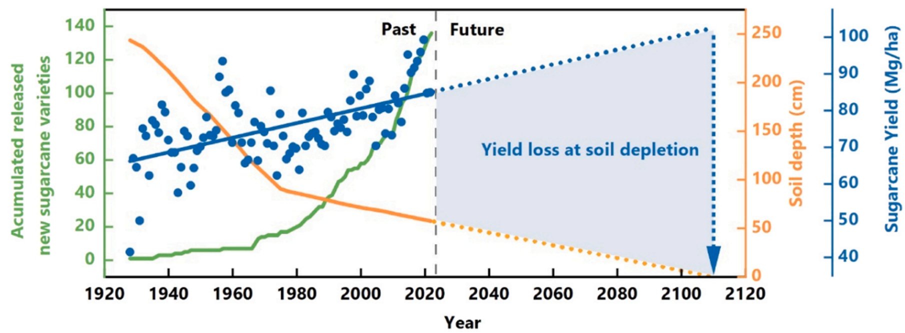

Fig. 8. Released sugarcane cultivars, sugarcane yield and soil depth changes from 1928 to 2020 in the EAA and sugarcane yield loss at soil depletion of EAA. The sugarcane cultivars data comes from Zhao (2020), soil depth data of EAA from Rodriguez et al. (2020), and sugarcane yields data of EAA from USDA NASS (NASS-USDA, 2023).

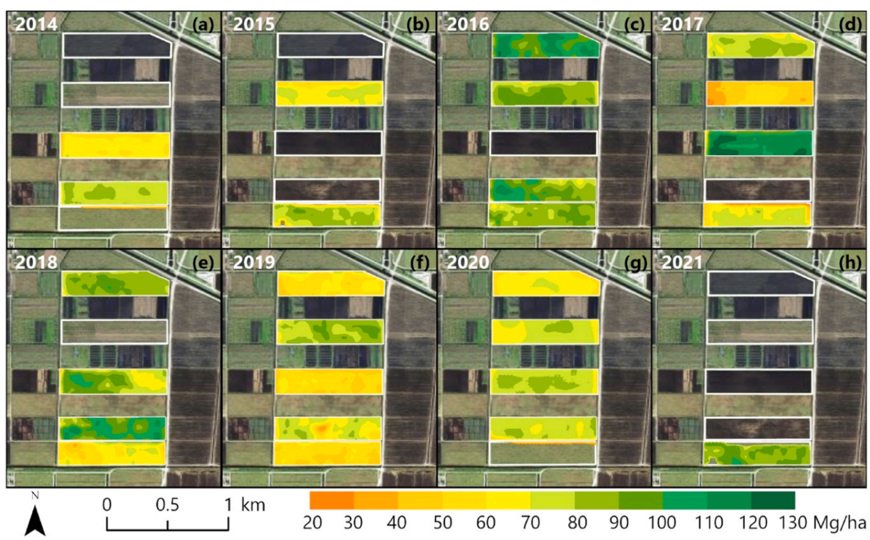

Fig. 6. Interpolated sugarcane yield distribution in agricultural fields A to E from 2014 to 2021. The blank area means the fields were planted with other crops such as rice and corn.

Table 1
Multiple linear regression analysis of factors influencing sugarcane yield.

Model	Unstandardized Coef.		Standardized Coef.	t	Sig.
	B	Std. Error	Beta		
(Constant)	110.37	0.746		148.01	0
Cane variety	−1.1	0.136	−0.086	−8.09	<.001
Cane age	−10.05	0.149	−0.724	−67.56	0
Soil depth	0.026	0.021	0.013	1.22	0.223

Note: The cane age increases progressively from plant cane to the 1st, 2nd, 3rd, and 4th ratoon canes.

Table 2
Average sugarcane yields for different varieties and age.

Variety	N	Average yield	Age	N	Average yield
CPCL02–0926	673	82.96^{a}	Plant cane	371	101.48 ^{A}
CP96–1252	1503	82.36^{a}	1st Ratoon	1053	85.38^{B}
CP88–1762	530	76.59^{b}	2nd Ratoon	1077	78.63 ^{C}
MIXED−999	1449	67.65^{c}	3rd Ratoon	871	70.94^{D}
MIXED−1000	151	59.97^{d}	4th Ratoon	934	57.03^{E}

Note: Different superscript letters indicate significant differences in average yields within variety and age group ($p < 0.05$).

4th rotation.

4. Discussion

4.1. Inherent qualities of Histosol soils

The lack of a relationship between soil depth and sugarcane yield demonstrates that the current soil depth has no effect on crop production in the EAA. This result challenges the broader knowledge that more soil depth can lead to greater crop production as plant growth is not limited by constrained soil conditions (e.g., root elongation and soil moisture). We suspect this is mainly due to the soil nutrient levels in EAA that can be inherently high, where the amount of nutrient mineralized from highly organic matter (> 70 %) is substantially greater than what crops consume (Rodriguez et al., 2021). Here, the local Histosols soil provides the primary nitrogen (N) and phosphorus (P) source from the mineralization of EAA soil organic matter for crops in the EAA (Porter et al., 1992; Sanchez and Porter, 1994). Although no N fertilizer was applied for sugarcane in the area over the decades, the N supply still occurs in adequate amounts for plants, even in shallow soils with a depth of 15–30 cm (McCray et al., 2016; de de de Camargo Santos et al., 2022), This maybe due to the presence of legacy N in the soil from other vegetable production that do require N inputs. For example, Santos et al. (2020) confirmed that soil depth had no effect on the nutrient concentration in the soil as well as N content in crops' leaves by conducting experiments on 30 commercial sugarcane fields in the EAA.

Simultaneously, the utilization of a "calibrated soil test" program within the framework of "Best Management Practice" (BMP) in the EAA has held a significant role as a tool for managing nutrient levels in field crops, which is required for each grower to integrate into their farms (Sievers et al., 2002). The process of soil testing evaluates the plant-available nutrient status, salinity, and elemental toxicity of the soil. This approach offers a quantifiable foundation for making informed decisions about soil management, ensuring that crops receive the precise nutrients essential for their growth. The soil tests for five study fields (Field A-E) were provided by the Everglades Soil Testing Laboratory (ESTL) at the EREC in Belle Glade, Florida (Table S2 in supplemental information), undertakes the analysis of soil test outcomes to formulate precise fertilizer recommendations tailored to the cultivation of crops within the organic soils of the EAA. Consequently, despite the gradual reduction and large spatial variations in soil depth across the EAA, the nutrient supply remains adequate to sustain the growth of crops.

In addition, crops themselves respond dynamically to soil conditions. The root system serves as a vital bridge between the crop and the soil, continuously absorbing nutrients and water from the soil to support its growth and significantly influencing crop performance and yield. Differences in root density and morphology were observed through a profile investigation of sugarcane roots at a mature stage in two different soil depths (74 cm and 36 cm) within the research area (Fig. 7). In both soil depths, sugarcane roots extended downward until encountering the limestone. However, roots in the shallower soil exhibited higher density within the same horizontal plane compared to those in deeper soil. Additionally, the roots in the shallower soil developed numerous lateral branches, playing a crucial role in facilitating nutrient and water absorption and providing structural stability to the plants.

4.2. Modern technologies and farming practices

The sugarcane grown in the EAA are particularly well-suited to accommodate the decreasing soil depth and have been genetically improved by breeders. Desirable genes (e.g., for disease resistance, high sugar content, flood tolerance, and yield) were selected and transferred to commodities based on Florida conditions (Edmé et al., 2005). Unlike vegetables, sugarcane has greater tolerance to water and can be grown in soils of only 15–20 cm depth in the EAA (Snyder, 2005). Moreover, breeders' cross high-yielding sugarcane varieties with disease-resistant ones to improve production. The CP (Canal Point) cultivars are the most representative, accounting for roughly 90 % of all cultivars grown in Florida (Comstock et al., 2004; Schmitz and Zhang, 2019). CP 96–1252 is one of the top-performing and most commonly grown commercial sugarcane varieties in Florida, successfully cultivated in both muck and sandy soils (VanWeelden al., 2020). About 69 % of the increase in sugarcane yield in the EAA was attributed to genetic improvement (Edmé et al., 2005), and the remaining 31 % of yield gain can be associated with improved management practices.

Less water retention capacity and inadequate water supply ability during droughts common to other shallow soils are often considered limiting factors for crop growth (Snyder, 2005). However, water control facilities were installed in South Florida after the 1947 hurricane to adjust water tables through a system of on-farm canals/ditches and pumps for drainage and sub-irrigation purposes (Snyder and Davidson, 1994). With improved handling of water in South Florida on a quantity basis, floods and droughts have been mitigated, and Everglades farmers have been able to consistently maintain desired water tables that maximize crop production (Snyder et al., 1978).

The financial commitments to improved management in crop production within the EAA of South Florida are substantial and multifaceted, encompassing breeding programs and comprehensive water management projects. Breeding initiatives, such as those by the Canal Point (CP) program, require significant investment to develop sugarcane varieties that are disease-resistant, high-yielding, and adaptable to local conditions. Although specific costs are not always detailed, these programs are supported by a combination of public and private funding. On a larger scale, water management projects like the EAA Reservoir Project, part of the Comprehensive Everglades Restoration Plan (CERP), illustrate the immense financial efforts required. This project alone is estimated to cost around $3.5 billion and involves constructing a 240,000 acre-foot reservoir and a 6,500-acre stormwater treatment area (STA) to improve water storage and quality (SFWMD, 2018), highlighting the significant investments needed to ensure sustainable and profitable agricultural practices in the EAA.

Fig. 7. Sugarcane root distribution at mature stage in deep (a) and shallow soil profile (b) of the study fields.

4.3. Sugarcane production in the EAA

This is a particularly notable observation as yields have continued to increase although the ongoing decrease in soil depths over time. Despite a significant reduction in the average thickness of soils in the EAA by 184.6 cm from 1928 to 2020 as reported by Rodriguez et al. (2020), agricultural advancements have results in increased productivity. For example, the introduction of over 130 sugarcane cultivars since 1920 has significantly contributed to a notable increase in overall sugarcane yields by 57.9 Mg/ha over the same period (Fig. 8). However, our study indicates there may not be a detectable threshold at which soil depth becomes prohibitive to crop production in the EAA, as yield values were comparable even in the shallowest of soils. If these trends continue, global agricultural markets accustomed to US sugar access could face supply disruptions as sugar production may remain locally high until it is entirely unproducible (i.e., the soil has been depleted).

While this effectively has not been a major discussion outside of the EAA to date, soil depletion has become increasingly more prevalent in recent years as EAA soil depths continue to decline toward depletion. Moreover, additional challenges like natural disasters and volatile global markets (e.g., (Glaz and Gilbert, 2006)) further stress sugar production in this region; Palm Beach County which includes EREC and much of the EAA has lost over 30 % of its sugarcane area (nearly 36, 000 ha) since 1999 (NASS-USDA, 2023). As the trends of increased yield despite decreased soil depth continue, coupled with our observations that soil depth has had no impact on production. In other words, since having no detectable soil depth threshold at which crop production declines, the risk of abruptly lost sugar production in the region and US continues to inflate with business-as-usual practices (Fig. 8).

4.4. Linear regression between soil depth and NDVI for corn and rice

Corn and rice were rotated during the sugarcane fallow period from 2014 to 2021. While their yields were not estimated in this study, the relationship between soil depth and maximum NDVI for corn and rice across different fields and years was examined (Fig. 9), as previous study indicates that the maximum NDVI value during the growth season exhibited the strongest correlation with the ultimate crop yields (Huang et al., 2013; Fernandes et al., 2017; Roy and Yan, 2020). For corn, only field A in 2014 and field E in 2019 exhibited a slight but significant correlation between soil depth and maximum NDVI ($p < 0.01$), with a low R^2 value of less than 0.12 (Fig. 9a). For rice, field A in 2020 and field E in 2019 showed a significant positive relationship ($p < 0.05$), with a relatively low R^2 value of less than 0.04 (Fig. 9b). The nearly horizontal fitting line further evidence the absence of a meaningful correlation between soil depth and crop growth.

4.5. Impacts on crop production and food supply

With soil depth decreasing, agriculture in the region will face increased agricultural investment and heightened environmental risks. Farms experience greater flood risks to their crops' root zones since there is substantial sub-surface seepage between fields or farms, depending on differences in the water table (Yoder, 2019). Less space in the soil profile can be used to store water, and restricted water tables on shallower soils result in reduced sugarcane yields (Glaz et al., 2002). Additional management and structural costs (e.g., adding more field drainage ditches, more water control facilities, and upgrading pumping facilities) are generally required to control water tables and minimize the risk of yield loss.

What's more, cultivation on resource-intensive shallow soils in the EAA requires more environmental-friendly farm practices. Changing cropping patterns may help to integrate agricultural production with natural hydrologic regimes. Rice production, currently grown in rotation with sugarcane on a limited scale in the EAA, has been recognized as a cost-effective method to control soil subsidence and enhance the following sugarcane yields (Porter et al., 1992). Traditional pre-harvest sugarcane burning may not be promoted as it accelerates organic soil loss in the region (Snyder, 2005). Even though shallowing soils may not provide sufficient mechanical support for tall crops, growing sugarcane can be challenging and costly due to soil loss in the coming years. Therefore, efforts should be taken to explore alternative commodities. Flooded rice as a potential crop that can be grown on a large scale in the EAA has become more and more popular (Bhadha et al., 2019).

4.6. Soil depth and subsidence over time

Due to continuous soil subsidence in the EAA over the past decades, our 2021 results indicate that the soils in the five fields at EREC require an updated classification to Dania muck (20.3–50.8 cm average soil depth). If the linear trend of soil loss (0.66 cm/yr) were to continue, another reclassification to Dania shallow (< 20.3 cm) would be needed by the end of the century (Rodriguez et al., 2020).

As soil depth decreases, over half the area of the five fields at EREC will have bedrock outcropping after 75 years. In addition, the near-surface bedrock is covered by a thin layer of organic soil which dries out faster than the surrounding soil, making it susceptible to burning during sugarcane harvests. This leads to an increase in the size of the exposed bedrock areas over time (Snyder, 2005).

4.7. Farming on drained organic soil worldwide

Subsidence has occurred everywhere that organic soils have been drained (Table 3). As one of the remaining drained organic soils in England, East Anglian Fenlands lost most of their peat resources to the point that some areas are no longer recognized as peatlands (Holman

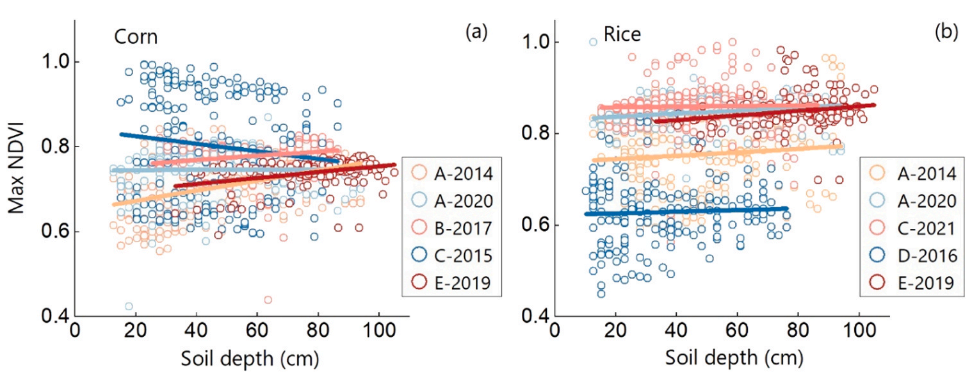

Fig. 9. Maximum NDVI against with soil depth for corn (a) and rice (b) cultivated in different years. The letter in the legend is the fields number. The lines are the fitting lines for each dataset, corresponding to the colors of the respective data points.

Table 3
Drained organic soil distribution and subsidence rate worldwide.

Location	Organic soil drained for Agriculture (km^2)	Subsidence rate (cm/yr)	Time period (yr)	Source
EAA, US	2800	0.66	20 (1998–2018)	(Rodriguez et al., 2020)
England	720	0.51–5.00	84	(Holzer, 1984)
Ireland	896	1.80	47	(Holzer, 1984)
Netherlands	2000	0.99–1.70	100	(Holzer, 1984)
Poland	7620	0.96	50 (1966–2016)	(Oleszczuk et al., 2022)
Sweden	3015	1.50–2.50	-	(Berglund and Berglund, 2010)
Ukraine	5000	2.00	133 (1882–2015)	(Lipka et al., 2017)
Germany	12000	0.27–1.50	90 (1913–2003)	(Kluge et al., 2008)

and Kechavarzi, 2011). Many other countries also suffer soil subsidence, with rates varying from 0.27 to 5.00 cm per year (Table 3). Thus, there is a need for further action to decrease the subsidence of organic soils and to develop effective strategies to address future food security challenges given the uncertainty of how crop production remains sustainable in subsiding environments.

5. Conclusions

This study integrated in-situ soil depth surveys with yields estimated by the remotely-sensed vegetation index (NDVI) to explore the relationship between soil depth and crop growth for sugarcane cultivation in the EAA from 2014 to 2021. Soil depth varied from 10.2 to 105.4 cm across five fields, with 50 % of the soil depth being between 10 and 50 cm. We found no statistically significant relationship between soil depth and sugarcane yield. We attribute this outcome to the region's ample nutrient and water supply, along with advancements in agricultural practices that effectively overcome the limitations of shallow soils, especially the breeding of high-yielding varieties. Based on these relationships, there appears to be no detectable impact on the crop production as soils become progressively shallower. This is contrary to other agricultural systems where declining crop production is observed in shallow soil environments. However, continued farming in the EAA can benefit from best management practices and conservation farming programs within this intensely managed landscape. These findings underscore the need for strategic planning and resource allocation to sustain agricultural productivity while minimizing environmental impact.

CRediT authorship contribution statement

Xue Bai: Writing – original draft, Methodology, Investigation, Formal analysis. **Samuel Smidt:** Writing – review & editing, Project administration, Formal analysis, Conceptualization. **Yuchuan Fan:** Writing – review & editing. **Trista Brophy:** Writing – review & editing, Software, Formal analysis. **Young Gu Her:** Writing – review & editing. **Noel Manirakiza:** Writing – review & editing. **Yuncong Li:** Writing – review & editing. **Jehangir H. Bhadha:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2024.109523.

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